



Research-Problem Validity in Primary Research: Precision and Transparency in Characterizing Past Knowledge

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Abstract

Four validity types evaluate the approximate truth of inferences communicated by primary research. However, current validity frameworks ignore the truthfulness of empirical inferences that are central to research-problem statements. Problem statements contrast a review of past research with other knowledge that extends, contradicts, or calls into question specific features of past research. Authors communicate empirical inferences, or quantitative judgments, about the frequency (e.g., “few,” “most”) and variability (e.g., “on the one hand,” “on the other hand”) in their reviews of existing theories, measures, samples, or results. We code a random sample of primary research articles and show that 83% of quantitative judgments in our sample are vague and do not have a transparent origin, making it difficult to assess their validity. We review validity threats of current practices. We propose that documenting the literature search, reporting how the search was coded, and quantifying the search results facilitates more precise judgments and makes their origin transparent. This practice enables research questions that are more closely tied to the existing body of knowledge and allows for more informed evaluations of the contribution of primary research articles, their design choices, and how they advance knowledge. We discuss potential limitations of our proposed framework.

Keywords

validity, reproducibility, open science, transparency, research process

The goal of this article is to define, examine, and discuss the validity of research problems in primary psychological research. The psychological-research process starts with (0) an idea about the phenomenon of interest, followed by (1) a research-problem statement that includes a literature review of past research on the phenomenon and the research question the studies seek to answer (ideas can also follow from a literature review); followed by (2) theory and, in the case of confirmatory research, predictions to answer the question; (3) study designs that use sampling, manipulation, and measurement; and (4) data analyses and discussion of study results to assess the extent to which they solve the research problem and answer the research question (see, e.g., Kerlinger, 1986; Trochim, 2006). Exploratory research follows a similar process, with the goal of generating rather than testing predictions and hypotheses (Swedberg, 2020). Empirical-research articles collectively advance the literature by prompting new research problems and questions.

An evaluation of validity currently takes place at Steps 3 (study design) and 4 (data analysis, results, and discussion) of the research process, in which researchers both document and communicate their inferences, or judgments, about issues involving, for example, causality, effect sizes, measurement, or generalizability. On the basis of the documentation provided, readers of such research can scrutinize and evaluate the validity of researcher judgments and assess the extent to which relevant evidence supports the communicated inferences as true or correct (Shadish et al., 2002, p. 34).

We argue that validity standards can also be meaningfully applied to what methodologists refer to as the *problem statement* (J. P. Campbell et al., 1982; Gall et al., 1996; Kerlinger, 1986), in which an idea is justified as worth studying by contrasting it with what is

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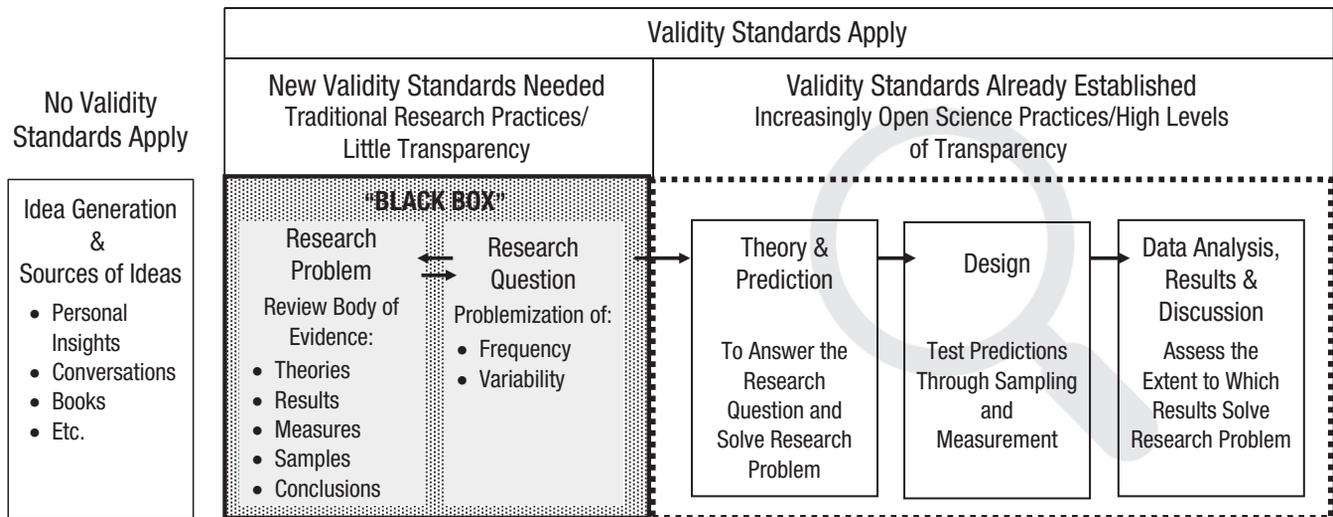


Fig. 1. The psychological-research process. Open-science practices have increased the validity and transparency of predictions, design, data analyses, and results.

already known in the literature. In problem statements, authors characterize aspects of past research through quantitative judgments, which are inferences about quantities or amounts (e.g., “most theories of past research on X-Y have . . .”; “the findings on X-Y are *inconsistent*”). These judgments are then contrasted with knowledge on the phenomenon (e.g., findings, theories, assumptions, or unstudied aspects of the phenomenon) that extend, contradict, or call into question the reviewed body of knowledge. The “contribution” of a primary research article is to offer an answer to the resulting research question and solution to the research problem (Gall et al., 1996). The characterization of past research in quantitative terms involves empirical inferences that can be, to varying degrees, truthful, accurate, or valid but to which we currently pay, as our empirical analyses show, little attention.

Our main argument is that the quantitative judgments used in problem statements in primary research are vague (instead of precise), and the origin of these judgments is obscured (instead of made transparent). In contrast, systematic reviews in secondary research (Denyer & Tranfield, 2009; Siddaway et al., 2019) make transparent the search parameters of the literature review. Authors of systematic reviews are called on to detail which articles were included in the review and explain how they were counted, coded, and classified to arrive at a precise judgment about past research. We believe that the reviews made to justify the purpose of primary research would benefit from a similarly precise and transparent approach. Note that we are not suggesting that researchers document and quantify where their ideas came from, which could come from personal experience, watching a movie, reading social

commentary, studying past research, and so on (Glueck & Jauch, 1975; Zechmeister et al., 2001, pp. 22–25). What we are proposing is that it is important to transparently and precisely describe how researchers reviewed past research that is used to justify that pursuing an idea through research is a contribution to knowledge.

We report an analysis of randomly selected articles in psychological-science journals to examine what type of quantitative judgments are used to communicate research problems and whether they are supported by any systematic documentation on its origins. We discuss the validity threats that result from using different standards to evaluate reviews in primary versus secondary research and offer solutions based on existing methodological practices. We explain the knowledge gains this approach promises and discuss its potential use and limitations.

Validity

Four types of validity (Cook & Campbell, 1979, Chapter 2; Shadish et al., 2002, Chapters 2–3) are typically discussed to evaluate Steps 3 (study design) and 4 (data analysis, results, and discussion) of the research process (see Fig. 1). *Internal validity* refers to the researcher inference that the manipulation of the independent variable is the sole cause of variation in the dependent variable. A key question in evaluating internal validity is whether alternative explanations are ruled out and/or whether the hypothesized mechanism is ruled in. Issues such as successful randomization, operationalization of the independent variable, and whether the dependent variable was measured consistently with its

definition are relevant in evaluating the internal validity of primary research (D. T. Campbell, 1957). *External validity* refers to the question of whether the sample, design, and measures correspond to real-world features of the phenomenon (D. T. Campbell, 1957). *Construct validity* refers to whether the relevant constructs are measured and operationalized consistent with their definition (Cronbach & Meehl, 1955) and whether the mechanisms relevant to the construct's measurement have been identified (Whitely, 1983). *Statistical-conclusion validity* describes whether the statistical model is consistent with the variance structure of the data (Cook & Campbell, 1979, pp. 39–44).

A careful discussion of validity threats, or specific reasons why inferences about causality, constructs, statistics, or generalizations could be more or less correct, along with the knowledge generated by the research process contributes to the emergence of new research problems and advances scientific progress (Chan & Arvey, 2012). Every scientific enterprise seeks to generate cumulative knowledge that is as accurate and truthful as possible (Bird, 2007; Giner-Sorolla, 2012; Meehl, 1978; Sismondo, 2004). Evaluating the validity of inferences made in the research process supports this goal by assessing the quality of the research and the informational value it generates (Brewer & Crano, 2014).

Despite the many articles and books on ways to define, evaluate, and reduce threats to validity (D. T. Campbell, 1957; Cronbach & Meehl, 1955; Shadish et al., 2002), current research practices frequently lack validity—be it low construct validity by the use of non-validated scales (Flake et al., 2017), internal validity by the use of nonvalidated manipulations (Chester & Lasko, 2021), or external validity by using biased samples, measures, or settings (Loyka et al., 2020; Yarkoni, 2020). This has led to calls for current validity standards to be given more attention and improved (Kenny, 2019; Vazire et al., 2022) because they otherwise impede scientific progress (Eronen & Bringmann, 2021).

We do not seek to improve existing validity types here but instead propose research-problem validity as an effort to define, scrutinize, and improve the extent of correctness of research problems in primary research. Research-problem validity helps scholars to articulate more precise and transparent research problems, which should also enable a more precise contribution to knowledge (Gall et al., 1996). With research problems directing many decisions of the subsequent research process (Kerlinger, 1986), the existing four validity types become meaningful once valid research problems are established. The construction of research problems and establishing their validity can be conceptualized as a superordinate step to the development of theory and predictions, just like theory and prediction can be

thought of as superordinate steps to research design and statistical analyses (c.f., Fiedler et al., 2021).

Research-Problem Validity Defined

A research problem in primary research consists of a review of past research that reveals two or more factors that bring about a contradiction or undesirable consequence (Clark et al., 1977, p. 6; Kerlinger, 1986, p. 17; Pillutla & Thau, 2013). Central to this process is a review of past research.¹ Typically, and as our analysis of a sample of published articles shows, this review involves making quantitative judgments about features of past research with regard to the frequency (e.g., “most,” “few”) and/or variability (e.g., “on the one hand,” “on the other hand”) of theories, measures, samples, tasks, analyses, results, or conclusions. The reviewed features are then problematized by making apparent one or multiple contradictions with other scientific knowledge and by pointing out the undesirability of not having an answer to these contradictions. The problematized review of past work is a crucial step that directly determines the research question and the professed magnitude of the potential contribution of the research. It informs the theory, predictions, and all other subsequent aspects of the research process, including the design and data analyses (Hernon & Schwartz, 2007).

Consider the following example. Authors reviewing the literature on group size and risk taking may juxtapose the direction of effects of group size on risk taking found in past research, stating that existing results are “mixed” (i.e., some studies find positive effects, others negative effects, others none), a judgment about the variability of results in past research. The problem would then be that we do not understand the source of variability. Frequency judgments are statements that characterize past research to rely “too much” on, for example, one specific risk-taking measure, and a problem may be that this measure lacks generalizability. Likewise, past research may be characterized as having “mostly” relied on a dominant theoretical paradigm, which could be a problem because alternative theories may account more accurately for results. Perhaps a handful of references are offered to support the quantitative judgments. These problem statements are similar in that they present vague summaries about features of past research, and the search parameters of the literature review are unknown. To what extent are these summaries truthful? Are past findings on group size and risk taking truly mixed? How mixed are the findings? To answer these questions, we would need to know what precisely is meant by “mixed.” And how did the researchers arrive at this conclusion? To answer this, we would need to know how the literature was

reviewed. In each instance, the answer concerns the validity of the research problem. We define research-problem validity as the extent to which judgments about past research informing the research problem are approximately truthful.

Like other validity definitions, ours highlights the degree of truthfulness of an inference as central to evaluating validity. More specifically, by “truthful” we mean the extent to which the judgment is correct given the available evidence in past research. Just like with other validity types (Cook & Campbell, 1979, Chapter 2; Shadish et al., 2002, Chapters 2–3), for a judgment to be evaluated as correct, multiple criteria need to be considered. We argue here that two key considerations are the extent to which the judgment is precise and how transparent it is how judgment came about.

Precision refers to the degree to which the inference is exact and accurately judges the available research. A judgment such as “most studies” could refer to anything between 50.01% and 99.99% of all studies and is therefore vague (Partee, 1989; Rett, 2018). The judgment conceals the distribution of past research.² A numerical statement such as “70% of reviewed studies,” on the other hand, is precise and clearly summarizes past research. The imprecision of summary statements in primary research has the potential to bias the interpretation of quantitative judgments. Medical research suggests that consumers of imprecise verbal descriptions tend to make extreme inferences about the meaning of verbal labels. For example, “rare” or “common” side effects are understood as extreme numerical estimates both by physicians and laypeople, although the underlying data are often not extreme (Andreadis et al., 2021). It is possible that readers of scientific communication make similarly extreme conclusions when they read about “most” or “few” results that have shown a specific pattern and choose, for example, not to pursue certain research interests. The practice to communicate summaries about past research in vague terms could also lead to collective misunderstandings. To the research community, it is unclear what type of summary the body of evidence warrants, creating a knowledge gap. It is also unclear what authors mean when they judge the body of evidence as “most” or “few” or “mixed,” and the interpretation of these terms varies substantially. In sum, imprecise quantitative judgments can lead to multiple misunderstandings and potentially cause poor scientific decisions.

Transparency refers to how clear the authors communicate how they arrived at their conclusions about past research, or whether the authors were open and explicit about the processes and methods they used to search, code, and characterize past research (Denyer & Tranfield, 2009). Transparency is of overarching

importance because it provides both an incentive to be more precise and to be more accurate. When researchers describe how their assessment of “most studies” came about, they are called on to show the sample of studies that was reviewed, how these studies were coded, and what this implies for certain features of past work. This process enables precision. Researchers could also state that “no other study” has certain features, used a particular paradigm, or found evidence for a given result. This judgment would be precise (because “no” equates to a numeric estimate of zero), but it is not transparent because it is unknown how the judgment came about. The correctness of a judgment on past research can be evaluated only when the judgment is both precise and transparent. Transparency should increase, then, on average, truthfulness because researchers are called on to document the process they used to arrive at the summary of past research. We note that transparency is not a sufficient condition for truthfulness of research problems, but it is necessary to be able to scrutinize them (cf. Vazire, 2020). The counterfactual of simply providing a short list of references to past work does, in our view, jeopardize truthfulness.

Current Practices

Although methodologists recognize that an “adequate statement of the research problem is one of the most important parts of research” (Kerlinger, 1986, pp. 16–17), the construct is not debated even in recent comprehensive frameworks for building better research and theory in psychology (Borsboom et al., 2021). Research problems are scrutinized during the review process by editors and reviewers who work under unprecedented pressure (Aczel et al., 2021), which may compromise their ability to review submissions thoroughly (Tsui & Hollenbeck, 2008). Moreover, they may not always have the time or even the specific domain expertise to assess the validity of inferences made about a specific literature or have access to the appropriate information to do so.

This lack of attention is problematic because empirical inferences are made about a large body of data generated by past research. Research-problem statements may correctly or incorrectly claim that past research is “one-sided” (e.g., Schaerer et al., 2018, p. 73) or has yielded “mixed” results (Wong & Howard, 2017, p. 216), or that it relies too heavily on a particular experimental paradigm (Schweinsberg et al., 2012). These examples illustrate inferences that make broad judgments on aspects of past research. Although such judgments may not be entirely false, it is possible that they are in some instances and that false statements take on a life of their own and perpetuate false beliefs (Carney et al., 2010; Letrud & Hernes, 2019).

Instead of being altogether false, it is more likely that the correctness of research problems varies because there is little attempt to make them as precise as they could be. Authors support inferences on the body of knowledge by offering a few references to past research, but this lacks precision, particularly when the field of research has received considerable academic attention, as many phenomena central to psychology have (Jones, 1998). If a body of past research yields mixed results, it would be more accurate to quantify “mixed” results through a meta-analysis of past data studies using one task versus another task that is a useful and fair comparison (Gerlach et al., 2019).

Not all research problems require meta-analyses to increase precision. Other transparent quantification practices to review past work exist that have the potential to be more informative than imprecise and possibly even biased statements. Take, for example, the judgment that past research relies “too heavily” on a particular experimental paradigm. This inference could be substantiated by counting the usage of the paradigm relative to others in the existing publication record on the phenomenon of interest, along with some coding of other interesting characteristics of this research (e.g., Schaerer et al., 2018). Likewise, the inference that prior literature is one-sided could be tested by a count to establish the frequency of the one-sidedness of past research with a description of what those one-sided studies have in common. By systematically engaging with the body of past research, more nuanced conclusions would be forthcoming, and more specific research questions would result.

This practice not only would increase transparency but also would provide readers who wish to evaluate this part of the research process with structured information that could inform their evaluations. Only 4% of the articles in our sample contained precise and transparent inferences, but even these articles did not provide structured information on how literature was searched, coded, and classified. If this information were provided by authors, then reviewers, editors, and subsequently readers would have the information relevant to evaluate the problem’s accuracy. For example, if authors document they have reviewed literature published between 1980 and 2022, then this may remind a reviewer of relevant articles from the 1970s, and that could change the quantitative judgment in the current formulation of the research problem.

We believe that the counterfactual of not documenting the literature review involved in research-problem statements puts too much faith in self-correcting mechanisms. It is possible that readers of published articles eventually conclude that the research problem described in an article is not entirely inaccurate or even false. But self-correcting mechanisms tend to operate slowly

(Piller, 2022) and do not always work (Vazire & Holcombe, 2022), and articles can have an impact on research long after their claims have been falsified. For example, Hardwicke et al. (2021) examined how citations of five prominent original studies changed by disconfirming replication evidence: For four of the five original studies, the percentage of subsequent citations that also cited the disconfirming replication study never exceeded 50%. Only one original study had a somewhat balanced citation pattern, with more than 88% of subsequent citations also citing the replication study. Likewise, Kelley and Blashfield (2009) presented the citation history of an influential article on sex bias among mental-health professionals (Broverman et al., 1970). Broverman et al. is considered to be a “citation classic” that has “impacted the thinking of a generation of psychologists and mental health professionals” (Kelley and Blashfield, 2009, p. 123), even though the conclusions have repeatedly been shown to be wrong (Phillips & Gilroy, 1985; Stricker, 1977; Widiger & Settle, 1987). These case studies on self-correction lower our faith in the self-correcting capabilities and speed of the scientific process.

An analysis of leading psychology journals

What are the current practices describing research problems in primary research in psychological science? The two first authors and a research assistant reviewed the 100 randomly selected articles published between January 1, 2011, to December 31, 2020, in six leading psychology journals (*Journal of Personality and Social Psychology*; *Journal of Experimental Social Psychology*; *Psychological Science*; *Journal of Experimental Psychology: General*; *Organizational Behavior and Human Decision Processes*; and *Personality and Social Psychology Bulletin*). Details on our random selection process are provided on OSF: https://osf.io/bq68u/wiki/home/?view_only=de923858992545e2891ed3daf21b3442. One article in our sample was a meta-analysis, and one article was a correction. We did not code these two articles because our analysis focused on primary research.

Coding process. First, we coded which of these articles made inferences, or summary statements, about past research informing the research problem. We also recorded the summary terms used to summarize past research and categorized these terms into frequency (i.e., “most studies in literature X show Y” or “most studies on topic X use paradigm Y”) and variability terms³ (i.e., “on the one hand X, on the other hand Y”). We also coded which features of the literature these summary statements described (results; theories; aspects of the phenomenon;

study design, methodology, and measures). Second, we coded whether these judgments can be considered precise and transparent, which we consider necessary but not sufficient conditions for evaluating the truthfulness, or validity, of research problems. We defined *precise* as “the quality, condition, or fact of being exact and accurate” (Oxford English Dictionary, n.d.) and *transparent* as “characterized by visibility or accessibility of information” (Merriam-Webster, n.d.).

We reviewed the 100 randomly selected articles and coded all text sections that made “inferences about past research informing the research problem” following a preregistered coding scheme (available at https://osf.io/79qdr/?view_only=7c0776b29a674777af6f20704a0c7a7c). Any coding disagreements were resolved through discussions.

We coded text that both made empirical inferences about past research and that was also used by the authors to generate a research problem. For example, we coded the following sentence in West et al. (2014) because it includes a frequency-type judgment about past research and informs the definition of the research problem: “Although previous studies have documented negative effects of perceived anxiety on cross-group relationships, to date, few studies have explored underlying psychological mechanisms that may account for these effects” (p. 826). The phrase “few studies” constitutes an inference about the frequency of mechanism-testing study designs in the literature, and this informs the research problem as the authors “sought to isolate one mechanism” of these relationships (West et al., 2014, p. 839). “Few” is an imprecise term, and how the inference came about is not transparent but remains unclear because no systematic literature review is provided. As an example of a variability judgment that informed the research problem, we coded the following section in Hilbig et al. (2014): “However, at closer inspection, the extant findings also reveal a noteworthy degree of variability, such that some individuals actually behave very much in line with self-interested individual utility maximization, whereas others display other-regarding preferences (e.g., Engel, 2011; Fischbacher, Gächter, & Fehr, 2001)” (p. 529). The inference is not precise because the degree of variability is not quantified, and it is also not clear how the inference came about because the authors did not share whether they systematically reviewed the existing literature.

We ignored statements that only reviewed past research, but that did not inform the research problem. For example, we did not code statements that merely summarized certain studies, were used as stylized facts, or that did not directly feed into the research problem. For example, Beckmann et al. (2013, p. 681) verbally

summarized the literature on muscle contractions. The review helps the reader understand why the studies in Beckmann et al. (2013, p. 681) are methodologically sound, but we did not code this section because the review did not inform the article’s research problem.

Results from coding 100 articles in leading psychology journals. First, our coding shows that 78 of the 100 randomly selected articles made summary statements about past research informing the research problem. The 100 randomly selected articles contained 133 inferences on past research that informed their research problems and questions.

Frequency judgments are most common (114/133), followed by variability judgments (12/133) and judgments relating to both frequency and variability (4/133). Three additional inferences (3/133) were based on the summary term “unclear” and were not coded on this dimension because they do not represent a quantitative judgment. We coded 77 different summary terms, 67 of which related to frequency judgments. To better understand the nature of these 67 frequency terms, we categorized them according to their function (Aarts, 2011): 30/67 were coded as *degree terms* that describe the intensity of an action or quality (e.g., largely, primarily); 23/67 were coded as *indefinite amount terms*, which do not specify how many things are being referred to (e.g., few, many); and 14/67 were coded as *indefinite occurrence terms*, which describe how often something takes place in indefinite terms (e.g., frequently, often; see Fig. 2). We did not subcategorize the 10 variability terms.

We also coded which parts of the research process these inferences relate to. An inference could be coded as relating to more than one part of the research process. The inferences we coded predominantly relate to aspects of the phenomenon (59/133) and results (47/133), and comparatively less to the study design, methodology, and measures (44/133), and to theories (16/133).

Second, we assessed to what extent these claims can be considered precise and transparent. Only 15% of the 133 inferences made in the 100 articles we coded were precise statements about past research. For example, Re and Rule (2016) claimed that “no study” has examined how internal features of the face relate to leadership ability (p. 87). Another example of a precise inference can be found in Murphy et al. (2015), in which the authors claimed that “only one study” has investigated a particular question (p. 200). Both “no study” and “one study” are precise summary terms. The remaining 113 inferences were imprecise judgments on the frequency or variability of past research that do not articulate a

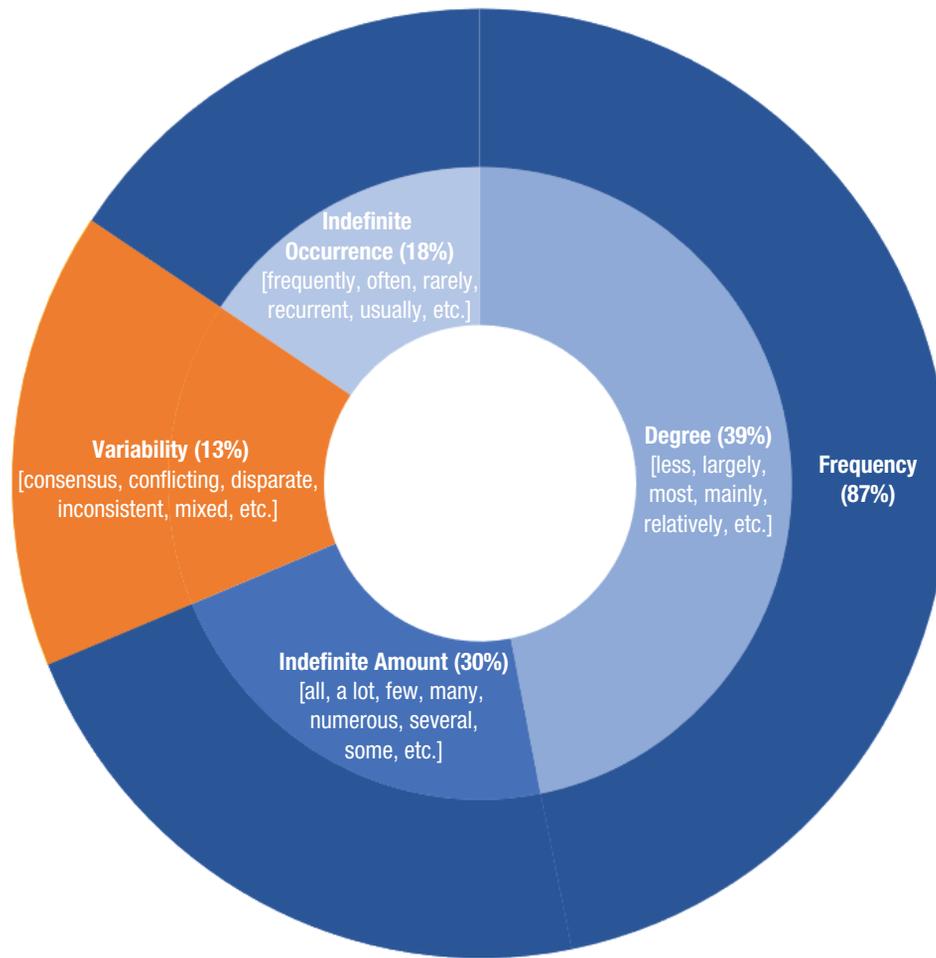


Fig. 2. Inference type, summary-term function and prevalence, and example summary terms in our review of 100 articles. See <https://airtable.com/shr5NNHGvUQFVRq8j> for the coding of each individual article.

precise numeric estimate (Bass et al., 1974). For example, one inference in an article on the nonconscious priming of communication (Pickering et al., 2015) suggested that

many studies have found that unconscious goal pursuit produces the same outcomes as conscious goal pursuit (Chartrand & Bargh, 1996; Dijksterhuis & Aarts, 2010; Dijksterhuis, Chartrand, & Aarts, 2007). However, there appear to be many mediators to effects of priming on goal pursuit (e.g., Locke & Latham, 2006). (p. 78)

We coded both the frequentist characterization of “many studies” and “many mediators” as imprecise. Another article that examined “the chills” as a psychological construct (Maruskin et al., 2012) included the inference that “the literature is a jumble of disparate claims and findings, a fact that has not been apparent

to date because the literature has never been reviewed thoroughly” (p. 136). We coded this inference as imprecise because the degree of inconsistency in the literature has not been evaluated, and it is not clear what the label “jumble of disparate findings” describes.

Only 5% of the 133 inferences made in the 100 articles we coded transparently explained how the inferences about past research came about. For example, van Scheppingen et al. (2019) transparently showed that their assessment of the literature is that the effects of personality similarity on attraction and satisfaction are small and inconclusive and that they based this judgment on the results of the two meta-analyses they cited. Ashworth et al. (2019) claimed that the endowment effect is one of the most robust and well-studied phenomena in the behavioral sciences, and they made it transparent that this claim is based on a Google Scholar search they conducted.

Threats to Research-Problem Validity, Possible Solutions, and Knowledge Gains

Threats to research-problem validity

When research problems communicate imprecise, non-transparent, quantitative judgments, psychological science holds them to lower standards of truthfulness, transparency, and replicability than other parts of the research process, and this threatens the validity of psychological science (Vazire, 2017, 2018). We found that 85% (113/133) of the quantitative judgments we coded in research-problem statements were imprecise. These inferences could be incomplete, inaccurate, and perhaps in some cases altogether incorrect. What explains this lack of precision?

Motivated cognition is likely one explanation for imprecise quantitative judgments. Confirmation bias can lead to a search process or to claims about past research that are one-sided, incomplete, or altogether false (Duyx et al., 2017; Rosenthal, 1979). Motivated cognition can also selectively shape evidence into dichotomies that are not warranted (Garcia-Marques & Ferreira, 2011). Carelessness or lack of processing depth is a second likely explanation for imprecision in quantitative judgments. Even when bias is not at play, unsystematic literature searches may omit entire relevant research fields from the problem statement, creating inefficiency in the scientific progress (Beaman, 1991). Generalized overall impressions of the state of past research may also be inconsistent with a structured and quantitative assessment of that research (Stanley, 2001).

Reporting norms are another strong explanation for the lack of precision. The current norm that literature searches and the corresponding quantitative judgments remain undocumented prevents other scholars from reproducing the search and, by extension, the characterization of past research in research-problem statements. For example, 95% of the articles we coded did not transparently describe how they selected the parts of the literature they brought to bear on the research problem. Readers of these articles cannot evaluate whether the quantitative judgments that inform the research problem correspond to the body of knowledge they are based on.

We do not put all of our faith in tightening reporting norms. Research-problem validity is also threatened when authors are either sufficiently motivated, or just happen to be careless, causing them to sidestep “actual” precision with incorrect or misleading summary statements that seem precise and transparent. Although our suggestions cannot completely prevent this, we believe that the alternative of not providing any attempts to increase transparency and precision in research-problem

statements is worse for reviewers, editors, and readers. Our proposal (or similar ones that could be developed) can help reviewers, editors, and other readers of a primary research article to scrutinize the documented literature search, their results, and the criteria that were defined for the search and coding of search results. Without this documentation, the reader’s judgments on the search are basically criterion-free, beyond the references that are provided and the expertise knowledge that is applied. Our suggested approach provides readers with the information they need to evaluate the search and the subsequent judgments on search results.

Possible solutions

Possible solutions for quantifying inferences on past research more precisely and transparently could be implemented relatively easily. For example, three articles from our sample, Fazio and Sherry (2020, p. 1150), Hughes et al. (2020, p. 2265), and West et al. (2014, p. 825), supported claims about the size of evidence by citing outcomes of literature reviews and meta-analyses. Another article from our sample, Wölfer et al. (2017), directly cited prevalence statistics from such reviews: “Previous studies primarily relied on self-reports to assess intergroup contact (81% of the studies included in Pettigrew & Tropp’s, 2006, meta-analysis used this approach)” (p. 1567). Zhou and Fishbach (2016), another article in our sample, presented a precise research problem when they argued that unattended, selective attrition can bias studies with online samples (e.g., Amazon Mechanical Turk). They pursued easily implemented strategies to increase the transparency and precision of their review of past work. For example, they substantiated their claim that “dropouts are *rarely* disclosed in published papers” by examining all articles published within a certain time frame in a specific journal for search terms that indicated both data collected online and the disclosure of dropout information and found that only four of 289 articles reported this information. This transparency helps the reader decide whether they agree with the conclusion (Zhou & Fishbach, 2016, p. 495).

Using systematic review guidelines to improve research-problem validity.

Implementing transparency in documenting the literature review that led to quantitative judgments about past research is simple, and reporting standards already exist in secondary research that could be borrowed or used as templates. For example, a recent article in *Perspectives on Psychological Science* (Antonoplis, 2022) transparently described the search parameters in a systematic review of socioeconomic status: the database used, publication time period, search

phrases, number of articles found, number of duplicates removed, and number of articles screened and assessed for whether they fit the eligibility criteria for inclusion in the summary of past research. The guidelines that Antonoplis (2022) followed are already used in systematic reviews in epidemiology (Page et al., 2021) and can improve the transparency of research-problem statements in primary research.

We believe that it is useful to precisely and transparently document literature reviews because the current practice remains closed to scientific scrutiny. Perhaps reviews motivating primary research are systematic, perhaps not; perhaps they follow a particular system, or another; we simply do not know. Just as data-analytic decisions for the same hypothesis test vary widely and cause heterogeneity in conclusions about data (Botvinik-Nezer et al., 2020; Schweinsberg et al., 2021), variation in how literature is searched and coded will yield heterogeneous conclusions about the same body of research. By not documenting this research step, we are unable to evaluate the comprehensiveness and quality of a review of the literature, and readers are unable to learn which review practices are superior to others.

Another solution could be to establish conventions for when to use specific summary terms to describe specific frequency or variability observations in the literature (Bass et al., 1974). These conventions could offer consistent rules for translating numeric estimates into verbal summary statements (e.g., use “few” when referring to quantities below five). Similar terminology conventions are used to communicate risk in national security (Kent, 1964) or probabilities in medicine (Andreadis et al., 2021). Cohen (1988) suggested simple conventions to generate consistency for verbal descriptions of effect sizes and when they should be described as small, medium, or large. Although global conventions are not perfect (Cohen, 1962), similar conventions could help clarify which numeric estimates are underlying the vague verbal summary terms we identified such as “several,” “few,” “many,” or “some” (Bass et al., 1974; Borges & Sawyers, 1974). Consistent terminology could also prevent instances in which authors strategically use ambiguity (Eisenberg, 1984) to advance their objectives (Frankenhuis et al., 2022; Rohrer, 2021) in research-problem construction.

Finally, recent calls to make distinct aspects of the scientific process machine-readable (Lakens & DeBruine, 2021; Spadaro et al., 2022) could enhance transparency, standardize the literature-review process, and reduce time and effort expenditure (Brisebois et al., 2017; Sabharwal & Miah, 2022)

Open-science practices to improve research-problem validity. A systematic literature review we conducted

showed that research practices related to research questions and problems (Fig. 1, Step 1) are still confined to traditional research practices. When we searched the Web of Science, we found 1,781 publications on open science and search terms relevant to Step 2 (“open science” & theory; “open science” & prediction); 1,720 publications for Step 3 search terms (“open science” & design); 9,286 publications for Step 4 search terms (“open science” & analysis; “open science” & results; “open science” & discussion); but only 23 publications for Step 1 search terms (“open science” & “research question”; “open science” & “research problem”). When we read these 23 publications in detail, not one publication discussed how to establish a research problem or research question using open-science practices (for a detailed review of these 23 publications, see <https://airtable.com/shrZWuX6bBQlbnmK>).

Open-science practices make transparency the default choice (Klein et al., 2018) for the steps in the scientific-research process, from sharing materials that inform study-design choices (Landy et al., 2020) and raw data (Simonsohn, 2013) to data analyses (Botvinik-Nezer et al., 2020; Schweinsberg et al., 2021). Open-science practices could also be implemented when reviewing the literature in primary research: Scholars could share the search terms they used, and search results, along with coding criteria, and the results of this coding process on an online repository such as OSF.

Possible knowledge gains

We believe that there could be several knowledge gains from adopting a more rigorous and systematic approach in the communication of research problems. First, the practice could lead to a more informed debate. Authors, reviewers, and readers may understand verbal summary terms of quantitative judgments differently (Bass et al., 1974) but seemingly agree when they do not. For example, “some” heterogeneity may mean 20% for Scholar A but 60% for Scholar B. Scholar A (who understands the term to mean 20%) might not see this amount of heterogeneity as large enough to plan a new study that would warrant a contribution. Scholar A may also think that a particular moderator would not produce enough variation to systematically affect the existing variance. However, Scholar B (who understands “some” heterogeneity to mean 60%) does see the heterogeneity judgments as informative for subsequent judgments about the potential contribution of a new study or moderator selection or for study-design choices.

Both scholars might agree with the other’s thresholds for what amount of heterogeneity is large enough to affect the decision to pursue a study or a specific

design. But they disagree on the actual extent of heterogeneity. Quantifying heterogeneity shows the amount of dispersion in findings. Larger amounts of heterogeneity might justify additional empirical investigations to identify (multiple) moderators and in that way have a greater scope for advancing the context-dependence of knowledge (Tipton et al., 2022). Precise and transparent literature reviews can reveal these sources of disagreement and make them explicit instead of concealing them behind verbal summary statements. We believe that an informed debate should improve the scholarly discourse and quality of beliefs (Duke, 2020, Chapter 5).

A second knowledge gain is to help readers and authors evaluate the amount of uncertainty in knowledge on a given phenomenon. Whether “the majority” of research refers to a majority in seven studies or in 700 studies communicates a different degree of confidence in the judgment itself because small samples contain more unusual information than large samples. Related, precise information clarifies the weight of evidence relative to vague statements. “Four studies showed positive effects and three studies showed negative effects” is a more precise characterization than “several studies showed positive effects and few studies showed negative effects.” Precise numeric estimates also help the reader evaluate the impact of minor changes: Not considering just one of the four studies documenting positive effects changes the pattern of results from a “majority” of findings documenting positive effects to a pattern in which “half” the study show positive effects and “half” the studies show negative effects. Precise estimates of variability help readers assess the nature of an effect and can help authors make their study-design choices on a structured and precise knowledge base, and not just on their subjective and potentially biased impression of the literature. For example, authors can benefit from precise estimates of heterogeneity to evaluate whether an effect is moderated by a third factor, and less variability may necessitate stronger manipulations. Finally, transparency can help reveal straw-man arguments by calling on authors to replace vague claims such as “critics argue” or “many people believe that” with precise evidence on the nature and origin of these claims.

Limitations

Our proposal to improve research-problem validity is not without limitations. First, we acknowledge that neither our nor any other framework of this type can fully eliminate misleading characterizations of past research without running the risk of excessive tightening of the research process (Fiedler, 2018). A radical alternative to what we propose here is to altogether abandon

current practices, in which research-problem statements justify cumulative contribution. The 199th study on the same phenomenon with similar methods can still be considered useful knowledge because psychological phenomena are highly variable and context-dependent (McGuire, 1973). Perhaps what matters is the correctness of methods and conclusions alone, but then we need to abandon the current practice of justifying primary research based on problem statements that claim to have reviewed the literature. Another limitation is that sufficiently motivated authors could seemingly review research with precision and transparency but do so in misleading ways. However, we believe that transparency and precision will make such mischaracterizations easier to identify, limit the scope for strategic ambiguity (Eisenberg, 1984; Frankenhuys et al., 2022; Rohrer, 2021) in the construction of research problems, and thereby contribute to a more truthful cumulative psychological science. Second, a variation of this risk is an only partial, potentially strategic adoption of our recommendations: For example, simply replacing “few articles” with “four articles” increases the precision of a summary statement but not its transparency. However, if authors also increase transparency and specify their search parameters, readers and reviewers can better assess which studies were considered, and which were ignored, compared with an otherwise vague and non-transparent literature review. Third, implementing our (or variations of our) suggestions do take time, although the time required can be minimized in simple ways: Authors are not called on to conduct meta-analyses for primary research articles, but simply sharing transparently how they arrive at their characterization of past research and increasing the precision with which they characterize this past research will bring methodological standards in secondary and primary research closer together.

Conclusion

Why should the review of past literature and how researchers identify their research problems remain a black box? Why develop sophisticated methodologies to evaluate the validity of research designs and data analysis in primary studies but not for the inferences and judgments on past research that justify this study in the first place? We proposed here that existing tools such as quantification and a documented, reproducible literature search and coding can increase the truthfulness of judgments that are central to the research problem a primary research article attempts to solve. Ignoring research-problem validity means that although the study design may be reproducible, externally valid, and truthful, the research problem may not be, resulting

in the right answer to the wrong problem (Kimball, 1957). More broadly, these loose practices may undermine the scientific goal of building an accurate and truthful cumulative body of knowledge.

Transparency

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Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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Notes

1. Certain research domains in experimental social psychology such as cognitive dissonance (Harmon-Jones & Harmon-Jones, 2007), conformity pressure (Cialdini & Goldstein, 2004), or intergroup bias (Hewstone et al., 2002) have now accumulated findings for 40 to 60 years, contributing to psychology as a cumulative science (but see also Meehl, 1978). However, even in younger research domains there will be structurally similar phenomena that could be reviewed.

2. Vagueness conceals not only the distribution of evidence but also features such as different quality levels of evidence. Precision reveals these features and allows quality differences in evidence to be coded (for examples of coding quality differences in evidence, see Cochrane Reviews; Higgins & Thomas, 2020).

3. Terms that describe the central tendency of past research (e.g., “typical,” “most”) were coded as part of the frequency category.

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