A Test-Retest Reliability Generalization Meta-Analysis of Judgments Via the Policy-Capturing Technique

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A Test-Retest Reliability Generalization Meta-Analysis of Judgments Via the Policy-Capturing Technique

Ze Zhu¹, Alan J. Tomassetti², Reeshad S. Dalal¹, Shannon W. Schrader¹, Kevin Loo¹, Isaac E. Sabat³, Balca Alaybek¹, You Zhou¹, Chelsea Jones¹, and Shea Fyffe¹

Abstract
Policy capturing is a widely used technique, but the temporal stability of policy-capturing judgments has long been a cause for concern. This article emphasizes the importance of reporting reliability, and in particular test-retest reliability, estimates in policy-capturing studies. We found that only 164 of 955 policy-capturing studies (i.e., 17.17%) reported a test-retest reliability estimate. We then conducted a reliability generalization meta-analysis on policy-capturing studies that did report test-retest reliability estimates—and we obtained an average reliability estimate of .78. We additionally examined 16 potential methodological and substantive antecedents to test-retest reliability (equivalent to moderators in validity generalization studies). We found that test-retest reliability was robust to variation in 14 of the 16 factors examined but that reliability was higher in paper-and-pencil studies than in web-based studies and was higher for behavioral intention judgments than for other (e.g., attitudinal and perceptual) judgments. We provide an agenda for future research. Finally, we provide several best-practice recommendations for researchers (and journal reviewers) with regard to (a) reporting test-retest reliability, (b) designing policy-capturing studies for appropriate reportage, and (c) properly interpreting test-retest reliability in policy-capturing studies.

Keywords
policy capturing, test-retest reliability, reliability generalization, judgment analysis, meta-analysis

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Policy capturing (also known as judgment analysis) is a long-standing survey technique that examines how people weigh different pieces of information when making judgments (Zedeck, 1977). Policy capturing has been used in a wide array of contexts, including job choice (Rynes et al., 1983), union voting (Leigh, 1986), receptivity to various forms of advice (Dalal & Bonaccio, 2010), promotion decisions (Viswesvaran et al., 1994), and counselor judgments of client acute suicide lethality (Brown, 1972). However, although the policy-capturing technique has been used widely for over four decades, until now, no reliability generalization study has been conducted. In much the same way as researchers have questioned the reliability of novel survey techniques—with some of these techniques ultimately proving more reliable (e.g., situational judgment tests; Catano et al., 2012) than others (e.g., most Rorschach-based tests; Garb, 1999)—in the current article, we examine the average test-retest reliability of the policy-capturing survey technique across studies as well as methodological and substantive factors that may influence reliability estimates. We focus specifically on test-retest reliability because the error source most relevant to policy capturing is temporal (in)stability over the course of the (potentially very long) policy-capturing measure (Aiman-Smith et al., 2002; Cooksey, 1996; Karren & Barringer, 2002). Because reliability is necessary (although not sufficient) for validity (Cronbach, 1988; Sireci & Sukin, 2013), the validity of conclusions from policy-capturing studies cannot be accepted uncritically without demonstrating that policy-capturing judgments are stable over time.

One explanation for the lack of a policy-capturing reliability generalization study may be the low rate at which estimates of policy-capturing reliability have historically been reported. In a 2002 policy-capturing review and tutorial published in *Organizational Research Methods*, Karren and Barringer found that only a very small number of policy-capturing studies had reported any index of reliability. Therefore, Karren and Barringer—as well as a companion piece in the same journal by Aiman-Smith et al. (2002)—advocated that policy-capturing studies routinely report estimates of, in particular, test-retest reliability. Given the passage of time since the publication of these best-practice tutorials, sufficient test-retest reliability estimates now exist to facilitate a reliability generalization meta-analysis. In addition to investigating the average test-retest reliability estimate reported in policy-capturing studies, the present meta-analysis examines the degree to which these reliability estimates generalize (vs. vary) across methodological choices made by the authors of policy-capturing studies and across substantive factors studied in policy-capturing studies.

### Estimating Reliability in Policy-Capturing Studies

In policy-capturing studies, decision-makers make judgments in response to a series of scenarios or profiles across which researchers have
manipulated the levels of several cues (e.g., present vs. absent or high vs. low cue levels). Decision-makers’ judgment “policies” are then “captured” by regressing their judgment(s) in response to the scenarios onto the combinations of cue levels present in those scenarios. This permits an assessment of the extent to which decision-makers used the cues in reaching their judgments. For example, Tomassetti et al. (2016) examined how a decision-maker’s willingness to accept a job is influenced by levels (high vs. low) of six job or organization characteristics (e.g., pay level and schedule flexibility). Figure 1 provides two example scenarios out of the 64 focal scenarios used in the Tomassetti et al. study.

Because decision-makers must make a relatively long series of judgments in policy-capturing studies, the stability of their judgment policies is a concern. Test-retest reliability is designed to assess temporal stability and is therefore the preferred method for assessing reliability in policy-capturing studies (Aiman-Smith et al., 2002; Karren & Barringer, 2002). The current research therefore focuses on test-retest reliability. However, because some policy-capturing studies have reported a reliability estimate other than (or in addition to) test-retest reliability, we discuss the appropriateness of various reliability measures, including test-retest reliability, in Table 1.

To use the test-retest method in policy-capturing studies, a few of (or all) the policy-capturing scenarios are repeated such that they are presented to the participants twice. Participants’ judgments across the two iterations of these scenarios are correlated to generate a test-retest reliability correlation coefficient for each decision-maker (within-person or idiographic reliability) and/or for each repeated scenario (between-person or nomothetic reliability). These coefficients are generally averaged across all the decision-makers or scenarios before being reported. It should be noted that although duplicate scenarios are obviously required for the estimation of test-retest reliability, they are unnecessary in the focal policy-capturing analyses: namely, estimating decision-makers’ judgment policies. One iteration of the duplicate scenarios (generally, the second iteration) is therefore removed from the data set after assessing test-retest reliability but prior to the focal analyses.

The Current Study

The present reliability generalization study focuses on policy-capturing studies that reported test-retest reliability, as recommended by the Karren and Barringer (2002) policy-capturing tutorial. At least at the time the tutorial was published, however, reportage of test-retest reliability was rare. Our first research question therefore pertains to the overall extent of reportage of test-retest reliability estimates.
Figure 1. Two example policy-capturing scenarios (from Tomassetti et al., 2016). Note: The first (or top) policy-capturing scenario contains all the cues with positive wording, and the second (or bottom) scenario contains all the cues with negative wording.

Research Question 1: What percentage of policy-capturing studies report a test-retest reliability estimate?

Next, we turn to the focal effect size in this reliability generalization meta-analysis: the test-retest reliability correlation coefficient. Specifically, what is the average test-retest reliability in policy-capturing studies that do report reliability information? This question is important because if policy-capturing studies do not exhibit high test-retest reliability, they cannot accurately capture decision-makers' judgment policies.
<table>
<thead>
<tr>
<th>Reliability</th>
<th>Appropriate for Policy-Capturing Technique?</th>
<th>Reason(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach's alpha</td>
<td>No, unless multiple judgments (i.e., responses) are required per scenario and these judgments must subsequently be aggregated into a composite judgment</td>
<td>With a policy-capturing study, a researcher would not expect all the judgments made by a specific decision-maker across policy-capturing scenarios to have high communalities (communality = $\frac{1}{4}$ the proportion of variance in one judgment accounted for by all the other judgments), and therefore Cronbach's alpha would be inappropriate. However, in the relatively infrequent case in which a policy-capturing study involves multiple judgments (vs. one) within each policy-capturing scenario, and if these judgments are furthermore assumed to represent indicators of the same underlying construct, Cronbach's alpha could be used to assess the appropriateness of aggregating these judgments into a single composite judgment per scenario (Cortina, 1993).</td>
</tr>
<tr>
<td>Kuder-Richardson coefficient of equivalence</td>
<td>No</td>
<td>A Kuder-Richardson coefficient of equivalence is inappropriate because policy-capturing response scales are generally not dichotomous (Aiman-Smith et al. 2002)—in other words, because the responses elicited from decision-makers are generally judgments rather than choices.</td>
</tr>
<tr>
<td>Interrater reliability</td>
<td>No, except possibly within clusters of judgment policies</td>
<td>Policy-capturing researchers do not necessarily expect two decision-makers to make the same judgments, even given identical scenarios. This is evident in the frequent use of cluster analysis in policy-capturing studies (e.g., Dalal &amp; Bonaccio, 2010), wherein researchers expect multiple clusters of judgment policies. Therefore, indices of interrater—as opposed to intrarater or test-retest—reliability (LeBreton &amp; Senter, 2008) are inappropriate, except possibly within a cluster of judgment policies.</td>
</tr>
<tr>
<td>Test-retest reliability</td>
<td>Yes</td>
<td>The error source most relevant in policy-capturing measures is that of temporal (in)stability over the course of the (potentially very long) policy-capturing measure (Aiman-Smith et al., 2002, Cooksey, 1996; Karren &amp; Barringer, 2002). Stated differently, the extent to which the decision-maker uses a temporally stable judgment policy across scenarios in the study is the primary reliability-based concern. Therefore, the use of a test-retest Pearson product-moment correlation is appropriate. In cases where not just reliability but also absolute agreement is of interest, a test-retest equivalent to $r_{wq}$ (LeBreton &amp; Senter, 2008; see also Berchtold, 2016) could also be included.</td>
</tr>
</tbody>
</table>
Research Question 2: What is the average test-retest reliability in policy-capturing studies?

Potential Methodological Antecedents of Test-Retest Reliability

Another important question pertains to the extent to which test-retest reliability estimates in policy-capturing studies generalize (vs. vary appreciably) across numerous methodological choices made by authors of policy-capturing studies. We grouped these potential methodological antecedents to reliability (equivalent to moderators in validity generalization studies) into three sets: (a) general study and sample characteristics, (b) scenario characteristics, and (c) design characteristics.

General Study Characteristics. General study characteristics are factors common to almost all social science research. An example is the year of publication, which we use to determine if more recent studies—with the advantage of having more existing empirical studies to model and more published tutorials to follow—on average yield higher reliability than older studies. Other general study characteristics include sample type (i.e., student vs. nonstudent samples), journal impact factor, and sample size.

Scenario Characteristics. Scenario characteristics describe how the policy-capturing scenarios were constructed. The first subset of scenario characteristics involves those characteristics impacting study length. Concerns about the length of the survey are often motivated by the expectation that participants’ cognitive resources or attention will decrease over the course of a survey. Research on vigilance decrement suggests that performance deteriorates as humans attempt to maintain continued attention on a specific task (Davies & Parasuraman, 1982; Mackworth, 1948). Similarly, ego depletion theory holds that performance deteriorates when regulatory resources are depleted (Baumeister & Heatherton, 1996; Hagger et al., 2010). In survey contexts, this expectation has been verified by self-reports of attention waning toward the middle or end of long surveys (Baer et al., 1997; Meade & Craig, 2012). The characteristics that determine the length of a policy-capturing study are factors that policy-capturing tutorials have identified as areas to which researchers should pay particular attention when designing studies. For example, with regard to recommendations regarding the ideal number of scenarios for a policy-capturing study, Rossi and Anderson (1982) recommended no more than 60 scenarios, whereas Cooksey (1996) suggested that up to 100 scenarios are acceptable. With regard to the number of cues per policy-capturing scenario, Aiman-Smith et al. (2002) recommended no more than five cues, whereas Karren and Barringer (2002) recommended no more than one fifth as many cues as scenarios. Based on the vigilance decrement effect and ego depletion theory, keeping track of a large
number of scenarios or a large number of cues per scenario may reduce the test-retest reliability of policy-capturing judgments. However, the ego depletion phenomenon has recently been called into question (e.g., Carter et al., 2015; Hagger et al., 2016). Moreover, it is possible that as the number of scenarios in a study and/or the number of cues in a scenario increase, decision-makers compensate by paying attention to only a very small number of cues—thereby minimizing fatigue. We therefore examine the impact of the number of scenarios and the number of cues per scenario on reliability in an exploratory manner.

The second subset of scenario characteristics is scenario presentation characteristics. These characteristics have the potential to be related to reliability estimates because scenarios with different presentation characteristics require different levels of cognitive effort to process and understand them. Specifically, the fundamental cognitive experience of a policy-capturing study involves a decision-maker understanding the cues (and cue levels) in a scenario and forming a judgment related to that scenario. As such, the key components to determining the cognitive demand of a scenario are (a) how easy or difficult the cue presentation format is to process and (b) how easy or difficult the changes in cue levels from one scenario to the next are to identify. Accordingly, we focus on two scenario presentation characteristics: cue presentation format and attention to cue levels.

Regarding cue presentation formats, cues are generally presented as (a) images (e.g., pictures, drawings), (b) tables and/or graphs, and (c) text only. Research on “scene gist” shows that individuals can rapidly (i.e., with minimal cognitive effort) and accurately extract meaning from a visual scene (Friedman, 1979; Li et al., 2002). Additionally, research on the “picture superiority effect” suggests that images are easier to remember and recall than written words because the dual encoding of images (i.e., images can be coded both as images and in verbal form) produces a more effective memory trace for response retrieval (Bevan & Steger, 1971; Paivio, 1969, 1971). Applied to policy-capturing studies, this means not only that decision-makers may understand what is being presented in an image-based scenario (e.g., cues presented in images, tables, or graphs) with less cognitive effort than if it were purely text-based but also that they may encode the information needed for judgment while using fewer cognitive resources than if the same scenario were purely text-based. Therefore, we examine whether cue presentation formats influence policy-capturing reliability.

Next, within the scenarios category (image, table/graph, or pure text), some formats specifically direct a decision-maker’s attention to the cue levels that change from scenario to scenario. Research on attention suggests that such formats may require fewer resources than formats that do not direct attention to changes across scenarios (Egly et al., 1994; Rensink, 2002). Thus, making policy-capturing judgments in scenarios...
where the portions of the scenarios that change across scenarios are highlighted by the researchers (e.g., boldface font) or are inherently prominent (e.g., the only value in a table’s row) may require less cognitive effort than when the change is not indicated. We therefore examine whether test-retest reliability varies as a function of whether changes across cue levels are highlighted.

Design Characteristics. Design characteristics describe methodological choices made by researchers in designing the study. One general example is survey medium—that is, pencil and paper or online—because there has been substantial debate as to the psychometric quality of data captured online (and not in front of the researcher) versus data captured in person via paper and pencil (Heerwegh, 2009; Marta-Pedroso et al., 2007). In-person paper-and-pencil studies conceivably exert pressure on decision-makers via a Hawthorne effect (Roethlisberger & Dickson, 1939), thus leading to more stable judgments. We therefore examine whether test-retest reliability differs for online versus paper-and-pencil studies.

An example specific to policy-capturing studies is study design. In a full factorial design, all factors (i.e., cues) are fully crossed and balanced. In contrast, confounded factorial designs, which include block designs and fractional factorial designs, involve systematically dividing the full factorial set into blocks (e.g., halves, quarters, eighths) and presenting each participant with one of the blocks (Graham & Cable, 2001; Karren & Barringer, 2002). Compared to block designs and fractional factorial designs, the corresponding full factorial designs are longer. Karren and Barringer (2002) emphasized the association between survey length and increases in participant stress and exhaustion, raising concerns about survey length resulting from a full factorial design (Graham & Cable, 2001). We therefore examine whether test-retest reliability differs across study designs.

Another study design characteristic is the time gap between the first and second iterations of the repeated scenarios. When the two iterations are in separate sessions with an intervening gap of days or weeks, decision-makers may deliberately or unwittingly (e.g., due to forgetfulness) change their judgment policy across sessions—thereby potentially leading to lower test-retest reliability estimates than in same-session designs. Conversely, however, compared to the corresponding same-session designs, the surveys in each session of different-session designs are shorter, thereby leading to lower cognitive load and, potentially, higher test-retest reliability. Thus, we explore whether test-retest reliability differs as a function of the time gap between iterations of repeated scenarios.

The last design characteristic is level of analysis for test-retest reliability. In policy-capturing studies, the test-retest reliability estimates can be calculated at the within-person (idiographic) level and/or at the between-person (nomothetic) level. To calculate within-person reliability, each
participant’s judgments are correlated across the initial and repeated versions of the repeated scenarios. Each participant has a test-retest reliability estimate, and the mean test-retest reliability across all participants is reported. At the between-person level, test-retest reliability is calculated for each repeated scenario by separately correlating the scores on the initial and repeated version of the scenarios across participants. Then, the mean test-retest reliability across all repeated scenarios is reported. It is worth examining whether the level of analysis influences test-retest reliability for two reasons. First, test-retest reliability estimates at the within- and between-person levels of analysis provide different information (i.e., the reliability for each participant across repeated scenarios vs. the reliability for each repeated scenario across participants, respectively). Second, in general, there is considerable interest in the extent to which results from the between-person level of analysis generalize to the within-person level (Dalal et al., 2014; Molenaar & Campbell, 2009). Hence, we examine whether test-retest reliability is a function of levels of analysis.

Overall, we examine the extent to which test-retest reliability in policy capturing generalizes (vs. varies appreciably) across the aforementioned methodological antecedents.

Research Question 3: Which methodological characteristics significantly influence test-retest reliability estimates in policy-capturing studies?

Potential Substantive Antecedents of Test-Retest Reliability

We also examine, in an exploratory manner, the extent to which test-retest reliability estimates in policy-capturing studies generalize (vs. vary appreciably) across two substantive antecedents: topic area and judgment type. Topic area includes organizational behavior and human resources (OBHR) research versus other—that is, non-OBHR—research. Judgment type consists of four types of judgment: (a) attitude (i.e., participants' latent disposition or tendency to respond with some degree of favorableness to a psychological object), (b) perception (i.e., the process of interpreting, selecting, and organizing objective information), (c) behavioral intention (i.e., indication of a person’s readiness to perform a behavior), and (d) mixed or undeterminable (Fishbein & Ajzen, 2009).
Table 2. Identification of Studies and Selection Criteria.

<table>
<thead>
<tr>
<th>Search Method</th>
<th>Search Scope</th>
<th>Search Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database search</td>
<td>PsycINFO, ProQuest Dissertation Abstracts Online, ABI/INFORM COMPLETE online, and Web of Science databases</td>
<td>“policy capturing,” “judgment analysis,” and “judgement analysis”</td>
</tr>
<tr>
<td>Conference programs</td>
<td>The Academy of Management (AOM), American Educational Research Association (AERA), American Nurses Association (ANA), American Psychiatric Nurses Association (APNA), Association for Psychological Science (APS), British Psychological Society (BPS), Brunswik Society, Society for Industrial and Organizational Psychology (SIOP), Society for Judgment and Decision Making (SJDM), and Society for Personality and Social Psychology (SPSP)</td>
<td>“policy capturing,” “judgment analysis,” and “judgement analysis”</td>
</tr>
<tr>
<td>Ancestry search</td>
<td>All coded articles from the aforementioned database and conference program searches as well as seven seminal articles: three seminal policy-capturing tutorials (i.e., Aiman-Smith et al., 2002; Graham &amp; Cable, 2001; Karren &amp; Barringer, 2002), one tutorial on experimental vignette studies (Aguinis &amp; Bradley, 2014), two meta-analyses on the lens model (Karelaia &amp; Hogarth, 2008; Kaufmann et al., 2013), and one review article on the test-retest reliability of professional judgment (Ashton, 2000)</td>
<td>“policy capturing,” “judgment analysis,” and “judgement analysis”</td>
</tr>
<tr>
<td>Descendent search</td>
<td>The aforementioned seven seminal articles</td>
<td>“reliability” or “retest”</td>
</tr>
<tr>
<td>Emails to listservs</td>
<td>AOM’s Organizational Behavior division listserv, AOM’s Research Methods division listserv, and the SJDM listserv</td>
<td>NA</td>
</tr>
</tbody>
</table>

Note: NA if not applicable.

aWe chose these conference programs based on the areas that emerged in the database search results. Specifically, we coded the research area of each included primary study from the database search. After identifying the areas where policy-capturing designs are used, we found the major conferences in each research area. Last, we searched the conference programs using the search terms in the table to find potential articles.

Research Question 4: Which substantive characteristics significantly influence test-retest reliability estimates in policy-capturing studies?

Method

Identification of Studies and Selection Criteria

To locate policy-capturing studies that reported test-retest reliability, we conducted a database search, a conference program search, and a search of articles that were “ancestors” and “descendants” of already located articles. Additionally, we sent emails to three listservs to request relevant unpublished research. See Table 2 for more details.

To evaluate an empirical study’s relevance for the current meta-analysis, we examined the study’s method section to determine whether the authors had in fact used a policy-capturing design. The flow diagram summarizing the study identification and evaluation process (Appelbaum et al., 2018; Moher et al., 2009) can be seen in Figure 2.
Figure 2. Flow diagram of studies through the meta-analysis inclusion process.

aThe total number of empirical policy-capturing papers is 465 326 1 163 955, which is used as the denominator to calculate the percentage of policy-capturing studies that reported a test-retest reliability estimate.

bOne policy-capturing study (Ebert & Kruse, 1978) that reported a test-retest reliability estimate was not included in the meta-analysis due to the small sample size. The formula for calculating the inverse variance weight used in calculating the mean effect size and in the weighted least squares regression involves the standard error of the reliability correlation. The equation for the standard error is \( \frac{1}{N} \), where \( N \) is the sample size in the study. The sample size of the Ebert and Kruse (1978) study was three, meaning that the denominator in the standard error formula was zero and therefore that the standard error for this study was undefined. As a result, this study was excluded from further analysis. Ebert and Kruse reported a test-retest reliability correlation of .93.

Coding of Studies

We developed a coding manual to help us code test-retest reliability and potential antecedents. Interrater agreement for two independent coders was 85.44% across an initial set of 16 studies and 90.31% across a second set of 21 studies—the latter comparable to other meta-analyses (e.g., B. J. Hoffman et al., 2015; Knight & Eisenkraft, 2015). The coding manual was refined after each stage of the interrater agreement process, and a single coder used the final version (provided in the online supplementary materials) to code the remaining studies while consulting a second coder regarding particularly challenging coding decisions.
Data Analysis

A random-effects meta-analysis model (Hedges & Olkin, 1985; Schmidt & Hunter, 2015) was used to estimate the population reliability of judgments made in policy-capturing studies. The effect size used in the analyses was the Fisher $z$-transformed test-retest reliability correlation between the original and repeated scenarios. The mean effect size analyses and the antecedent analyses were run in SPSS Version 19 (IBM Corp., 2010), using the MeanES and MetaReg macros (Lipsey & Wilson, 2001; Wilson, 2006), respectively, as well as the metafor package (Viechtbauer, 2010) in R 3.6.1. Weighted least squares (WLS) regression was applied for the antecedent analyses. For categorical (vs. continuous) antecedents, antecedent categories with fewer than 10 observed cases (see the rows marked “NA” in Table 4) were omitted prior to analysis. In practice, this resulted in all categorical antecedents except judgment type being reduced to dichotomous variables for the analyses. For example, for survey medium, the analysis compared only paper-and-pencil (in-person) text versus web-based (online) text because additional categories (e.g., audio and video) were excluded due to low observed frequencies.

Results

Test-Retest Reliability Reportage

Vis-a`-vis Research Question 1, we found that 17.17% (164 out of 955) of policy-capturing studies reported test-retest reliability estimates. Thus, although the number of policy-capturing studies reporting test-retest reliability estimates is large enough to conduct a reliability generalization study, the percentage of the total is low despite recommendations provided in policy-capturing tutorials (Aiman-Smith et al., 2002; Karren &
To examine trends in reportage over time, we furthermore calculated a point-biserial correlation between year of publication and whether test-retest reliability estimates were reported in the publication. Results showed a statistically significant but small tendency for more recent publications to be more likely to report test-retest reliability ($r = .10, p=.002$). Additionally, Table 3 depicts the frequencies (and percentages) of reportage as well as the means and standard deviations of test-retest reliability estimates reported in studies published before versus after the Aiman-Smith et al. (2002) and Karren and Barringer (2002) policy-capturing tutorials were published. The percentage of policy-capturing studies that actually reported test-retest reliability estimates was significantly higher after (20.39\%) than before (14.23\%) the tutorials were published: $z = 2.70, p = .007$. Interestingly, the mean test-retest reliability in studies published after the tutorials ($M_{\text{weighted}} = 0.76, SD_{\rho} =0.12\,$) was actually lower than that in studies published before the tutorials ($M_{\text{weighted}} = 0.80, SD_{\rho} = 0.10\,$), $t(161) = −2.06, p = .041$. Finally, the standard deviation of the test-retest reliability did not differ across studies published before versus after the tutorials, Levene’s $F(1,161) = 0.03, p=.864$. These results suggest that the policy-capturing tutorials were associated with a beneficial effect on reportage of test-retest reliability per se. Moreover, the policy-capturing tutorials did not appear to lead authors to avoid reporting low test-retest reliability estimates: Doing so would presumably have manifested as higher reported means and truncated standard deviations in studies published after (vs. before) the tutorials, which is not what we found.

**Mean Level of Test-Retest Reliability**

Across 163 independent samples and 20,244 participants, the mean meta-analytic effect size for test-retest reliability was $r = .78$ (95\% CI [0.75, 0.80], $SE = 0.03$), thereby addressing Research Question 2. Figure 3 shows the distribution of test-retest reliability estimates in primary studies. It should be noted that one policy-capturing study (Ebert & Kruse, 1978) that reported a test-retest reliability estimate was not included in the meta-analysis due to the small sample size (for details, see the note under Figure 2). For the meta-analysis, this reduced the $k$ from 164 to 163.
Table 3. Frequencies, Proportions, Means, and Standard Deviations of Test-Retest Reliability in Articles Published Before Versus After the 2002 Policy-Capturing Tutorials (i.e., Aiman-Smith et al., 2002; Karren & Barringer, 2002).

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Policy-Capturing Studies That Reported Test-Retest Reliability</th>
<th>Total Number of Policy-Capturing Studies</th>
<th>Percentage of Policy-Capturing Studies That Reported Test-Retest Reliability</th>
<th>Mean of Reported Test-Retest Reliability</th>
<th>Standard Deviation of Reported Test-Retest Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up to 2002 (including 2002)</td>
<td>71</td>
<td>499</td>
<td>14.23%</td>
<td>0.80</td>
<td>0.10</td>
</tr>
<tr>
<td>After 2002 (since 2003)</td>
<td>93</td>
<td>456</td>
<td>20.39%</td>
<td>0.76</td>
<td>0.12</td>
</tr>
<tr>
<td>Total (all years)</td>
<td>164a</td>
<td>955</td>
<td>17.17%</td>
<td>0.78</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Note: The “Total” row provides the overall average test-retest reliability estimate for policy-capturing studies (mean \( r_{p}^{2} \)).

aOne policy-capturing study (Ebert & Kruse, 1978) that reported a test-retest reliability estimate was included to compute the frequencies and percentages but was not included in the meta-analytic results (means and standard deviations) due to the small sample size. The formula for calculating the inverse variance weight used in calculating the mean effect size and in the weighted least squares regression involves the standard error of the reliability correlation. The equation for the standard error is \( \sqrt{\frac{1}{N}} \), where \( N \) is the sample size in the study. The sample size of the Ebert and Kruse (1978) study was three, meaning that the denominator in the standard error formula was zero and therefore that the standard error for this study was undefined. As a result, this study was excluded from further analysis. Ebert and Kruse reported a test-retest reliability correlation of .93. For the meta-analytic results reported in subsequent tables, the exclusion of the Ebert and Kruse (1978) study reduced the \( k \) from 164 to 163.

Potential Antecedents to Test-Retest Reliability Estimates

We used three methods to test for heterogeneity across primary studies: (a) the omnibus Q test for heterogeneity (Lipsey & Wilson, 2001), (b) the standard deviation of the effect sizes, corrected for sampling error (i.e., \( SD_{rho} \); Schmidt & Hunter, 2015), and (c) the 80% credibility interval (Koslowsky & Sagie, 1993). The omnibus Q test was statistically significant (\( Q = 2,519.21, df = 162, p < .001 \)), the \( SD_{rho} \) was greater than zero \( (SD_{rho} = 0.12) \), and the 80% credibility interval (i.e., \([0.63, 0.93]\) was wider than the 0.11 rule of thumb proposed by Koslowsky and Sagie (1993). All three methods therefore suggested heterogeneity. Because of this and because we had specified the potential antecedents a priori (Schmidt & Hunter, 2015), we proceeded with antecedent analyses (equivalent to moderator analyses in validity generalization studies).

Examining Potential Antecedents to Test-Retest Reliability. To answer Research Questions 3 and 4, we conducted WLS regression analyses to test whether methodological and substantive characteristics influence reliability estimates in policy-capturing studies (see Tables 4 and 5). However, with one exception (described in the following paragraph), we tested each antecedent separately—that is, one at a time—to maximize the \( k \) (number of independent samples) in each analysis because the \( k \) varied dramatically across antecedents and because the listwise \( k \) in a model containing multiple antecedents was often quite low.
### Table 4. Descriptive and Meta-Analytic Statistics for Categorical Putative Antecedents to Test-Retest Reliability.

<table>
<thead>
<tr>
<th>Antecedent Type</th>
<th>Categorical Putative Antecedent</th>
<th>Category</th>
<th>Frequency (Percentage)</th>
<th>Mean Test-Retest Reliability Estimate (SE)</th>
<th>95% CI</th>
<th>SD &lt;sub&gt;rho&lt;/sub&gt;</th>
<th>80% CV &lt;sub&gt;b&lt;/sub&gt;</th>
<th>b (SE) &lt;sub&gt;c&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>General study and sample characteristics</td>
<td>Sample type&lt;sup&gt;d&lt;/sup&gt;</td>
<td>Student</td>
<td>53 (32.50%)</td>
<td>0.77 (0.05)</td>
<td>[0.73, 0.81]</td>
<td>0.14</td>
<td>[0.59, 0.95]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nonstudent</td>
<td></td>
<td>101 (62.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.11</td>
<td>[0.64, 0.92]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mixed&lt;sup&gt;e&lt;/sup&gt;</td>
<td></td>
<td>9 (5.50%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.04 (0.06)</td>
</tr>
<tr>
<td>Scenario characteristics</td>
<td>Cue presentation format&lt;sup&gt;c&lt;/sup&gt;</td>
<td>Text</td>
<td>94 (63.10%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Table and/or graph</td>
<td></td>
<td>50 (33.60%)</td>
<td>0.78 (0.05)</td>
<td>[0.73, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Image</td>
<td></td>
<td>4 (2.70%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Video</td>
<td></td>
<td>1 (0.70%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>163 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td>−0.01 (0.06)</td>
</tr>
<tr>
<td>Attention to cue levels</td>
<td>Draws attention to changing cue levels</td>
<td></td>
<td>72 (53.30%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Does not draw attention to changing cue levels</td>
<td></td>
<td>63 (46.70%)</td>
<td>0.77 (0.05)</td>
<td>[0.73, 0.80]</td>
<td>0.12</td>
<td>[0.62, 0.92]</td>
<td></td>
</tr>
<tr>
<td>Study design characteristics</td>
<td>Survey medium&lt;sup&gt;d&lt;/sup&gt;</td>
<td>Paper-and-pencil (in-person) text</td>
<td>90 (63.40%)</td>
<td>0.80 (0.04)</td>
<td>[0.77, 0.82]</td>
<td>0.12</td>
<td>[0.65, 0.95]</td>
<td>−0.04 (0.06)</td>
</tr>
<tr>
<td></td>
<td>Web-based (online) text</td>
<td></td>
<td>43 (30.30%)</td>
<td>0.74 (0.05)</td>
<td>[0.69, 0.78]</td>
<td>0.10</td>
<td>[0.61, 0.87]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Audio</td>
<td></td>
<td>1 (0.70%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Web-based (online) video</td>
<td></td>
<td>1 (0.70%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Other&lt;sup&gt;f&lt;/sup&gt;</td>
<td></td>
<td>7 (4.90%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>142 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.74, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td>−0.20* (0.06)</td>
</tr>
<tr>
<td>Study design&lt;sup&gt;d&lt;/sup&gt;</td>
<td>Full-factorial (orthogonal) design</td>
<td></td>
<td>81 (49.70%)</td>
<td>0.78 (0.04)</td>
<td>[0.74, 0.81]</td>
<td>0.12</td>
<td>[0.63, 0.93]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fractional design</td>
<td></td>
<td>45 (27.60%)</td>
<td>0.80 (0.05)</td>
<td>[0.76, 0.84]</td>
<td>0.12</td>
<td>[0.65, 0.95]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Block design</td>
<td></td>
<td>9 (5.50%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Other&lt;sup&gt;g&lt;/sup&gt;</td>
<td></td>
<td>28 (17.20%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>163 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.76, 0.80]</td>
<td>0.12</td>
<td>[0.62, 0.93]</td>
<td>0.08 (0.07)</td>
</tr>
<tr>
<td>Time gap</td>
<td>Same session</td>
<td></td>
<td>147 (90.20%)</td>
<td>0.78 (0.04)</td>
<td>[0.76, 0.81]</td>
<td>0.09</td>
<td>[0.61, 0.85]</td>
<td>−0.08 (0.11)</td>
</tr>
<tr>
<td></td>
<td>Separate sessions</td>
<td></td>
<td>16 (9.80%)</td>
<td>0.73 (0.10)</td>
<td>[0.62, 0.81]</td>
<td>0.09</td>
<td>[0.61, 0.85]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>163 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.76, 0.81]</td>
<td>0.12</td>
<td>[0.62, 0.93]</td>
<td></td>
</tr>
</tbody>
</table>

(continued)
Table 4. (continued)

<table>
<thead>
<tr>
<th>Antecedent Type</th>
<th>Categorical Putative Antecedent</th>
<th>Category</th>
<th>Frequency (Percentage)</th>
<th>Mean Test-Retest Reliability Estimate (SE)&lt;sup&gt;b&lt;/sup&gt;</th>
<th>95% CI</th>
<th>SD&lt;sub&gt;ho&lt;/sub&gt;</th>
<th>80% CV&lt;sup&gt;b&lt;/sup&gt;</th>
<th>b (SE)&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test-retest reliability level of analysis&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Within-person</td>
<td>75 (57.30%)</td>
<td>0.79 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.13</td>
<td>[0.62, 0.96]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Between-persons</td>
<td>51 (38.90%)</td>
<td>0.76 (0.05)</td>
<td>[0.72, 0.80]</td>
<td>0.11</td>
<td>[0.62, 0.90]</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Both&lt;sup&gt;i&lt;/sup&gt;</td>
<td>5 (3.80%)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>131 (100.00%)</td>
<td>0.79 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.13</td>
<td>[0.62, 0.96]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Substantive characteristics</td>
<td>Topic area</td>
<td>OBHR</td>
<td>82 (50.31%)</td>
<td>0.77 (0.04)</td>
<td>[0.74, 0.80]</td>
<td>0.12</td>
<td>[0.62, 0.92]</td>
<td>-0.09 (0.06)</td>
</tr>
<tr>
<td></td>
<td>Other (i.e., non-OBHR)</td>
<td>81 (49.69%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.11</td>
<td>[0.64, 0.92]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>163 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.11</td>
<td>[0.64, 0.92]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Judgment type</td>
<td>Attitude</td>
<td>36 (22.09%)</td>
<td>0.76 (0.06)</td>
<td>[0.71, 0.81]</td>
<td>0.09</td>
<td>[0.64, 0.88]</td>
<td>0.12 (0.09)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Perception</td>
<td>47 (28.83%)</td>
<td>0.79 (0.05)</td>
<td>[0.74, 0.82]</td>
<td>0.10</td>
<td>[0.66, 0.92]</td>
<td>0.20 (0.08)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Behavioral intention</td>
<td>52 (31.90%)</td>
<td>0.80 (0.05)</td>
<td>[0.76, 0.83]</td>
<td>0.13</td>
<td>[0.63, 0.97]</td>
<td>0.26&lt;sup&gt;*&lt;/sup&gt; (0.08)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mixed/undetermined</td>
<td>28 (17.18%)</td>
<td>0.72 (0.06)</td>
<td>[0.66, 0.78]</td>
<td>0.12</td>
<td>[0.57, 0.87]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>163 (100.00%)</td>
<td>0.78 (0.04)</td>
<td>[0.75, 0.81]</td>
<td>0.11</td>
<td>[0.64, 0.92]</td>
<td></td>
<td>-0.06 (0.03)</td>
<td></td>
</tr>
</tbody>
</table>

Note. We tested each putative antecedent to reliability (equivalent to a moderator in a validity generalization analysis) separately—that is, one at a time—to maximize the k (number of independent samples) in each analysis because the k varies dramatically across antecedents and because the listwise k in a model containing multiple antecedents was often quite low. As can be seen in the online supplementary materials, most (although not all) of these results were replicated when the data were analyzed separately at the within-person versus between-person levels of analysis. OBHR = organizational behavior and human resources.

<sup>a</sup>Mean test-retest reliability is reported for each category (subgroup) of each antecedent. We only reported mean test-retest reliability for categories with enough data. Categories with insufficient data are marked as NA. <sup>b</sup>SD<sub>ho</sub> and 80% credibility interval are computed using Schmidt and Hunter’s (2015) method. <sup>c</sup>Standardized regression coefficients from metaregression equations where the Fisher z<sub>r</sub>-transformed test-retest correlation is regressed onto each predictor are reported. Because we examined the effect of each putative antecedent separately (except for judgment type), there is only one predictor in each metaregression equation. <sup>i</sup>Categories with fewer than 10 effect sizes were omitted from analyses; these categories are represented by NA in the table. Each putative antecedent except judgment type was ultimately treated as dichotomous in the analyses, whereas judgment type was treated as a set of three dummy variables. <sup>j</sup>Samples in this category included both students and nonstudents. <sup>Either</sup> a computer was used to project the policy-capturing scenarios while participants provided their judgments on paper or else some participants used web-based surveys and other participants used paper-and-pencil surveys. <sup>g</sup>The “Other” study design category includes either nonorthogonal designs or orthogonal designs in which each participant receives a random set of scenarios. <sup>h</sup>The “Other” study design category includes different designs (e.g., random subsets of scenarios, designs that do not specify cue levels). Given the difficulty in interpreting the mean test-retest reliability for this category, we omit the mean test-retest reliability for this category. Five studies reported both the within-person and between-person test-retest reliability estimates. In the analysis to compute the mean meta-analytic test-retest reliability estimate and the analyses for all antecedents except one (see next sentence), we took the average of the within-person and between-person test-retest reliability estimates for each of these primary studies. These five studies were, however, not included in the analysis for the antecedent of levels of analysis. Standardized regression coefficients from a multiple metaregression equation where the Fisher z<sub>r</sub>-transformed test-retest correlation is regressed onto the three dummy variables, each with the corresponding category coded as 1 and the rest coded as 0. This analysis revealed that behavioral intention judgments exhibited significantly higher test-retest reliability than did the set of other types of judgments (i.e., attitudinal, perceptual, and mixed/undetermined). <sup>*p < .05</sup>
Table 5. Descriptive and Meta-Analytic Statistics for Continuous Putative Antecedents to Test-Retest Reliability.

<table>
<thead>
<tr>
<th>Antecedent Type</th>
<th>Continuous Putative Antecedent</th>
<th>k</th>
<th>M</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>$b$</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>General study and sample characteristics</td>
<td>Corrected year of publication$^b$</td>
<td>163</td>
<td>2003.90</td>
<td>11.17</td>
<td>1968</td>
<td>2021</td>
<td>-0.06</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Sample size$^c$ | 163 | 124.20 | 147.48 | 4 | 864 | -0.03 | 0.01  |
Journal impact factor$^c$ | 163 | 6.58 | 11.91 | 2 | 13.25 | -0.07 | 0.07  |
| Scenario characteristics            | Number of cues$^c$          | 163 | 6.58 | 11.91 | 2 | 150 | -0.08 | 0.03  |
Number of unique scenarios$^c$ | 162 | 45.97 | 44.44 | 8 | 390 | 0.01 | 0.01  |
Number of repeated scenarios$^c$ | 160 | 11.08 | 15.84 | 1 | 100 | -0.01 | 0.02  |
Total number of scenarios$^c$ | 159 | 56.61 | 54.71 | 9 | 480 | 0.00 | 0.01  |

Note. We tested each putative antecedent to reliability (equivalent to a moderator in a validity generalization analysis) separately—that is, one at a time—to maximize the $k$ (number of independent samples) in each analysis because the $k$ varies dramatically across antecedents and because the listwise $k$ in a model containing multiple antecedents was often quite low. As can be seen in the online supplementary materials, most (although not all) of these results were replicated when the data were analyzed separately at the within-person versus between-person levels of analysis.

$^a$Standardized regression coefficients from metaregression equations where the Fisher $z$-transformed test-retest correlation is regressed onto each predictor are reported. Because we examined the effect of each putative antecedent separately, there is only one predictor in each metaregression equation.

$^b$To correct for time spent on the future publication process, the corrected publication year for doctoral dissertations, master’s theses, and other theses is equal to (Original Year $^2$), and the corrected publication year for conference presentations is equal to (Original Year $^{-1}$); in contrast, the corrected publication year for journal articles is equal to the original publication year (Evans et al., 2018; cf. Wegman et al., 2018). It should be noted that the analysis described in text and in Table 3 contrasted policy-capturing studies conducted before versus after the 2002 policy-capturing tutorials (i.e., Aiman-Smith et al., 2002; Karren & Barringer, 2002), whereas the current analysis examined corrected publication year as a continuous antecedent variable. See also, in this regard, the analogous analysis in the online supplementary materials in which influential studies were removed.

$^c$Due to high skewness, this variable was square-root-transformed before being used in the meta-analysis.

Based on these analyses, among the methodological antecedents, only the survey medium was significantly associated with test-retest reliability: reliability estimates were higher for paper-and-pencil surveys ($k = 90$, $N = 8,746$, $M_{\text{weighted}} = 0.80$) than for online surveys ($k = 43$, $N = 7,648$, $M_{\text{weighted}} = 0.74$; $b = -0.20$, $SE = 0.06$, $p = .020$). According to the Common Language Effect Size Indicator (McGraw & Wong, 1992), in 55 out of 100 comparisons, a study involving a paper-and-pencil policy-capturing survey will have a higher test-retest reliability than a study involving an online survey. Among the substantive antecedents, the test-retest reliability estimates were higher from studies using behavioral intention judgments ($k = 52$, $N = 6,482$, $M_{\text{weighted}} = 0.80$) versus nonbehavioral intention judgments ($k = 111$, $N = 13,762$, $M_{\text{weighted}} = 0.76$) while controlling for other judgment types (i.e., two additional dummy variables for the attitudinal and perceptual judgment types, with the mixed/undeterminable judgment type serving as the reference group); $b$ for the behavioral
intention judgments dummy variable = 0.26, SE = 0.08, p = .017. Using the Common Language Effect Size Indicator, in 53 out of 100 random comparisons, a policy-capturing study with behavioral intention judgments will have a higher level of test-retest reliability than a policy-capturing study with nonbehavioral intention judgments.

These results were largely replicated across an array of robustness checks described further in the online supplementary materials: (a) four sets of sensitivity analyses, (b) a multilevel meta-analysis that accounted for the nesting of studies within authors, and (c) an exploratory metaregression model containing the two predictors that were significant in the focal analyses—survey medium and the dummy variable for behavioral intention judgments—while controlling for the dummy variables for attitudinal and perceptual judgments.

Discussion

As we demonstrate in this article, the percentage of policy-capturing studies reporting test-retest reliability is very low: 17.17% (164 out of 955). As such, the most important conclusion from this review is a reiteration of previous advice published in Organizational Research Methods (Aiman-Smith et al., 2002; Karren & Barringer, 2002) regarding the need to measure and report test-retest reliability correlations in policy-capturing studies. Reliability estimates are often required for the publication of other social science measures, and policy-capturing measures should be no different. In the case of policy capturing, test-retest reliability is necessary, although not sufficient, for a valid judgment policy. It is worth noting, however, that the available evidence suggests that the afore-mentioned tutorials may have had a modest positive effect on overall reliability reportage while seemingly having little effect on selective reliability reportage (i.e., failure to report low reliability). Of primary importance, this meta-analysis was conducted to determine the average test-retest reliability estimate reported in policy-capturing studies and the extent to which this average estimate generalizes across various factors. Results support the conclusion that on the whole, policy capturing is a relatively reliable way to assess the factors decision-makers use to make judgments (mean $r$.78). Furthermore, the test-retest reliability of policy capturing generalizes across several methodological choices made by primary study authors. An exception was survey medium. Specifically, test-retest reliability estimates were higher for paper-and-pencil surveys than for web-based (online) surveys. It may be the case that in-person paper-and-pencil studies put external pressure on decision-makers via a Hawthorne effect, leading to more stable judgments and thus higher test-retest reliability. For substantive factors, although reliability generalizes across OBHR versus non-OBHR studies, it varies across studies with
different types of judgments. Specifically, individuals make more stable behavioral intention than nonbehavioral intention (e.g., attitudinal, perceptual) judgments.

**Limitations, Implications, and Suggestions for Future Research**

This meta-analysis, like any other, has several limitations. Primary among the current limitations is that prior advice to the contrary (Aiman-Smith et al., 2002; Karren & Barringer, 2002) notwithstanding, the modal policy-capturing study did not report a test-retest reliability estimate—and therefore could not be included in the meta-analysis. Although many primary study authors may well have been inattentive to test-retest reliability because it was not the focus of their research, we cannot rule out the possibility that some authors may have found test-retest reliability to be low and then opted not to report it. Importantly, selective nonreportage may mask (i.e., attenuate) the impact of antecedents on test-retest reliability. Therefore, although meta-analyses frequently have a chilling effect on subsequent primary studies, we encourage continued research on antecedents to test-retest reliability in policy-capturing studies. Moreover, we encourage journal editors and reviewers to insist that authors report test-retest reliability estimates in policy-capturing studies.

Second, although the total number of independent samples that did report a test-retest reliability estimate was more than sufficient to estimate an average effect size estimate, it did somewhat constrain our ability to examine potential methodological and substantive antecedents to test-retest reliability. Specifically, although we were able to examine the impact of each antecedent separately, we were unable (due to often low listwise-deleted *k*) to examine the impact of multiple antecedents simultaneously or interactions between antecedents. Future primary studies could therefore manipulate and examine interactions between conceptually meaningful combinations of antecedents (e.g., number of cues per scenario, scenario design, and time gap) to determine the importance of making tradeoffs to control the length of the policy-capturing component of the survey (e.g., compensating for a high number of cues per scenario by using a block vs. full orthogonal design).

Third, although we proposed that the number of scenarios and the number of cues per scenario may have had an effect on test-retest reliability as a function of survey length, we were unable to directly assess survey length. Specifically, survey length in a given primary study is attributable not only to the policy-capturing component but also to other components (e.g., Likert-type self-report measures). Future primary studies could therefore manipulate and examine interactions between the lengths of the policy-capturing component and other components of the survey to determine the importance of making tradeoffs to control the length of the overall survey (e.g., compensating for a long policy-capturing
measure by shortening the non-policy-capturing components of the survey). Fourth, although we discussed vigilance decrement and ego depletion as possible reasons why certain methodological factors may exert effects on test-retest reliability, we were unable to actually measure vigilance decrement or ego depletion directly. Given recent concerns regarding the replicability of the ego-depletion phenomenon (e.g., Hagger et al., 2016), it seems important for future policy-capturing research to measure this phenomenon directly, ideally using preregistered studies. Preregistration can make a clear distinction between a priori and post hoc analyses, thus promoting transparency and reducing “opportunistic researcher degrees of freedom” (Toth et al., 2020).

Fifth, we were unable to examine some potentially important methodological antecedents because primary studies rarely reported this information. In particular, primary studies rarely reported either the extremity (in terms of cue values) or the order (i.e., location or serial position within the set of scenarios) of the first iteration of the repeated scenarios. For example, based on the “peak-end rule” (Fredrickson & Kahneman, 1993), scenarios with all positive (negative) cue values and scenarios located at the end of the original set of scenarios may be most salient to decision-makers such that test-retest reliability may be higher if these scenarios are repeated. Future primary studies could test such assertions.

Finally, because the survey medium was the sole statistically significant methodological antecedent to test-retest reliability, this methodological factor deserves further attention. Future primary studies could identify additional (beyond the Hawthorne effect) explanations for this effect and could then manipulate each potential explanation independently from survey medium. Moreover, due to the observed frequencies of primary studies in categories within the survey medium factor, this factor was ultimately examined as a comparison between paper-and-pencil studies and web-based (online) studies. More primary studies are needed that use audio, video, and other media.

Similarly, because the behavioral intention versus nonbehavioral intention judgment type was the sole statistically significant substantive antecedent to test-retest reliability, this substantive factor deserves further attention. For many policy-capturing studies, researchers may have some flexibility regarding which type of judgments to use. For example, in a policy-capturing study on job choice, researchers can either use a behavioral intention question, by asking about one’s likelihood of
accepting a job offer, or an attitudinal question, by asking about the favorableness of a job offer. When theory does not dictate the judgment type, researchers may wish to maximize reliability by using behavioral intention judgments.

Our findings have implications for stimulus-material adaptations in policy-capturing studies. The current meta-analysis demonstrates that test-retest reliability in policy-capturing designs generalizes across observed variation in most of the methodological factors examined. This in turn suggests that vis-à-vis reliability, researchers do have some leeway in adapting stimulus materials. Less certainty, however, exists with regard to adapting the number of cues and scenarios in particular: Although the focal meta-analytic results as well as the ancillary within-person results in the online supplementary materials suggest that test-retest reliability generalizes across observed variation in the number of cues and several operationalizations of the number of scenarios, the ancillary between-person results in the online supplementary materials suggest that cutting the number of cues or unique scenarios reduces reliability. Cuts to the number of cues or unique scenarios (e.g., in an effort to shorten an existing policy-capturing measure) should therefore be made judiciously.

**Best-Practice Recommendations for Future Policy-Capturing Studies**

It seems only fitting to end this article by providing guidance for future policy-capturing studies, drawn from what was—and what was unable to be—examined in this meta-analysis. In particular, we provide recommendations associated with (a) reporting reliability, (b) designing policy-capturing studies for the reportage of reliability, and (c) interpreting reliability. Table 6 provides a summary of our recommendations.

**Reporting Reliability.** First, we repeat previous recommendations (e.g., Aiman-Smith et al., 2002; Karren & Barringer, 2002) that future policy-capturing studies should routinely report test-retest reliability estimates. We moreover encourage researchers to report both within-person and between-person reliability estimates because these estimates provide unique information. Moreover, we suggest that researchers report the standard deviation of within-person reliability estimates (across people, perhaps as a function of individual differences such as conscientiousness that may result in higher vs. lower reliability) and the standard deviation of between-person reliability estimates (across scenarios that might be expected to exhibit higher or lower reliability due, e.g., to the peak-end rule).

We moreover recommend that researchers take action to improve the
reliability of their policy-capturing measures. As noted previously, for instance, in cases where the type of judgment is not dictated by theory, researchers have the potential to improve test-retest reliability by using behavioral intention judgments rather than, say, attitudinal judgments. Having said this, we acknowledge that researchers have limited options to increase reliability due to the fact that reliability generalized across virtually all the antecedents we examined.

*Designing Policy-Capturing Studies for the Reportage of Reliability.* To compute test-retest reliability, researchers need to repeat some scenarios and correlate the scores across the first and second iterations of these scenarios. Therefore, researchers need to consider the number of scenarios to repeat and which scenarios to repeat. We therefore provide some best-practice recommendations on these issues.

**Number of scenarios to repeat.** The ideal number of scenarios to repeat presents a tradeoff. On the one hand, controlling the length of a policy-capturing measure to reduce any vigilance decrement effect is generally a concern. On the other hand, a test-retest reliability correlation coefficient, like any correlation coefficient, is calculated by correlating two vectors of data points. If each vector contains only a few values, the correlation coefficient is likely to be very unstable (Schönbrodt & Perugini, 2013). Therefore, especially when reporting within-person test-retest correlations in policy-capturing studies, we recommend repeating at least 10 scenarios (i.e., the median number of repeated scenarios in the within-person studies in our meta-analysis).

**Which scenarios to repeat.** We recommend that researchers consider the potential extremity effects and order effects mentioned previously (e.g., the peak-end rule). Future research can not only facilitate the empirical examination of such effects but also, at a practical level, can ensure that the selection of scenarios is systematic and therefore more comparable across studies. Thus, we recommend that researchers repeat salient scenarios under extremity and order effects along with randomly selected scenarios.

*Interpreting Reliability.* We discourage policy-capturing researchers from using hard reliability cutoffs (and then selectively underreporting reliability estimates that fall below these cutoffs). Our recommendation is consistent with guidelines in other quantitative research areas (e.g., Greco et al., 2018; Williams et al., 2020). Moreover, researchers should carefully contextualize reliability estimates (see Table 6 for details).
Table 6. Recommendations for Future Policy-Capturing Studies.

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| Reportage              | 1. Reporting test-retest reliability        | • Researchers should report test-retest reliability!  
• Journal reviewers should require that researchers report test-retest reliability!  
• When the outcome variables are continuous rather than nominal, we suggest that researchers report the test-retest Pearson product-moment correlation coefficient. | • In policy capturing, as elsewhere, reliability is necessary but not sufficient for validity.  
• The primary reliability-based concern in policy-capturing measures is the extent to which the decision-maker is using a temporally stable judgment policy across scenarios in the measure.  
• Almost all the primary studies in our meta-analysis involved judgments (vs. choices). Therefore, the outcome variables (e.g., scores on decision-makers’ responses to the two iterations of the repeated scenarios) are generally continuous rather than nominal variables. In this case, Pearson’s product-moment correlation coefficient, a pure estimate of reliability (LeBreton & Senter, 2008), is the appropriate test-retest reliability statistic. |
|                        | 2. Reporting additional types of reliability (or agreement) | • If researchers are interested in absolute agreement in addition to reliability, they can additionally report a test-retest equivalent of \( r_{\text{ag}} \) (LeBreton & Senter, 2008; see also Berchtold, 2016).  
• In the more infrequent cases where multiple judgments are elicited per policy-capturing scenario, researchers can additionally report Cronbach’s alpha. | • Test-retest reliability refers to the relative stability of scores across iterations, but test-retest agreement, which refers to the absolute agreement of scores across iterations, may also frequently be of interest.  
• Internal consistency (assessed by Cronbach’s alpha) is likely to be of interest only in the more infrequent cases when multiple |
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<td>3. Reporting test-retest reliability at multiple levels of analysis</td>
<td></td>
<td>Researchers should report both between-person and within-person reliability estimates.</td>
<td>judgments (rather than one) are elicited per policy-capturing scenario—and when these judgments are moreover assumed to be indicators of the same underlying construct. Between-person and within-person reliability estimates provide unique—and complementary—information. Between-person test-retest reliability captures the stability of judgments across participants (nomothetic). Within-person test-retest reliability captures the stability of judgments across policy-capturing scenarios (idiographic). Both similarities and differences in obtained estimates across the between-person and within-person levels are noteworthy (Dalal et al., 2014). We found similar reliability estimates across the two levels, but future research that follows the subsequent recommendations in this table (e.g., recommendations involving the number and nature of scenarios that should be repeated) should continue to report—and compare—reliability estimates at both levels. The standard deviation of within-person reliability estimates across people provides information regarding</td>
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<td>4. Reporting sufficient information about test-retest reliability</td>
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<td>Researchers should report not only the mean reliability estimate but also the standard deviation of estimates</td>
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<td><strong>Designing policy-capturing studies for the reportage of reliability</strong></td>
<td>1. Including enough repeated scenarios</td>
<td>Researchers should include enough scenarios (i.e., at least 10 scenarios) to estimate within-person test-retest reliability.</td>
<td>The extent to which judgments differ in test-retest reliability across people. A large standard deviation across people would suggest the need to examine the impact of traits (e.g., general mental ability, conscientiousness, self-monitoring) and/or states (e.g., positive and negative mood). The standard deviation of between-person reliability estimates across scenarios shows the differences in reliability across scenarios. A large standard deviation across scenarios would suggest the need to examine the impact of scenario or cue characteristics (e.g., scenario serial position, cue extremity). When estimating within-person reliability, we recommend repeating at least 10 scenarios (i.e., the median number of repeated scenarios in the within-person reliability studies). A test-retest reliability correlation coefficient, like any correlation coefficient, is calculated by correlating two vectors of data points. If each vector contains only a few values, the correlation coefficient is likely to be very unstable (Scho¨ nbrodt &amp; Perugini, 2013).</td>
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## Table 6. (continued)

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<td>Interpreting reliability</td>
<td>1. Avoiding hard reliability cutoffs and selective reporting of reliability</td>
<td>We recommend that researchers repeat the scenarios that would be most salient under extremity and order effects (i.e., the last scenario, the first scenario, the scenario with the highest possible value on all cues, and the scenario with the lowest possible value on all cues) along with at least 6 other randomly selected scenarios.</td>
<td>We speculate that extremity and/or order effects may influence test-retest reliability estimates. We speculate that extremity and/or order effects may influence test-retest reliability estimates. Higher reliability estimates may be found for scenarios that contain extreme (i.e., lowest or highest) levels of all cues compared to randomly selected scenarios. Higher reliability estimates may be found for scenarios whose first iteration occurs at the end or beginning of the set of scenarios compared to randomly selected scenarios. Higher reliability estimates may be found for scenarios whose first iteration occurs at the end or beginning of the set of scenarios compared to randomly selected scenarios. We discourage policy-capturing researchers from using hard reliability cutoffs because: (a) researchers may then underreport reliability estimates that fall below these cutoffs, and (b) reliability estimates should be contextualized.</td>
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<td>Researchers should neither use hard reliability cutoffs in policy-capturing studies nor selectively underreport reliability estimates that fall below hard cutoffs. Instead, researchers should interpret obtained reliability estimates in light of the 95% confidence interval from the current meta-analysis (i.e., .75 to .80) as well as in light of the specific domain being studied, the stage of scale validation, and the purpose of the study (e.g., basic research vs. high-stakes decisions in applied settings).</td>
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*a*Our recommendation to repeat at least 10 scenarios exceeds that of Aiman-Smith et al. (2002), who recommended repeating “4 to 5” scenarios (p. 409) even for within-person test-retest correlations. Our recommendation is different because the stability of within-person test-retest correlations is likely to be appreciably higher when repeating 10 rather than four to five scenarios (Scho¨nbrodt & Perugini, 2013). The downside of repeating 10 or more scenarios is that doing so increases the length of the study, potentially leading to lower quality responses. However, the burden on decision-makers is unlikely to be appreciably higher when repeating 10 rather than four or five scenarios. Moreover, if needed, researchers can divide the study into two sessions. Although we speculate that extremity and/or order effects may influence test-retest reliability estimates, we could not test such effects meta-analytically because very few primary studies reported the cue levels in each repeated scenario or the location of the first iteration of each repeated scenario within the set of scenarios. Our recommendation, if followed, would, by definition, increase such reportage.
Acknowledgements
The authors thank Jeremy Wong for his help with the literature search; Jesse Olsen, Hannes Zacher, Joel Marcus, and Nadine Raaphorst for conducting additional analyses on their data sets for us; and Mark Reynolds, Esther Kaufmann, and Una Adderley for providing us with unpublished papers or data sets.

Declaration of Conflicting Interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Supplemental Material
Supplemental material for this article is available online.

Notes
1. Due to space constraints, this Short Report does not aim to provide readers with a comprehensive understanding of the policy-capturing technique. For more detailed information, we recommend Cooksey (1996), Aiman-Smith et al. (2002), and Karren and Barringer (2002).
2. In practice, nonstudents in policy-capturing studies are often (but not always) domain experts. Research has shown that novices and experts approach judgment tasks differently (Aiman-Smith et al., 2002; Hardiman et al., 1989; Mackay et al., 1992), and some researchers have suggested that the results from judgment tasks that use students are unlikely to generalize to judgment tasks requiring domain expertise (Barr & Hitt, 1986; Shanteau & Stewart, 1992).
3. Mathematically, assuming the sample size is large enough to compute a
test-retest reliability coefficient, sample size should affect the standard error and therefore the width of the confidence interval associated with the reliability estimate rather than affecting the size of the point estimate itself.

4. It is also possible for policy-capturing studies to use auditory scenarios or video-based scenarios, and thus we also coded for these cue presentation formats.

5. Whereas block designs use all possible blocks (i.e., each group of participants receives a different block of scenarios), fractional factorial designs include only one subset (i.e., all participants receive the same block of scenarios).

6. It is worth noting that the desirability (or feasibility) of computing within-person test-retest reliability depends on the number of repeated scenarios. Mathematically, a correlation coefficient can be estimated and moreover can exhibit values other than –1 and þ1 with at least three data points—here, three repeated policy-capturing scenarios. However, even beyond this minimum number of data points, researchers should be concerned about the potential for sampling error and departures from normality.

7. In addition to examining level of analysis as a potential antecedent to test-retest reliability, we conducted analyses separately at each level of analysis to examine whether the impact of the other potential antecedents was similar at both levels. See the online supplementary materials for these additional analyses.

8. In contrast, the median number of repeated scenarios in the between-person studies in our meta-analysis was two.

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References marked with an asterisk indicate primary studies included in the meta-analysis.


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and outcomes of decision making in an educational context


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