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Evidence Quality, Transparency, and Translucency for Replication in Information Systems Survey Research

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Abstract:

Replicability represents the cornerstone of reliable development in science. In this paper, we develop a framework for enhancing current data-collection practices' replicability in survey research in information systems. To develop the framework, we built on literature, benchmarks of various scientific associations, and a review of policies and best practices in leading business journals. The framework identifies best practices for transparently collecting data, sharing data and methods, and developing high-quality evidence. We analyzed 82 recently published survey research in nine IS journals as a sample that represents high-quality IS research to identify their replicability and found that not one papers provided enough details for replication. We conclude by discussing our framework's implications for researchers, journals, and scientific institutions and the role that these entities can play in enhancing IS research's replicability.

Keywords: Replicability, Transparency, Translucency, Evidence Quality, Information Systems, Survey Research.

1   Introduction

Replicable research findings create a coherent, reliable, and robust body of knowledge (Schmidt, 2009)—
"the cornerstone of science" (Simons, 2014, p. 76). As such, one would expect to find a well-developed
body of research on research replicability. However, the research community has started to discuss
replicability only in recent years, and we still lack related discussions. Recent concerns regarding social
science research replicability (Collins & Tabak, 2014; The Economist, 2013), such as the inability to
reproduce most prior findings in major social science outlets (e.g., Van Bavel, Mende-Siedlecki, Brady, &
Reinero, 2016) and data-falsification scandals (e.g., Fang, Steen, & Casadevall, 2012), stem from
researchers who have poorly deployed the scientific process. For instance, researchers have drifted into
thinking that published data or theory is correct and does not need replication. Furthermore, journals and
scientific communities also have set a sense that only new and novel work can contribute to academia.
Social science scholars have perceived the pitfalls of existing practices and have called for a discourse on
replication. Information systems (IS) scholars have also called for in-depth discussions on the topic
(Dennis & Valacich, 2015; Marsden & Pingry, 2018; Olbrich, Frank, Gregor, Niederman, & Rowe, 2017).

We join this discussion and contribute to IS research's replicability by focusing on survey data collection.
Researchers have relied on survey research to develop many high-range theories, and leading IS journals
publish a relatively large volume of survey research. Thus, survey research has a significant impact on
how IS researchers, at least those who ascribe to the positivist paradigm, perceive the socio-technical
world and explain and predict the mutual impact of technology, individuals, and organizations. However,
despite the potential significant impact that survey research can have, researchers face a high potential
for mistakes and errors in collecting data for such research, which can impact replicability (Collins &
Tabak, 2014; The Economist, 2013; Li, Hu, Xie, & He, 2015; Marsden & Pingry, 2018). Researchers can
impact replicability of survey research in several ways: for instance, researchers may generalize results
despite contextual factors without sufficiently documenting the contextual factors (Lynch, Bradlow, Huber,
& Lehmann, 2015; Stroebe & Strack, 2014), they may use poorly designed data-collection procedures and
practices (Simons, 2014), or they may fraudulently falsify data (Fang et al., 2012).

Replication studies exist on a fuzzy continuum with pure replication and new studies at the two ends and
extension studies in the middle (Berthon, Pitt, Ewing, & Carr, 2002; Toncar & Munch, 2010). A pure
replication study, also known as reproduction, duplicates an original study by keeping all its key
parameters (i.e., theory, context, and method) constant. An extension study replicates an original study by
altering one or more of its key parameters (Berthon et al., 2002). A study is replicable when pure
replications can derive similar findings from a random sample of a population that represents the
population that the original study used (Asendorpf et al., 2013). Also, replicability means that theories
developed in an original study should hold and predict how systems behave in extension studies.

Researchers continue to discuss the challenges associated with literature's replicability (Asendorpf et al.,
2013; Yong, 2012). On one side of the debate, researchers argue the low replicability rate has arisen due
studies' non-replicable nature. They support their position with recent studies that report that researchers
have unambiguously replicated studies in accounting, management, finance, marketing, economics,
sociology, pharmacology, ontology, and biology at a low rate (Chang & Li, 2015; Hubbard & Vetter, 1996;
Martin & Clarke, 2017; McCullough, McGeary, & Harrison, 2006; Van Bavel et al., 2016). On the other side
of the debate, researchers argue that the low replicability rate has arisen due to contextual factors in
populations that impact results. We take a neutral stance without entering the debate. We believe that we
can attribute differences between replication and original studies to arguments on both sides of the debate.

On the one hand, differences can identify new research opportunities by showing variability and the
presence of various moderators that can impact findings in different samples, such as changes in
assumptions and underlying reality over time and disparity in data-analysis methods. On the other hand,
the inability to replicate may stem from poor (and costly in some cases) research practices. For instance,
researchers have estimated that the replicability challenge in pre-clinical research costs US$28 billion
annually in the US (Freedman, Cockburn, & Simcoe, 2015). Therefore, we argue that the academic
community requires replication studies no matter their results. If a replication study fails to reproduce an
original study's findings, its failure can show variability across populations and identify potential
moderators and control variables and extend the literature. Replication failures can also indicate potential
issues in how researchers designed and operationalized an original study. If successful, replication
studies increase confidence in an original study's findings and support its credibility and legitimacy
(Olbrich et al., 2017).

IS research has "a tradition that builds on the transfer and extension of existing knowledge" (Olbrich et al., 2017, p. 2). Thus, IS research has required replication studies to expand. Despite this essential role, IS journals have paid little attention to publishing pure replication studies due to a misconception that replications lack innovativeness and contribution. Nevertheless, replication studies play a significant role in developing IS agenda. Pure replication studies contribute to the field by increasing our confidence in the literature. Extension studies, on the other hand, can serve the IS field by allowing researchers to borrow theories from other fields and extend them to incorporate various parameters in different settings. Therefore, replications can promote "the systematic accretion of valid knowledge through the creation of a research program from an isolated finding" (Berthon et al., 2002, p. 419).

Even though the IS academic community now better knows about the need for replication studies to advance IS research, we still lack research that has examined replicability. On a positive note, *AIS Transactions on Replication Research* has begun a partnership with *MIS Quarterly* to execute the IS Replication Project and plans to measure IS research's replicability by analyzing 25 published studies (Dennis, Brown, Wells, & Rai, 2020). However, the project remains in its early stages. While we did not find a recent study that addresses IS research's replicability, we argue that the IS field, similar to other social science fields, faces opportunities and challenges associated with replicability. Studying and addressing replicability can impact how efficiency we develop IS research by promoting confidence in what we already know and by finding problems and identifying areas with opportunities for further investigation. Therefore, we believe that IS research should facilitate and promote replication.

Facilitating and promoting replication studies depends on researchers, scientific journals, and academic institutions. Researchers need to provide enough details to facilitate future replication studies, journals should actively promote replication studies, and academic institutions should set policies to extend their support to replication research. To this end, we study best practices for collecting survey data, develop a framework for collecting survey data in a replicable way, and suggest policies for researchers to provide details required for future replication and verification studies. We also provide suggestions for journals and academic institutions to support replicability by motivating researchers to do so and facilitating the process for researchers.

This paper proceeds as follows: in Section 2, we review best practices for collecting and reporting on survey data. We also discuss the replicability dimensions for collecting data and review best practices that scientific institutions and leading business journals have developed and adopted for supporting replication. Then, based on the reviewed practices, we then develop a framework. In Section 3, we compare the data-collection practices in a sample of recent survey-based IS publications with the best practices suggested in the framework to identify existing gaps and potential improvement areas. In Section 4, we propose policies for improving replication practices in IS research informed by the framework and the gap analysis. Finally, in Section 5, we conclude the paper.

2   Research Replicability

In this section, we focus on how authors and journals can facilitate replication studies. We first review best practices that authors need to follow to allow others to replicate their studies. We then review how journals and scientific associations develop their policies to enhance replicability and facilitate future replication studies. Finally, we combine our findings and develop a framework to enable researchers to replicate survey research.

2.1   Replication and Data-collection Practices

The poor replicability that researchers reported in various fields (Chang & Li, 2015; Martin & Clarke, 2017; Van Bavel et al., 2016) stems from two sources of systematic errors in research methodology: 1) sampling and data-collection errors and 2) study design and execution errors. To prevent the errors from the first source, researchers should report their studies' parameters. A pure replication needs to use the same sampling technique, data-collection instrument, and data-collection administration procedure in the same population that the original one did. Replicating original research, even with a slight deviation from the original study's data-collection parameters, introduces systematic errors and may lead to substantially different results. The difference exists due to the presence of various effects across different populations that moderate a study's results (Easley, Madden, & Dunn, 2000; Klein et al., 2014). Therefore, to successfully interpret a replication study's results, one needs to be aware of differences between parameters in original and replication studies.

The way in which researchers design and execute a study can contaminate findings with systematic errors. For instance, the increasing competition to publish in top-tier journals and journals' inclination to publish positive findings rather than null hypotheses may encourage various questionable data-collection and -analysis practices (Nosek, Spies, & Motyl, 2012; Świątkowski & Dompnier, 2017). Besides fraud and falsification, "researcher degrees of freedom" impacts results (Simmons, Nelson, & Simonsohn, 2011, p. 1359). Researcher degrees of freedom refers to the freedom that researchers have in making decisions about how to collect and analyze data, such as whether to include a specific measure and control variable in a study (Simmons et al., 2011; Świątkowski & Dompnier, 2017). Due to this freedom, researchers do "not commit themselves to a method of data analysis before they see the actual data" (Wagenmakers, Wetzels, Borsboom, van der Maas, & Kievit, 2012, p. 632). This practice may lead researchers to explore alternative approaches to analyze data and fine-tune the results (Neuroskeptic, 2012). While a subculture that has resulted in some researchers' moral failure and pressure on authentic researchers who get rejections or never submit the results from their work exist, we focus on how replication can reduce the potential impact that researchers' freedom has on publishing false-positive findings. Differences in replication studies' findings can help the academic community identify fraud, falsification, and data and method manipulation or at least can initiate a path to identify potential issues. Therefore, pure replications and extension studies can help to redirect a field's attention.

Subsequently, the question arises as to how one should interpret results that differ between replication and original studies. The literature suggests that journals and original studies should follow certain best practices to reduce the two errors that we mention above, facilitate future replication studies, and enable researchers to interpret replication results. These best practices belong to three categories: evidence quality, transparency, and translucency (Asendorpf et al., 2013; Freese & Peterson, 2017; Guyatt et al., 2008b; Nosek et al., 2012; Rogelberg & Stanton, 2007; Simmons et al., 2011; Świątkowski & Dompnier, 2017).

Evidence quality refers to the level of confidence in a study's findings and impacts implications' usefulness. Transparency refers to clearly documented data-collection and -analysis practices. Finally, translucency refers to sharing data and methods in a limited and controlled way. Light's physical characteristics inspire the latter two definitions: light passes a transparent object, whereas only specific wavelengths can pass a translucent object. Transparent data and procedures means that all readers can see the data-collection and -analysis processes that researchers used. We follow Lombardi and use translucency as a metaphor to express controlled access to data (Lombardi, 2018). In referring to translucent data and procedures, we refer to limitations in public data sharing. Accordingly, translucent data sharing does not mean that authors need to give up their data ownership. Instead, authors need to provide controlled access to data or related statistics for the review process or authentic replication requests.

2.1.1 Evidence Quality

A high-quality inference ensures findings' validity in a population (Asendorpf et al., 2013). A high-quality inference requires one to use high-quality evidence as input (i.e., data collection) and high-quality inference mechanisms (i.e., data analysis methodologies). In this paper, we focus on inference quality's evidence quality aspect as numerous past papers have previously examined methodologies (Palvia et al., 2015, 2004; Pinsonneault & Kraemer, 1993). Evidence quality plays a critical role in replicability, and poorly executing data-collection practices constitutes a barrier to clearly linking raw data to analysis and interpretation and hampers data integrity and verifiability (Frye et al., 2015).

Discussions about evidence quality originated in medical studies since doctors need to rely on studies' findings to make critical decisions. To ensure that enough confidence exists in a study's inferences to support its recommendations, medical scholars created a structured and transparent system to rate evidence quality (Guyatt et al., 2008a). This rating system prevents readers from overly trusting a study's recommendations by factoring the results' statistical power into the rating. This system also ensures that the context in which one uses evidence pertains to the population that the data comes from[1]. As Guyatt et al. (2008b) show in their work, evidence quality depends on how researchers design their data-collection tools and procedures, the quality of the data they collect, and the data's ability to represent a population.

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[1] Medical researchers use this system—the grading of recommendations assessment, development, and evaluation (GRADE)—to rate recommendations developed based on experimental studies (Guyatt et al., 2008a). GRADE uses evidence quality as a measure to identify confidence in recommendations. The system evaluates three factors that have a positive impact and five factors that have a negative impact on the confidence in estimated effect size and suggests a level for evidence quality. This system has guidelines judging the quality of evidence relative to the context that the recommendations developed based on evidence are being used.

Similarly, the literature categorizes evidence quality into three factors: 1) study designs that can introduce methodological error sources (Cavusgil & Das, 1997; Dillman, 2007), 2) unreliable measures that can increase errors (Asendorpf et al., 2013), and 3) non-observation (Groves & Peytcheva, 2008).

First, designing, choosing what content to include in, and delivering a questionnaire impacts measurement errors. A specific delivery medium, such as email and online surveys, excludes audiences with lower computer literacy. Also, some delivery media hinder researchers from ensuring respondents' true identity. Online surveys maintain participant anonymity, which may impact the trustworthiness of the data that one collects from them (Chang & Krosnick, 2009; Kreuter, Presser, & Tourangeau, 2008). For instance, researchers who share a questionnaire with their audience on a social media platform and ask them to share it with other potential respondents lose their control over the audience demographics. This challenge increases when social media users complete the survey to win a monetary reward even if they do not meet inclusion criteria. In addition, evidence quality involves issues associated with designing questionnaires and collecting data (Dillman, 2007). Misstated words and definitions (especially in cross-cultural studies) lead to respondent confusion, inconsistent responses, and missing answers. Moreover, using words that some participants might consider offensive may impact response quality and response rate. Furthermore, privacy concerns and insufficient trust in a study can impact the quality of the responses that researchers receive unless they properly address these issues when administering a survey.

Second, reliability identifies the consistency of measurement model's results across different populations. A reliable measurement model has lower error levels, and one can replicate it in various contexts (Kline, 2015). The error associated with measurement negatively impacts findings' reliability score and reduces their replicability (John & Benet-Martinez, 2000).

Third, non-observation results from three errors: misrepresentation, trustworthiness, and statistical power (Groves, 2006; Groves & Peytcheva, 2008; Lindgren, Markstedt, Martinsson, & Andreasson, 2018; Pinsonneault & Kraemer, 1993). Misrepresentation and trustworthiness can happen when a sample does not correctly represent the population due to non-responses. When analyzing data that non-responses contaminate, the findings misrepresent the population and do not apply to it. Non-observation also impacts statistical power by impacting comparisons between the actual distribution and the hypothesized one. Therefore, non-observation negatively impacts hypothesis testing and decreases statistical power (Moher, Dulberg, & Wells, 1994).

Various data-collection practices can lead to non-observation, such as participation bias. Non-observation arises when data that one has collected under- or overrepresents specific population groups. For instance, existing research shows a difference between the traits of employees who agree to participate in a survey and those who do not (Rogelberg, Luong, Sederburg, & Cristol, 2000). Employees who lack interest in completing a survey have lower organizational commitment and job satisfaction and are more likely to quit; therefore, a study that focuses on a behavioral theory concerning employees cannot capture the variance that exists in organizations with a low response rate due to the self-selection bias. Researchers could trigger participation bias when they collect data on social media, hire marketing companies for survey administration, and use online communities and crowdsourcing services such as Amazon Mechanical Turk (MTurk). Whereas some authors justify adopting such data-collection approaches based on arguments such as higher demographic diversity in MTurk (Buhrmester, Kwang, & Gosling, 2011), one should note that collecting data from respondents who do not represent a study's target population distorts findings' validity (Schalm & Kelloway, 2001). Such data-collection practices raise concerns about individuals who participate in surveys and impact the collected data's credibility (Chang & Krosnick, 2009; Kreuter et al., 2008). Using these data-collection approaches without paying careful attention to what the collected data covers leads to a sample that contextual variables affect.

These three factors can introduce contextual variables to the evidence that a study uses. Therefore, subsequent replication studies should also consider these factors in the original study to be able to interpret potential differences.

2.1.2   Transparent Data-collection Practices

Replication studies require high transparency in the data-collection and -analysis practices that original studies use (Freese & Peterson, 2017). Insufficient transparency has four primary roots. The first root relates to the potential challenges in data-collection procedures that authors prefer to hide (Rogelberg & Stanton, 2007). The flood of online surveys together with lengthy questionnaires, spam blockers, personal security concerns, and organizational information security policies that prohibits users from clicking on links from unknown sources lead to significantly low response rates (Fan & Yan, 2010; Li, Ragu-Nathan,

Ragu-Nathan, & Subba Rao, 2006). With the falling participation in surveys, nonresponse has become a key challenge in social science (Brüggen & Dholakia, 2010; Fan & Yan, 2010; Sivo, Saunders, Chang, & Jiang, 2006) that impacts how well researchers can control the data they collect and leads to biased results (Marsden & Pingry, 2018). The increasing challenge that low response rates present raises questions about collected data's accuracy, the degree to which it covers the targeted population, and the degree to which findings contain non-response and other contextual variables (Fan & Yan, 2010; Lindgren, Markstedt, Martinsson, & Andreasson, 2018; Marsden & Pingry, 2018). Subsequently and since reviewers consider response rate to significantly indicate data quality, authors may deliberately avoid reporting response rates or details related to their data collection to hide the potential bias issues in their studies (Collins & Tabak, 2014; Rogelberg & Stanton, 2007).

Besides deliberately hiding details, using the Web and social media to collect data has introduced challenges in transparently reporting data-collection procedures. Potential variables that pertain to collecting data via the Web include number of views, number of engagements, number of people who started responding to a survey, number of submitted responses, and number of acceptable responses. Researchers cannot use the earlier formula (i.e., acceptable responses divided by the total distributed surveys) to calculate the response rate when they collect data from the Web. Researchers exacerbate this lack of clarity in calculating response rates when they collect data via multiple modes. Researchers cannot easily transparently report data-collection details as no standard approach for it exists.

The second root relates to the rise in how frequently researchers use marketing services to collect data. By using such services, researchers lose control over the process and do not have proper data to report the details. The third root relates to maintaining exclusive access to methods or data sources. Researchers may want to avoid releasing their data-collection details and methods or describe them vaguely in order to retain their exclusive access to the method or data source (Collins & Tabak, 2014). Finally, the fourth root relates to manuscript length limits that journals impose. Some researchers choose to remove critical details about data-collection process due to these limitations (Freese, 2007).

2.1.3 Translucency of Data and Methods

Replication studies may need access to an original study's data or methods. For various reasons, such as mistakes in the analysis that can lead to issues in inference, the scientific community has to be able to check and validate existing published results. However, in general, most researchers can rarely check and validate published studies. For such checks and validation, researchers need the raw data, metadata, and the statistical program that researchers used in the original study (Asendorpf et al., 2013).

Authors assume responsibility for the content in their work. This responsibility comes with the need to provide data and methods that they need to test their work's content. By sharing data and methods, researchers contribute in two ways. First, the provided details facilitate future pure replications. Second, sharing can serve as a preventive measure against fraud, data fabrication, and falsification. Even though a requirement to share may not entirely prevent misbehavior, it can help as a preventive measure.

When we talk about sharing data and methods, we recognize that it has some limitations and pitfalls. For instance, researchers often cannot share market-bought or proprietary data. Also, disreputable researchers may possibly abuse shared content if no one controls such sharing. We further discuss the topic and suggest mechanisms for safe translucency in upcoming sections.

2.2 Data Policies in Social Science

Several successful efforts have improved replicability in social sciences, and many scientific associations have developed policies to improve and promote replicability in their journals (Freese & Peterson, 2017). These efforts provide a benchmark for replicable IS research. Therefore, we review such policies that scientific business and social science associations and leading social science journals have developed to check for best practices to enhance replicability. Readers should note that the data policies that we discuss in this section deal with various data-collection approaches, which includes the survey approach. While we try to focus on survey-related policies, some policies have a generic nature and cover many different methods. Therefore, researchers need to properly interpret and consider these policies before applying them to survey research, which we discuss further in subsequent sections.

2.2.1   Data Policies Adopted by Scientific Associations

The American Economic Association adopted a "data availability policy" to address replicability challenges (Clemens, 2017; Freese, 2007). The association encourages journals to adopt the policy, and many leading economic journals such as *American Economic Review*, *The Quarterly Journal of Economics*, *Journal of Political Economy*, *Review of Economic Studies*, and *Econometrica* adopt the policy. The policy indicates that a journal will consider a paper for publication "only if the data used in the analysis are clearly and precisely documented and are readily available to any researcher for purposes of replication" (American Economic Association, 2019). Authors should provide "the data, programs, and other details of the computations sufficient to permit replication" before publishing their work. Each respective journal stores the details that authors provide in a repository. Also, if authors use proprietary data, they should clearly explain how they obtained the data and how other researchers can access it (American Economic Association, 2020).

Other associations follow more voluntary and encouraging policies than obligatory policies. For instance, the American Marketing Association has an integral data policy for its journals *Journal of Marketing*, *Journal of Marketing Research*, *Journal of International Marketing*, and *Journal of Public Policy & Marketing* (American Marketing Association, 2019). The data policy motivates researchers to submit their data and methodological tools. However, the policy does not mandate sharing unless journal editors deem it necessary. In this case, authors need to submit data for reviewers to privately review and verify. Also, the association has a strict process for dealing with falsified and misreported data and considers various penalties at various levels for authors who engage in such misconduct.

In Table 1, we summarize replicability-related policies that major business associations that publish journals and organize conferences suggest and enforce. We collected the data that we present in Table 1 in March, 2019. The listed associations have developed clear measures to deal with replicability. Some associations, such as the Academy of International Business and Academy of Management, have adopted policies that the Committee on Publication Ethics (COPE), which promotes integrity in research and publication, developed. Also, some associations, such as Institute for Operations Research and the Management Sciences (INFORMS) and Association for Business Communication, do not have an integrated policy that their journals adopt; rather, each journal enforces its own data-integration policy. We do not list such associations here since we present policies that their journals adopt in Appendix A.

Table 1. Replicability Measures that Scientific Associations Suggest

Association	Evidence quality	Transparency	Translucency
American Accounting Association	• Evidence ethical practices in data collection by providing institutional research board approval • Fully disclose data limits for exculpation from falsification		• Identify one author as a data steward who is responsible for sharing data with journals and preserving data for six years after publication. • Voluntarily share data for replication
American Finance Association	• Follow guidelines for collecting data from human subjects to maintain high-quality data • Report errors if any found after publication • Avoid selectively reporting data and findings to mislead or deceive readers	• Discuss data, research methods, and related choices	• Engage with reasonable requests for clarification • Assist in replication requests
American Marketing Association	• Adhere to standards of integrity in research and communication of research results and findings	• Include enough information related to details of work • Precisely describe the research and analysis procedures	• Share additional details of findings when a journal editor requests them during the review process • Voluntarily share additional information such as code and instrument

Table 1. Replicability Measures that Scientific Associations Suggest

American Economic Association		• Clearly and precisely document data and codes used in the analysis	• Clearly and precisely document access to data • Provide access to data and program to journal and reviewers if requested • Assure readers that data will remain available for a sufficiently long time
American Psychological Association	• Evidence ethical practices in data collection by providing institutional research board approval • Avoid fabricating and falsifying data		• Provide the data used in research for replication.

2.2.2 Data Policies that Leading Business Journals Adopt

In order to comprehensively examine existing benchmarks, we review journal policies related to published research's replicability. We specifically review the policies that the Financial Times (FT) list of top 50 journals adopts. The FT list encompasses top-tier journals in various business fields (Burgess & Shaw, 2010) according to deans in leading business schools. Therefore, this list provides a sample of policies that support replication in various business fields. In Table 2, we summarize the practices that the FT 50 journals adopt. Note that we collected the information that we present in Table 2 in March, 2019. We show the journals on the FT list and their associated data policies in more detail in Appendix A.

We found that 26 FT 50 journals (52%) discussed **evidence quality** practices. Overall, most requirements dealt with promoting ethical conduct and punishing unethical conduct. Accordingly, journals considered it authors' ethical responsibility to use real data, represent results accurately, avoid fraudulent or inaccurate statements, adhere to ethical research guidelines in their specific field, and avoid adopting methods primarily to produce specific results from their collected data. Authors have responsibility for their manuscript content and need to attest that they have adhered to field-specific regulations for collecting and analyzing data and their country's legal requirements. Moreover, some journals required authors to identify one person with responsibility for data collection and analysis. In case a mistake or fraudulent activity causes any substantial issue with a paper, journals reported that they would retract or correct the paper. Also, they could initiate a procedure that may lead to punishment for the authors responsible for the unethical behavior.

Whereas most of the 26 journals included ethical requirements in their data policies, few journals had objective requirements for evidence quality. We categorize these requirements into four groups. The first category relates to human subjects and data-collection practices. Researchers need to develop and follow a proper data-collection procedure that an ethics committee approves. The approved procedure ensures that the collected data lacks bias due to a potential lack of trust in the research. The second category relates to the data's representativeness. Some journals reported not accepting studies that authors developed based on analyzing survey results that they or others collected for other studies given that the data may not correctly represent the study's constructs and the sample may not be able to represent the targeted population. Similarly, the journals generally did not accept student samples or online crowdsourcing services such as mechanical Turk (mTurk) unless researchers justify that the sample represents the target population. The third category relates to reliability of measurement items in the instrument. Accordingly, authors should report reliability coefficients. Finally, the fourth category relates to results: authors should objectively discuss results with support from data.

Table 2. Replicability Measures that the 50 Journals on the FT List Suggest

Dimension	Practice[1,2]
Evidence quality	• Obtain ethics committee approval and informed consent when collecting data from human subjects • Declare all authors responsible for research content • Identify one author accountable for data collection • Identify one author accountable for data analysis • Use real and authentic data (avoiding falsifying or fabricating data) • Represent underlying data accurately (avoiding falsifying or fabricating results) • Avoid fraudulent or knowingly inaccurate statements • Adhere to fields' ethical research guidelines • Adhere to the legal requirements of the country in which one collects data • Use data originally collected for one's specific research • Do not adopt a method primarily to produce statistically significant results • Justify that the sample represents the study population (the journals do not generally accept samples such as student samples or those generated from MTurk) • Retract or submit a correction for papers with significant errors or inaccuracies

Transparency	• Report data-collection and -analysis techniques in line with the accepted norms for survey research
	• Describe and document data and methods in sufficient detail:
	    • Sampling method
	    • Participant-recruitment methods
	    • Interaction between researchers and respondents
	    • Researchers' involvement in data-collection practices
	    • Data-collection location and period
	    • Incentives used to encourage individuals to participate in study
	    • Measures used to quantify constructs
	    • Measures developed or links to resources that developed measures
	    • Data-collection instrument (questionnaire) with full phrasing of the questions and scales
	    • Data-cleansing methods
	    • Data-screening and -discarding procedure
	    • Thresholds used for data-screening measures
	    • Method for handling missing data
	    • Distribution of discarded responses across the study population
	    • Sample's descriptive statistics (e.g., Ns, means, standard deviations)
	    • Sample demographics
	    • Reliability coefficients
	    • Programs and codes used in the analysis
	• Describe procedures for managing/archiving, anonymizing, and de-identifying data and procedures for ensuring data security.
	• Describe methods clearly (if using a method for the first time or in a significantly modified way) or provide references to relevant resources (for well-established methods)

Translucency[3]	• Be prepared to share raw data for editorial review during the review process
	• Share data, software, code, models, algorithms, protocols, methods with the reader
	• State data's availability in a data availability statement during submission and assure readers that the data will remain available for a sufficiently long time
	• When sharing data, explain variables and include sufficient details on how to read and interpret data
	• In situations where legal, ethical, or confidential reasons limit authors' ability to discuss/share data and methods, provide a means to verify data sources:
	    • Provide the editor with contact information of a representative in the organization that you collected data from (to confirm that authors obtained data)
	    • Respond to queries about data by sharing specific results as opposed to raw data
	    • Rather than providing the details that one would require to replicate every element of a paper, provide sufficient material to reproduce the research's essential content
	    • Describe the code in detail and step-by-step
	    • Provide a full correlation matrix or covariance matrix plus descriptive statistics (scale range, means, SDs, etc.) if the paper uses SEM techniques
	• De-identify data before sharing to maintain institutional policies and privacy of respondents

[1] We collected the practices that we list here across all journals, and no one single journal had adopted all these suggested practices.

[2] We ordered the practices listed in each dimension based on two factors. First, we listed the most frequent practice that journals addressed. Then, we tried to create a logical flow between practices with a low frequency of appearance in journals.

[3] Some journals mandated the policies that we mention, while others simply recommended them.

We found that 28 FT 50 journals (56%) discussed **transparency**-related policies. Overall, the journals demanded that authors provide enough detail related to the data-collection and -analysis procedures that they used to enable subsequent replication studies. The details relate to the three phases data-collection phases (i.e., before, during, and after data collection). Before collecting data, authors need to identify their population, sampling method, the method they used to recruit participants, and the stimuli they used to recruit participants. When collecting data, authors need to clearly explain different the dimensions of their data-collection practices, such as the data-collection location and period, the instrument they used to collect data, the full questions that respondents saw, communication and data-collection media, and participant-researcher interaction. After collecting data, authors need to describe the collected data's characteristics, such as sample size, means, and standard deviations; report their sample's demographics; and describe the data-cleaning process they performed. Accordingly, they should clearly discuss details about the data-screening methods they used to deal with outliers, lack of attention, and poor comprehension. They should also justify the cut-off values they used to screen measures. Furthermore, authors also need to clarify how they dealt with missing data should provide details about the data-imputation methods they used. Finally, authors should present the demographic information of participants whose responses they discarded.

We found that 32 FT 50 journals (64%) discussed **translucency**. Journals imposed sharing requirements at varying levels in two pre-publication stages (review process) and after publication. During the review process, the journals required authors either to submit their data and program used for data analysis or have it ready for submission when journal editors request it. Authors should explain variables and include sufficient details on how to read and interpret data when submitting data. Post-publication policies about sharing data and programs varied across different journals. Whereas some journals considered data sharing mandatory, others encouraged sharing but left it to authors' discretion. Some journals required authors to provide a data availability statement and identify one author as a contact point to provide data and programs for others interested in replication studies. Furthermore, the journals required authors to assure their readers about their data's availability for a sufficiently long time after publication. Authors could share their data and method on online repositories that journals or publishers provided and interlink their data with their research.

Sharing data and tools may create concerns among researchers due to legal or ethical ramifications or they may be reluctant to give up control over their analysis tools. Therefore, some journals had developed mechanisms to protect their authors. In situations where authors collect proprietary data from a specific organization, authors can share the data provider's contact information so that journal editors can confirm that the authors used authentic data. Regarding codes and programs, authors may only share step-by-step guidelines to replicate the methodological approach, especially for proprietary methodological tools. Further, authors can provide a verification method to their readers. Authors can respond to queries about their data by sharing specific reports and statistical outputs rather than data. For instance, authors may only share a correlation or covariance matrix along with essential descriptive statistics to enable replication studies based on structural equation modeling. In any case, the journals advised authors to ensure that they de-identified their data so that it would not impact human subjects. As authors have worked hard to collect data and develop methods, journals protected their work by requiring readers to certify that they would use material only for replication purposes.

2.2.3   Reviewing and Analyzing Practices and Policies

We used our findings to develop a research framework for replicating data-collection efforts in IS survey research. Before presenting the framework in Section 2.3, we first discuss and clarify some retrieved policies related to scientific associations and leading journals. We noticed that policies varied across associations. Therefore, before drawing any conclusion from reviewing the policies, we talk about the roots of this variability.

Associations put different levels of emphasis on evidence quality, transparency, and translucency. To understand this variability in detail, we need familiarity with different fields' context, which falls outside our scope here. However, we can hypothesize several possible causes for the variability. This variance can stem from certain fields' attitude towards replication. Some fields may perceive replication studies as a way to detect misbehaviors. Others may perceive replication studies as an opportunity to extend prior findings. Also, the discussion might be new and evolving in some fields, and the policies may change in the future.

While some covariance generally exists between journals in the same field, the journals exhibited relatively high variability between them. For instance, we found that 13 journals (26%) adopted replicability policies that publishers, scientific associations, and the Committee on Publication Ethics (COPE) developed. Also, we found that 10 (20%) journals did not have any policy related to replicability. The remaining 27 journals (54%) had policies that addressed replicability from different perspectives. Again, we assume that the journals, perhaps due to the general discussions in their related field(s), may have a particular standpoint about replication. Besides, some journals might be behind in regard to replication discussions. Also, journals may have a specific inclination toward specific methods and techniques, which may also explain the variability.

Some policies and practices that we discuss in this section appeared in only a handful of journals. The fact that only a few journals presented them might be due to their specificity to a field. The fact that some journals did not use these practices might stem from insufficient support from some scholars and policymakers. Therefore, we argue that authors should not adopt scientific associations' and journals' requirements *as is* without considering factors associated with the IS field and factors related to survey research.

2.3   A Framework to Enable Researchers to Replicate Survey Data Collection

In Figure 1, we show a framework for improving the replicability of data-collection practices in survey-based IS research. We developed this framework based on reviewing the existing literature and relevant policy and practice benchmarks that scientific associations and leading business journals have discussed and developed (see above). We refined the findings and suggestions and developed the framework based on our familiarity with the IS field and our experience with survey research. The framework posits that developing replicable survey research depends on three pillars: 1) evidence quality, 2) transparent data-collection practices, and 3) translucent data and analysis. The framework suggests that authors undertake various inter-related practices to maintain each pillar in order to facilitate future replications. We discuss important topics about adopting the framework in this section. We define suggested practices in the framework in Appendix B.

Each practice in the framework can enhance a study's replicability. Therefore, we suggest that authors follow the framework as a set of best practices to facilitate future replication studies. Also, we suggest that journals and reviewers consider the relevant suggested practices in the framework when reviewing a paper. While the framework helps to improve data-collection practices, we understand that it may not be possible to include all practices in a paper. We do not recommend that one use the framework as a rigid requirement for publishing in IS journals because some categories may not pertain to some data-collection approaches. For instance, "adopting a sampling technique" does not pertain to snowball data collection. Therefore, we do not expect that a paper would incorporate all the listed practices. However, authors need to incorporate essential practices based on their research's specific details. Rigid enforcement may prevent authors from submitting new and creative works to journals and may result in methodologically sound but potentially uninteresting papers. Instead, we suggest that both authors and journals try to adhere the framework in a more liberal way and consider best practices that pertain more to their studies' context.

Another important consideration relates to the translucency dimension. Sharing data, programs, and other required tools for replication benefits the IS field. However, if authors decide to share their data and tools, they should do so with trusted recipients. We discuss how authors and journals can use this framework in Sections 3 to 4.

Evidence quality	Transparent data-collection practices	Translucent data and analysis
Before collecting data	***Before collecting data***	
Adhere to research ethical guidelines	Report population of study	
Assume responsibility of data collection by one of the authors	Explain sampling method	
Assume responsibility of data analysis by one of the authors	Describe participant recruitment method	***Review process***
Gain approval of ethics committee for collecting data from human subjects or follow requirements of the country/institution of study	Explain incentives used for subject recruitment	Make data and methods available for reviewers if requested
Follow literature guidelines for adoption/design of data collection instrument	***While collecting data***	Provide alternative justifications for proprietary data if requested
While collecting data	Report context of study (time, duration, location, media of data collection)	***After publication***
Obtain consent of human subjects to participate in the study	Present instrument used for data collection	Ensure the reader about the availability of data and methods ☆
Consider measures to monitor quality of collected data	Report participant-researcher interaction during data collection	Identify one author as data steward ☆
After collecting data	***After collecting data***	Store data in a safe place
Provide evidence that sample represents population of study	Report descriptive statistics of collected data	De-identify data before sharing
Avoid abusing researcher's degrees of freedom in data preparation	Report demographic characteristics of data	Provide reports and statistics required for replicability studies in case of proprietary data ☆
Report reliability measures	Report data cleansing methods	
Discuss limitations related to sample, population, and generalizability of results	Explain screening methods	
Report errors and issues found in the published paper	Report missed data handling methods	
	Report demographic information of discarded data	

*Following best practices marked with a star remains at authors' discretion.
We strongly suggest that authors consider the rest of non-marked best practices if they fit their study's context.

Figure 1. Framework for Best Practices for Data Collection Replicability in IS Survey Research

3 Reviewing Replicability in IS Research

In this section, we evaluate the existing state of IS research with benchmarks and the above framework. Therefore, we first examine IS journals' policies related to replicability and then analyze published survey research. Thus, we highlight existing gaps and subsequently propose potential improvement opportunities. As the scope for our analysis, we focus on a small sample of well-recognized top IS journals rather than a more expansive analysis. Specifically, we selected the following journals for the analysis: *European Journal of Information Systems* (*EJIS*), *Information & Management* (I&M), *Information Systems Journal* (ISJ), *Information Systems Research* (*ISR*), *Journal of Information Technology* (*JIT*), *Journal of Management Information Systems* (*JMIS*), *Journal of the Association for Information Systems* (*JAIS*), *MIS Quarterly* (*MISQ*), and *Journal of Strategic Information Systems* (*JSIS*). These journals cover a wide range of topics and methodologies and represent mainstream research in the US and other countries. Furthermore, researchers generally use them as a sample to analyze the IS literature (Palvia et al., 2015, 2004, 2017). Some of these journals appear in the IS Senior Scholar's basket of eight journals as the

Association for Information Systems (AIS) identifies. Besides these journals, we review *Information & Management*, a high-quality IS journal that started publication in 1977 and publishes a considerable number of survey studies (Palvia et al., 2015, 2017).

In reviewing data policies and ethical guidelines for publishing in these journals, we found that both *JAIS* and *MISQ* required that authors acknowledge their adherence to the AIS Code of Research Conduct in the submission process. The code of research conduct requires that AIS members adhere to it, and it focuses highly on ethical behavior towards high-quality research. The code identifies "instances of possible scholarly misconduct by a member in relation to research and publication activities" (Association for Information Systems, 2014). Other journals also refer to a general statement for publication ethics that their publishers (e.g., Taylor & Francis and Elsevier) or other external bodies such as COPE developed. While most of these journals provide repositories for storing data and encourage authors to submit data as a complementary source for journal audience, only *JAIS* demands that authors submit correlation/covariance matrix along with descriptive statistics. Other journals consider data submission as optional. Table 3 summarizes the existing data policies related to these journals.

Table 3. Journal Policies for Survey Data Collection

Journal	Evidence quality	Transparency	Translucency
EJIS			• Encourages data sharing and provides an online repository
ISJ			• Encourages data sharing and provides an online repository
ISR	• Requires authors to follow ethical behavior guidelines • Demands authors use authentic data and accurately represent data	• Demands authors provide enough detail and references to permit others to replicate the work	• May ask authors to provide the raw data for editorial review • Requires authors to retain data used in their paper during the review process and after publication for a reasonable time
I&M	• Requires authors to comply with the journal's data policy		• Encourages data sharing and provides an online repository • Requires authors to provide data availability statement • If the data is not suitable for sharing, authors need to explain it during the submission process
JAIS	• Requires authors to comply with the journal's data policy		• Submit correlation or covariance matrix and sample statistics during the review process • Provide a complete dataset during the review process if reviewers request it
JIT	• Requires authors to comply with requirements of the Committee on Publication Ethics (COPE)		• Encourages data sharing and provides an online repository
JMIS	• Requires authors to comply with the journal's publishing ethics • Requires authors to use accurate data that represent research		• Encourages data sharing and provides an online repository • Requires authors to retain data used in their paper and provide it for further evaluation to the editorial team if requested
JSIS			• Provide research data for editorial review if asked for • Comply with open data requirements of the journal if asked for • Provide public access to data if asked for • Retain data used in their research for a reasonable number of years after publication
MISQ	• Requires authors to comply with the code of research conduct that the Association for Information Systems developed		

* We collected the data that we present in this table in March, 2019.

Analyzing policies allows one to understand what journals expect from authors, whereas analyzing published papers shows how authors and reviewers commit to these policies. We reviewed the replication-oriented practices in the papers published in the same IS journals that we discuss above to gauge the existing state of replicability in survey research. We reviewed the most recent survey studies that these journals published in 2018. Out of the 385 research papers published during 2018 in the reviewed journals, 82 papers used a questionnaire to collect survey data. Table 4 summarizes the journals and their papers.

Table 4. List of Select Journals and Papers

Journal	EJIS	ISJ	ISR	I&M	JAIS	JIT	JMIS	JSIS	MISQ	Total
Total papers (2018)	33	44	51	80	37	19	40	21	60	385
Survey papers (2018)	4	7	3	39	4	2	4	8	11	82

We note that each reviewed paper results from its authors' hard work and has gone through a rigorous blind review process with experienced reviewers and scholars. Therefore, our analysis in no way, shape, or form discredits the quality of the papers or their data-collection procedures. Instead, in our analysis, we identify areas where researchers need to clarify their data-collection procedures for enhanced replicability.

We identified and coded data from the 82 published survey studies based on a taxonomy that the framework we present in Figure 1 informed to identify whether a paper included or did not include data-collection practices that one would need for replication. The first two authors performed the coding in April, 2019. Each coder coded all the papers individually. To ensure that they had consistent coding results, the authors had several meetings to clarify codes and their definitions and ensure consistency. They resolved inconsistencies and achieved 100 percent agreement on the coding results.

3.1 Quality of Evidence in IS Survey Research

Most papers (73%) discussed at least one type of quality control measures in the data-collection process. Some papers (44%) clearly explained the inclusion criteria, such as job position, experience, and technical capabilities that they required participants to have. Some papers (50%) reported using quality checks such as checks for response completeness, patterned responses, proper answers to attention questions, and so on. Paradata, which refers to data about the data-collection process, constitute another quality-control tool that new technologies enable. Using paradata can help one identify responses' quality (McClain et al., 2019). Paradata encompasses controls such as how long respondents spent completing a survey and their Internet Protocol (IP)-based location. Correctly and using paradata enables researchers to identify multiple responses from one person or one firm and to recognize response quality based on how long participants spend completing a survey. Most papers (90%) used online tools to collect data. However, while one can collect paradata relatively easily using online data-collection tools, only 12 percent of papers reported using paradata to control response quality.

The collected responses should represent the target population so that research findings generalize to that population. Therefore, besides the controls that we mention above, researchers should justify the extent to which data represents the target population by discussing non-response bias and self-selection bias. While the two biases share similarities, one uses different approaches to check for them. Among the papers in our sample that needed to justify nonresponse bias, only 52 percent did so. Only 23 percent of the papers discussed self-selection bias. One can also use other methods to report sampling bias, such as comparison between responses collected in different data-collection waves, but only 29 percent of papers reported calculating this bias.

We checked various evidence-quality measures. Some journals required that authors adhere to ethical guidelines and assume responsibility for data and methods during the submission process. We found that 82 percent of the papers appeared in journals that required authors adhere to research ethical guidelines. However, only 12 percent of papers appeared in journals that mandated authors accept responsibility for research content. Most papers (85%) did not report whether they gained approval for collecting data from human subjects from any ethics committee. Also, 79 percent of studies did not report on whether they obtained consent from human subjects. Most studies clearly discussed their instrument development and adoption process (95%) and most reported reliability measures (80%). Overall, we found no single paper that provided all evidence quality attributes that we recommend. We summarize our results in Figure 2.
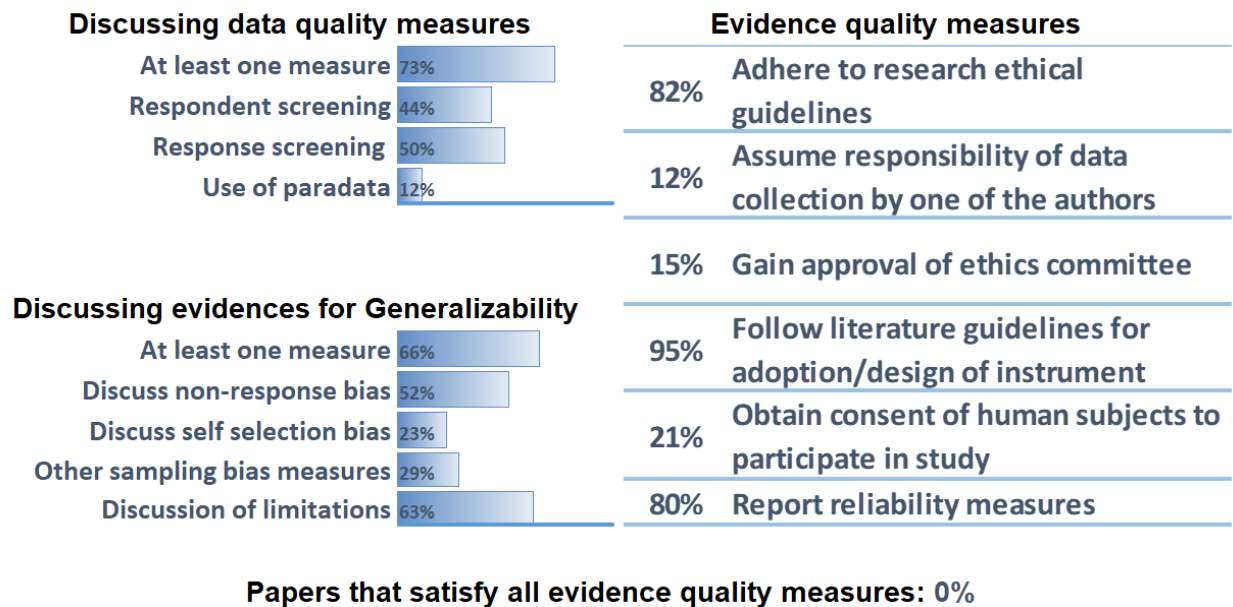
Discussing data quality measures

At least one measure	73%
Respondent screening	44%
Response screening	50%
Use of paradata	12%

Discussing evidences for Generalizability

At least one measure	66%
Discuss non-response bias	52%
Discuss self selection bias	23%
Other sampling bias measures	29%
Discussion of limitations	63%

Evidence quality measures

82%	Adhere to research ethical guidelines
12%	Assume responsibility of data collection by one of the authors
15%	Gain approval of ethics committee
95%	Follow literature guidelines for adoption/design of instrument
21%	Obtain consent of human subjects to participate in study
80%	Report reliability measures

Papers that satisfy all evidence quality measures: 0%

Figure 2. Evidence Quality in the IS Publication Sample

3.2   IS Survey Research Transparency

We found a wide gap between the desired transparency that enables researchers to reproduce results and the current situation in the studies we examined. No paper reported all the recommended practices related to transparent data collection. In examining how transparently the studies in our sample reported their pre-data-collection procedures, we found that most identified their targeted population clearly; however, most (95%) failed to discuss how they determined a proper sample size for their analysis. Furthermore, 16 percent failed to report how they assembled a representative contact list for their targeted data-collection subjects, and most papers (68%) did not discuss their sampling technique to select potential participants.

In analyzing the papers' subject-recruitment procedures, we found poor documentation and insufficient clarity regarding the activities at the recruitment stage. The medium for contacting study subjects (e.g., meetings, emails, etc.) has an impact on response rate and on potential self-selection and non-response biases; however, only 81 percent of papers reported it. Only 31 percent of papers explained whether they offered incentives (e.g., a gift card) to participants to complete their survey. Those studies that considered an incentive should clarify the measures they took to prevent participants from submitting multiple responses. Only 16 percent of these studies explained how they controlled for multiple submissions. In addition, the lack of incentives may cause participants to invest less time and attention in completing a survey. Therefore, studies that do not consider an incentive for participation should discuss the motivation of their respondents for participating in the survey. Finally, researchers need to provide information related to the data-collection period's duration since it informs the non-response bias discussion. However, only 23 percent of papers reported this information.

Furthermore, papers should report how many individuals received the survey request (e.g., viewing an email that links to the survey). However, only 10 percent of the papers identified it. We found that 12 percent of papers reported the actual number of subjects who opened the survey instrument. In general, we found that most papers did not report the number of recorded responses and the acceptable sample size after dropping low-quality responses. While most papers (97%) reported one of the two, only 60 percent of papers document the number of collected responses, the number of responses that they could not use due to quality issues, and the final sample size. Thus, many papers did not provide enough information to calculate the response rate, and only 40 percent of papers reported response rates (we exclude papers that could not identify the exact number of their targeted subjects, such as those that shared their questionnaire on social media and those that adopted the snowball method to distribute their survey, from this calculation). We summarize our findings in Figure 3.

Most studies' authors collected data on their own. However, nearly a quarter of papers used third-party services and crowdsourcing services. Interestingly, we observed that, when authors did not collect data, they tended to report minimal detail. For instance, no paper that outsourced data collection reported the study population, sampling method, participant incentives, data-collection context, demographic characteristics, and data-cleansing methods.
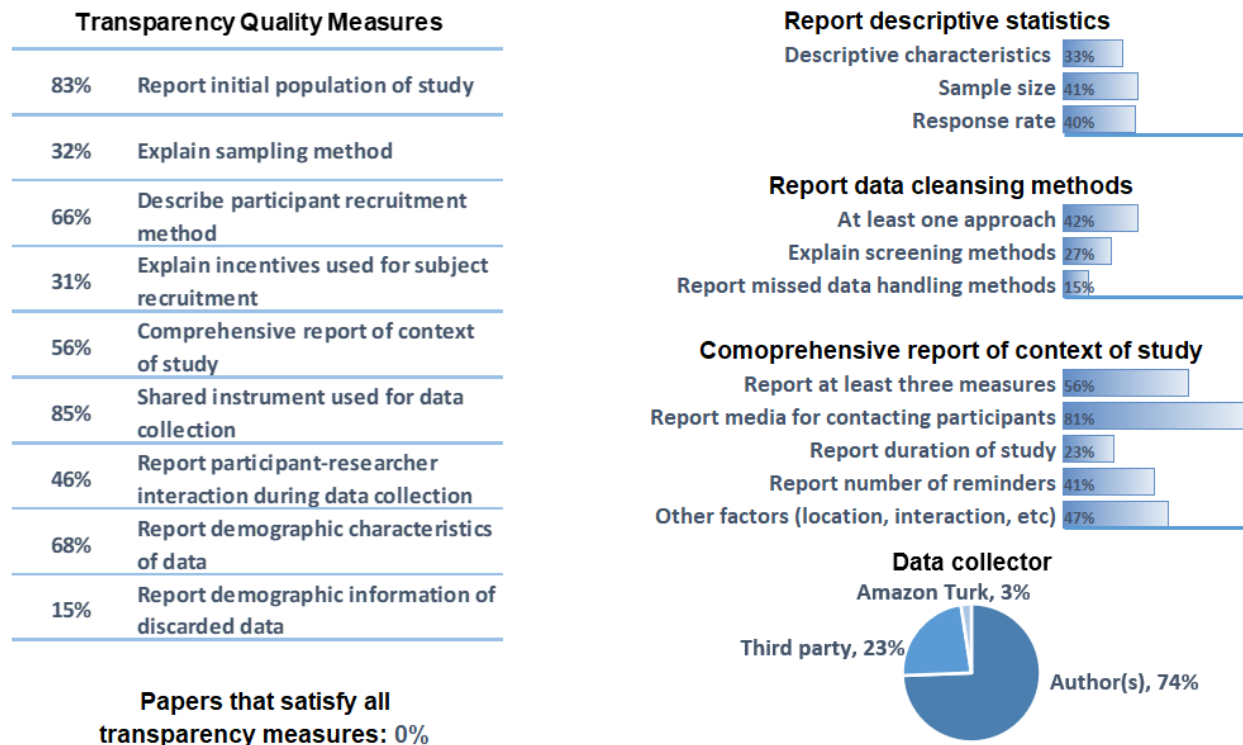
Transparency Quality Measures

83%	Report initial population of study
32%	Explain sampling method
66%	Describe participant recruitment method
31%	Explain incentives used for subject recruitment
56%	Comprehensive report of context of study
85%	Shared instrument used for data collection
46%	Report participant-researcher interaction during data collection
68%	Report demographic characteristics of data
15%	Report demographic information of discarded data

Papers that satisfy all transparency measures: 0%

Report descriptive statistics
- Descriptive characteristics 33%
- Sample size 41%
- Response rate 40%

Report data cleansing methods
- At least one approach 42%
- Explain screening methods 27%
- Report missed data handling methods 15%

Comprehensive report of context of study
- Report at least three measures 56%
- Report media for contacting participants 81%
- Report duration of study 23%
- Report number of reminders 41%
- Other factors (location, interaction, etc) 47%

Data collector
- Amazon Turk, 3%
- Third party, 23%
- Author(s), 74%

Figure 3. Transparency of Data-collection Practices in the IS Publication Sample

3.3 Translucency of IS Survey Research

We checked all papers to see if authors shared a covariance or correlation matrix in their papers or online supplements or indicated they would willingly share it on request. Only one paper shared its covariance matrix, and not one paper among the 82 shared or stated their willingness to share. Finally, we checked for acknowledgments regarding authors' assuming data-collection and data-analysis responsibilities. No paper had any such reporting or related discussions.

4 Potential Resolutions for Replicability in IS Survey Research

Our findings point to a wide gap between suggested best practices that we list in our developed framework and current IS survey research. This gap means that authors themselves need to interpret potential differences between the results from replication and original studies—a challenging task. We believe that the IS field can set a goal to replicate and reproduce specific surveys. Therefore, researchers can fill the gaps the gaps that we found in the literature to make future replication easier. We think that authors themselves need to ensure they present honest work with clarity and enough details. Journals and academic education institutions can facilitate this process by providing incentives for authors to follow best practices. Below, we offer suggestions for authors, journals, and academic institutions to support replicability.

4.1 Authors

We know that researchers work hard to develop and publish their research. We also understand that focusing on rendering enough details for replicability poses an extra burden on them. However, we argue that researchers do not just publish a paper. Rather, they initiate or continue a research stream on a particular topic. Therefore, authors should follow best practices and provide enough details to facilitate subsequent replication studies even when at a great personal cost. Generally, we recommend that

authors follow the relevant guidelines related to the three replicability pillars that we present in our framework. Here, we elaborate on their replicability-enhancement opportunities based on reviewing IS scholarly publications:

1) **Discuss generalizability**: analyzing a sample using statistical tools enables one to conclude about the entire population that the sample represents (Kothari, 2004). Small sample sizes that we observe in published studies may lead to nonresponse bias, which impacts results' generalizability (Groves, 2006). Therefore, we encourage researchers to discuss the influence that non-respondents may have on results by contrasting their sample with the target population. Accordingly, researchers should be objective about presenting their sample-based findings and identify potential limitations in other settings.

2) **Recruit representative participants**: to increase the response rate, researchers tend to adopt approaches such as recruiting students, exercising snowball methods, sharing surveys on social media, using crowdsourcing platforms, and hiring marketing companies. Researchers may be able to justify each such approach in specific cases. For instance, one would find it apt to collect data from MTurk, a crowdsourcing website, to study the crowdsourcing workforce. However, such data-collection approaches target a population with limited diversity in most studies (e.g., Woo, Keith, & Thornton, 2015). Therefore, authors need to justify their sample with the target population and discuss the impact that the data-collection method they used has on generalizability or collect further data to enhance representativeness (Seddon & Scheepers, 2012).

3) **Report data-collection details**: Churchill (1979) explains that replication failure does not result from false data; rather, it results from the specific conditions in which authors conducted their original research. Therefore, replicability and contributing to existing knowledge requires authors to properly document the research process. Our review shows that existing IS literature lacks enough details on data-collection practices, and we suggest that authors include the details that our framework provides. An emerging and severe situation has appeared as authors increasingly use data that marketing companies collect; these companies seem to have the least transparent data-collection practices. The researchers who author these papers need to try to obtain related data and clearly identify their subjects' demographic information and response rates.

4) **Report data-cleansing decisions**: researchers have high degrees of freedom in how they prepare data. They can adopt various measures such as demographic characteristics and outliers to initially screen data. Moreover, various imputation methods exist for dealing with missing data. Since this freedom impacts research results (Simmons et al., 2011), IS researchers need to explain their data-preparation methods in enough detail.

5) **Share data, instruments, and methods**: authors need to perceive a publication beyond a single PDF file. Reproducing a study's results or testing alternative explanations requires that one can access not only the study but also its data, programs, and methods (Asendorpf et al., 2013). We suggest that authors consider legitimate requests from trusted colleagues who clearly indicate why they make their request. Also, authors need to consider collaborating with replication projects sponsored by academic journals and scientific institutions.

6) **Engage in more replication research**: higher author engagement in replication research establishes norms required for publishing replicable research and ensures authors adopt higher ethical standards. Alternatively, authors may join the Information Systems Replication Project, a joint effort between *AIS Transactions on Replication Research* and *MIS Quarterly*. The project focuses on addressing replicability and analyzing it in the IS field (Dennis et al.,2020). IS scholars should also encourage journals to publish more replication studies.

4.2 Journals

Authors are more likely to practice the recommendations that we provide in this paper if journals promoted, facilitated, and rewarded such behavior. We find it heartwarming that the AIS has begun working on initiatives to enhance IS research's replicability and that the IS community knows about replicability's importance. However, data-collection practices in IS studies as we show in our review remain far away from supporting replication studies. Thus, journals need to promote and motivate the right behavior. Accordingly, we suggest journals to employ our framework as a checklist in evaluating submissions. Below, we discuss actions that journals, editors, and reviewers need to undertake:

1) **Require and accommodate details**: some researchers suggest that the length limitations that journals impose lead to shorter discussions about data-collection procedures and a lack of necessary details (Collins & Tabak, 2014; Freese & Peterson, 2017). Therefore, we encourage journals to accommodate details about research practices by publishing online supplements. Also, journals need to do more than simply accommodate such details: they should also ask authors to include the details in their submissions.

2) **Be considerate about data-collection limitations**: on the one hand, collecting survey data has become increasingly challenging, and response rates continue to decrease. On the other hand, reviewers criticize data-collection biases and expect near-perfect data-collection efforts. As a result, authors may try to hide the potential issues that they face to bypass any criticism. We suggest that reviewers demand details related to data-collection practices while being considerate about limitations and open to explanations regarding how circumstances prevented that particular assessment. Rather than criticizing potential biases, they should request authors to fully explain and discuss any issues in terms of generalizability and reward authors for honestly and properly reporting findings.

3) **Provide incentives for replicability**: publishing a paper constitutes a laborious task, and researchers experience pressure to publish in high-quality journals. Adding replicability requirements only exacerbates the pressure. Scientists prefer to adopt good practices rather than being forced into mandatory changes (Fuchs, Jenny, & Fiedler, 2012). As such, they need to consider proper incentives to promote replicability. For instance, in the National Institute of Health's (NIH) Big Data Initiative, authors share their data. When someone uses the shared data in a new work, they cite the data's owner. This citation creates a new metric for authors' scientific contribution (Collins & Tabak, 2014). Another example of incentive is the badges that the Association for Computing Machinery (ACM) awards for papers that provide replication details and sustain replication evaluations (ACM, 2018).

4) **Motivate and sponsor replication studies:** we propose this recommendation with caution as journals cannot easily control replicators and prevent malicious intentions. Therefore, while we suggest that journals need to consider more space for publishing replication studies similar to the initiatives that the *Strategic Management Journal* (Bettis, Ethiraj, Gambardella, Helfat, & Mitchell, 2016) and *Journal of Finance* (The American Finance Association, 2019) have announced, we support sponsored replication projects. The recent initiative to replicate IS research, which the *AIS Transactions of Replication Research* and *MISQ* co-sponsor, exemplifies a sponsored replication project. Since replication studies require high statistical power to replicate an original study's results (Maxwell, Lau, & Howard, 2015), journals need to increase their engagement in sponsored replication studies. Such practices would incentivize authors and promote replicability norms in the IS research community.

5) **Expand methodological discussions on replicability**: IS researchers employ various methodologies to conduct research, such as surveys, experiments, mathematical modeling of secondary data, and so on. Our work only addresses data collection in survey research. Replicability practices across various methods involve axiomatic principles; however, each research method demands more focused discussion. One area that replicability debates in recent years have focused on concerns properly using and interpreting statistical methods (Świątkowski & Dompnier, 2017), and journals have introduced new requirements to report statistics and discuss results (Bettis et al., 2016). We believe that we need such discussions to develop reliable knowledge in the IS field.

4.3 Academic Institutions

Researchers' and journals' efforts alone cannot sufficiently address replication unless academic institutions join the movement. Universities need to create a healthy environment for researchers to promote replication in research. We make two suggestions as to how they can do so:

1) **Connect scientists' wellness to science's wellness**: researchers need to publish to succeed in the academic world, and high-quality research identifies better researchers. Whereas researchers will not likely make up findings due to its drastic impact on their reputation and academic career, researchers still can justify their research decisions as truth-seeking when they actually make them to advance their career (Nosek et al., 2012). Therefore, and as the NIH suggests, universities need to revisit their promotion and tenure requirements and refocus their values from publication in journals with high impact factors to scientific contributions and potential (Collins & Tabak, 2014). While promotion decisions should consider

a minimum level of publication productivity, they also ought to consider other factors such as quality, potential impact, and direction of research agenda (Nosek et al., 2012). Subsequently, academic institutions and professional associations such as the Association to Advance Collegiate Schools of Business can work on new procedures and routines to accommodate this suggestion.

2) **Teach the importance of replicability to graduate students**: future researchers need to understand the role of replicability and reliable knowledge. Accordingly, academic institutions should expose students to recent discussions on replicability during their research methodology-related courses. They can also promote ethical behavior and transparency. Students should learn how to use statistical tools properly so as to produce reliable and replicable results. Finally, students should have opportunities to engage in projects to reproduce and replicate existing publications. Besides this engagement's educational impact, students who replicate research under experienced faculty's supervision can create a valuable resource for examining IS research's replicability. Hopefully, IS publications will have sufficient transparency and translucency in the near future so that students can practice as investigators in several replication projects.

5   Concluding Remarks

In this study, informed from the literature and benchmarks of replicability-driven policies, we develop a framework that suggests best practices in different data-collection aspects to enhance data collection's replicability in survey research in the IS field. We then use the framework to evaluate the current state of IS survey research in relation to replicability. Overall, we conclude that IS survey research lacks the necessary elements required for replicability. The primary gap concerns insufficient transparency in reporting study details.

Based on our framework and its evaluation in the IS context, we develop recommendations for enhancing replicability. These recommendations have implications for authors, journals, and academic institutions. For the new and less experienced researchers, we broadly overview the replicability topic, which will help them improve their data-collection procedures. Established researchers can use the material that we present to educate their graduate students and use relevant best practices as a guideline for the papers they review themselves. This study has implications for journal editors and reviewers as well. Editors and reviewers can mentor potential authors and provide guidance in manuscript preparation. At the very least, they can develop replication policies for their journals and inform future authors. Finally, the recommendations have implications for academic institutions and graduate programs as they develop appropriate policies in this regard and include them in doctoral pedagogy.

In this paper, we focus on transparency and data-collection quality assurance in survey research for enhanced replicability. However, the need for replication studies does not pertain only to survey research. Promoting replication studies requires many different practices that should be in place for other research methodologies as well. We exhort the IS research community to join this endeavor and develop guidelines for enhancing IS replicability across different methods and employ established guidelines in preparing their manuscripts.

6   Data Availability

The corresponding author assumes responsibility for data collection and analysis. We do not publicly share our codes from analyzing the 82 survey studies and the *Financial Times* list of 50 journals to avoid readers from interpreting our efforts as criticizing specific publications' or journals' quality. However, readers can communicate with the corresponding author to obtain the data and the codes. We will make the data available for at least five years after this study's publication.

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Appendix A

Table A1. Data Policies that Journals in the FT-50 List Use and the Coverage of the Three Replicability Pillars

Journal	Evidence quality	Transparency	Translucency	Description
Academy of Management Journal				Adopted COPE data policies
Academy of Management Review				Adopted COPE data policies
Accounting, Organizations and Society	✓	✓	✓	
Administrative Science Quarterly				
American Economic Review		✓	✓	
Contemporary Accounting Research	✓	✓	✓	
Econometrica			✓	
Entrepreneurship Theory and Practice	✓			
Harvard Business Review				No data policy
Human Relations				Adopted COPE data policies
Human Resource Management	✓		✓	Adopted a modified version of the COPE data policies
Information Systems Research	✓	✓	✓	
Journal of Accounting and Economics	✓	✓	✓	
Journal of Accounting Research		✓	✓	
Journal of Applied Psychology	✓	✓	✓	
Journal of Business Ethics	✓	✓	✓	Adopted a modified version of the COPE data policies
Journal of Business Venturing	✓	✓	✓	
Journal of Consumer Psychology	✓	✓	✓	
Journal of Consumer Research	✓	✓	✓	
Journal of Finance			✓	
Journal of Financial and Quantitative Analysis				No data policy
Journal of Financial Economics		✓	✓	Adopted a modified version of the publisher's policy (Elsevier)
Journal of International Business Studies	✓	✓	✓	
Journal of Management	✓	✓	✓	
Journal of Management Information Systems	✓		✓	Adopted a modified version of the publisher's policy (Taylor & Francis)
Journal of Management Studies		✓		
Journal of Marketing	✓	✓	✓	
Journal of Marketing Research				No data policy
Journal of Operations Management				Adopted publisher's policy (Wiley)
Journal of Political Economy		✓	✓	Adopted a modified version of the Association's Policy (AEA)
Journal of the Academy of Marketing Science				No data policy
Management Science	✓	✓	✓	

Table A1. Data Policies that Journals in the FT-50 List Use and the Coverage of the Three Replicability Pillars

Manufacturing and Service Operations Management	✓	✓	✓	
Marketing Science	✓	✓	✓	
MIS Quarterly				Adopted Association's Policy (AIS)
Operations Research	✓	✓	✓	
Organization Science	✓	✓	✓	
Organization Studies				No data policy
Organizational Behavior and Human Decision Processes	✓	✓	✓	
Production and Operations Management	✓	✓		
Quarterly Journal of Economics	✓	✓	✓	Adopted a modified version of the Association's Policy (AEA)
Research Policy		✓	✓	
Review of Accounting Studies	✓		✓	Adopted a modified version of the COPE data policies
Review of Economic Studies		✓	✓	
Review of Finance				No data policy
Review of Financial Studies				No data policy
Sloan Management Review				No data policy
Strategic Entrepreneurship Journal				No data policy
Strategic Management Journal	✓		✓	
The Accounting Review	✓	✓	✓	Adopted Association's Policy (AAA)

Appendix B

Table B1. Description of Practices Related to Evidence Quality, Transparency, and Translucency

Categories and practices	Description
Before data collection	
Adhere to ethical research guidelines	A statement that authors sign to ensure that they have presented their research clearly and truthfully and not fabricated, distorted, or manipulated data in order to alter their results.
One author assumes responsibility for data collection	A statement in which one author assumes responsibility for collected data's accuracy and authenticity.
One author assumes responsibility for data analysis	A statement in which one author assumes the responsibility for data-analysis methods' accuracy and solidity.
Gain ethics committee approval for collecting data from human subjects or follow requirements of the country/institution of study	An ethics committee evaluates a research proposal and approves it if the study does not harm the rights and welfare of human subjects involved in the study. In institutions that do not have ethics committees, authors should ensure that they follow the law and regulation of their country. Also, they need to run the survey by their experienced colleagues and consult about potential challenges associated with their survey research.
Follow literature guidelines for adopting/designing data-collection instrument	Authors need to adopt a well-studied and working survey or follow guidelines in the literature (Churchill, 1979) for changing an existing survey or developing a new one.
During data collection	
Obtain human subjects' consent to participate in the study	Make human subjects aware of the data-collection duration, data-collection context, and potential risks and benefits that participation in the study may have. Participating in a study requires the participants' willingness and they can leave the study during any stage.
Consider measures to monitor collected data's quality	Authors need to collect and use various measures such as demographic information, attention and comprehension questions in a questionnaire, and paradata to ensure that they study relevant respondents, prevent multiple submissions, and obtain responses that meet quality-control criteria (McClain et al., 2019). Paradata can be contaminated with noise. For instance, researchers cannot tell if spending a long time on a question means that the subject focused on finding a proper response to the question or was busy with other non-survey-related activities. Therefore, researchers need to use paradata correctly along with other quality measures.
After data collection	
Provide evidence that the sample represents the study population	Authors need to include discussions and statistical checks to ensure that various factors involved in the study did not lead authors to systematically eliminate subject subgroups. Discussions and statistical checks also ensure that non-respondents do not impact the demography of collected responses and responses properly represent the study population. Authors can use three methods to ensure that nonresponse bias does not exist: compare sample demographics and population, compare early and late respondents, and weight adjustments (Sivo et al., 2006).
Avoid abusing degrees of freedom in data preparation	Authors need to pre-register methods and stick to it so that the results are confirmatory rather than exploratory (Wagenmakers et al., 2012). Authors need can identify their research design and submit it to ethical review boards before they begin collecting data.
Report reliability measures	Authors need to report reliability measures to ensure that the items used in data collection are consistent and can reliably measure the constructs that the research uses.
Discuss limitations related to sample, population, and results' generalizability	Authors need to contrast the sample and study population demographics to reveal study limitations. Research generalization requires a clear argument based on the induction that the findings in a specific sample remain true across the entire population (Seddon & Scheepers, 2012). Therefore, authors need to identify study limitations for proper evidence induction and to understand the extent to which the findings generalize to the target population.
Report errors and issues found in the published paper	Authors may find issues in their data or methodology after publication. They should properly report these issues to journal editors and resolve them via retracting the paper or publishing a correction.

Table B2. Description of Practices Related to the Transparency of Data-collection Practices

Categories and practices	Description
| Before data collection	
Report population of the study	The population that a study draws sample from impacts findings' generalizability. Therefore, the sample should reflect details about characteristics and qualities of the population.
Explain sampling method	Sampling deals with drawing from the population in a way that ensures that findings generalize from a sample to the population (Pinsonneault & Kraemer, 1993). Incorporating a proper sampling method ensures that the final dataset represents the study population. Authors should justify the sampling methods they use and discuss their impact on generalizability.
Describe the participant-recruitment method	Authors should describe how they found participants that represent the population, such as via recruiting online and snowballing. Each method has merits and pitfalls and authors need to be aware of the potential impact that each method may have on creating a skewed picture of the population (Devlin, 2017). They should clearly describe the recruitment method and its impact on findings' generalizability.
Explain incentives used for subject recruitment	The type and value of incentive (e.g., a draw for a camera, a $10 gift card, extra credit, a customized finding report) impacts participants and the quality of their responses. The selected incentive should be suitable for study subjects. Thus, authors need to report on the incentive and its relevance. If they offer no incentive, authors need to discuss participants' motivation to provide quality responses.
| During data collection	
Report the study's context (data-collection time, duration, location, media)	Authors should report various details: • Location of data collection (online or in a physical location) • Time required to fill each questionnaire • Number of reminders sent to respondents • Data-collection duration • Communication medium, such as emails, mails, and social media
Present instrument used for data collection	Authors need to provide the instrument with its related guidelines and questions with exact phrases as respondents saw them. If the survey is in another language, authors need to explain the translation process and provide an authentic translation to the publication language.
Report participant-researcher interaction during data collection	Any interaction between researchers (survey administrators) and participants may impact the sample. Therefore, authors should report details about any such interaction such as communication mode, communication content, and provided explanations and clarifications.
| After data collection	
Report data's descriptive statistics	Authors need to report each sample's descriptive characteristics, which includes the number of initially submitted questionnaires, received questionnaires, complete responses, acceptable responses, response rate, means for responses, and standard deviations for responses.
Report data's demographic characteristics	Authors need to report demographic information for respondents that researchers need to compare the sample with the population and to identify results' generalizability. Accordingly, demographics vary across different studies. Such demographics can include age, gender, location, income, job position, experience, and expertise.
Report data-cleansing methods	Authors need to explain the methods used to identify outliers, non-relevant, and duplicate responses.
Explain screening methods	Authors need to explain the quality measures such as attention questions and paradata that they used to screen data and identify thresholds used for discarding data.
Report missed data-handling methods	Authors need to report imputation methods that they used to handle missing data.
Report discarded data's demographic information	Authors need to identify the demographic information of respondents whose responses they discarded and compare it to the demographic information of respondents with acceptable responses. They need to identify any significant differences between the two groups that may lead to bias.

Table B3. Description of Practices Related to the Translucency of Data and Analysis

Categories and Practices	Description
Review process	
Make data and methods available for reviewers	Authors need to provide raw data, explain variables, and describe how to handle specific data files. Authors need to provide a survey instrument that includes constructs, items, and exact wording that they used for data collection. Authors need to share codes and programs necessary to reproduce the results of the study.
Provide alternative justifications for proprietary data	Authors need to provide a means of justification that proves they collected data (a report created by data-collection platform such as Qualtrics that identifies the number of responses, their location, the study's duration, and so on). Authors need to share specific statistical analysis that reviewers and editors request.
After publication	
Ensure the reader about the availability of data and methods	Authors need to include a statement in the paper in which they identify how readers who want to replicate the results can get access to the data. If authors cannot share data, the statement should explain why.
Identify one author as data steward	Authors need to identify a data steward who will respond to replication requests.
Store data in a safe place	The data steward needs to maintain data for a long enough time after publication by storing it in a safe place.
De-identify data before sharing	Authors need to protect respondents' privacy by de-identifying data before sharing it.
Provide reports and statistics required for replicability studies in case of ethical, legal limitations for data sharing	Authors need to share specific statistical analyses when reviewers and editors request them. For instance, provide the covariance matrix plus descriptive statistics to enable SEM analysis.

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