Hedges, mottes, and baileys:

Causally ambiguous statistical language can increase perceived study quality and policy
relevance

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Abstract

There is a norm in psychological research to use causally ambiguous statistical language, rather than straightforward causal language, when describing methods and results of nonexperimental studies. We hypothesized that this norm leads to higher ratings of study quality and greater acceptance of policy recommendations that rely on causal interpretations of the results. In a preregistered experiment, we presented psychology faculty, postdocs, and doctoral students ($n=142$) with abstracts from hypothetical studies. Abstracts described studies' results using either straightforward causal or causally ambiguous statistical language, but all concluded with policy recommendations relying on causal interpretations of the results. As hypothesized, participants rated studies with causally ambiguous statistical language as of higher quality (by .48-.59 *SD*) and as similarly or more supportive (by .16-.26 *SD*) of policy recommendations. Thus, causally ambiguous statistical language may allow psychologists to communicate causal interpretations to readers without being punished for violating the norm against straightforward causal language.

Keywords: causal inference, research methods, causal language, nonexperimental

Effects of causal framing on perceived quality of nonexperimental research results

There is a norm in psychological research to avoid causal language, such as “causes” or “impacts,” when describing results of nonexperimental studies (Grosz, Rohrer, & Thoemmes, 2020). Instead, researchers describe such results using causally ambiguous statistical language, such as “predicts” or “is associated with.” This norm likely reflects good intentions on the part of researchers, reviewers, and editors to discourage researchers from making claims that are not well supported by their data.

However, the norm may have unintended and harmful consequences. Using causal language to describe results may make threats to internal validity more salient, leading readers to assess studies more critically. In contrast, descriptions that use causally ambiguous statistical language may not be critiqued as thoroughly as is warranted. Furthermore, critical concerns about causality often do not extend to the discussion sections—consequently, researchers are free to make policy recommendations that implicitly rely on causal interpretations. Counter-intuitively, the norm against using causal language could increase acceptance of such recommendations by lowering the standards of evidence that are applied to the results on which the recommendations are based. The present study tested the hypothesis that using causally ambiguous statistical language, rather than causal language, to describe nonexperimental results improves evaluations of study quality and acceptance of policy prescriptions based on the results.

Potential Costs and Benefits of a Norm against Causal Language

Describing results using causally ambiguous statistical language could serve a useful function by preventing readers from incorrectly assuming that a causal relation has been definitively demonstrated (AMA Style Insider, 2017; Azar, 2006). When a nonexperimental study finds evidence of a statistical association that was predicted based on a hypothesized causal

mechanism, such language permits researchers to describe their findings accurately while hedging against the possibility that the hypothesized causal mechanism does not exist, as future studies might demonstrate. When studies have potential policy implications, avoiding causal language could engender healthy skepticism of policy recommendations that rely on causal interpretation of the findings. Perhaps such claims could filter down to overconfident causal interpretations found in media reports summarizing nonexperimental studies (Buhse et al., 2018).

A possible unintended consequence of the norm, however, is that causally ambiguous statistical language paired with discussions of policy implications may permit studies that *seem* causal to be published without being held to the same standards of evidence as studies that make causal claims explicit. For example, if a researcher transparently states their interest in estimating the causal effect of children's early academic skills on their later academic achievement, it will be clear to an informed reader that models that make no attempt to adjust for potential confounds including a variety of baseline cognitive, emotional, and contextual variables will yield (likely upwardly) biased estimates. A model or set of models that attempt to do so might be subject to further robustness checks or falsification tests that could detect the presence of and perhaps establish the direction and range of plausible magnitudes of additional bias in these estimates (Bailey et al., 2018). These models might even make quantitative predictions that could be tested in a subsequent experiment (Brick & Bailey, 2020).

By contrast, a researcher who claims they are interested in which kinds of early skills “predict” later achievement might analyze data differently. Instead of selecting covariates on the basis of their hypothesized causal relation to the key predictor and outcome of interest (Grosz et al., 2020; Hernán, 2018a, 2018b; Pearl & Mackenzie, 2018; Rohrer, 2018; Watts & Duncan, 2019), a researcher might include a more limited set of covariates based on common practice

within the field or what the researcher finds most interesting. The researcher might address a skeptical reviewer's concerns by (a) explaining in the discussion section that no causal conclusions can be drawn from nonexperimental studies, and (b) explaining that they chose not to consider alternative models because the study's goals were predictive and not causal. Consequently, the study might avoid the stringent standards of evidence to which it would have been subjected if it had explicitly made causal claims.

Estimates in such a study may differ from causal effects in a variety of (sometimes predictable) ways. This would be understandable if the end goal of such research were prediction *per se*. Prediction is often a useful goal in and of itself (for review, see Yarkoni & Westfall, 2017), and our critique of the use of causally ambiguous statistical language does not apply to work that seeks to build models for purely predictive purposes. Still, based on researchers' descriptions of their findings (see examples in Grosz et al., 2020) and the mismatch between the methodological approaches taken in most psychological research and approaches designed to maximize prediction for applied purposes, we note that many, if not most, nonexperimental studies in psychology are indeed intended to inform theory about causal mechanisms underlying relations between variables.

Supporting this possibility, many nonexperimental studies use prescriptive language in their discussion sections despite avoiding causal language in describing their results. Critically, this prescriptive language implicitly relies on causal interpretation of the findings (Reinhart et al., 2013). For example, a study that demonstrates a "predictive" relation between early skills and later achievement might also recommend intervening on early skills to improve later achievement. Such an intervention could only achieve the stated goal if the relation between

early skills and later achievement were causal, not fully explained by confounding factors influencing both early skills and later achievement.

Grosz and colleagues (2020) label this approach a motte-and-bailey strategy, “in which researchers profit from the more interesting but difficult to defend causal interpretation of their effect (the bailey), but once challenged, they retreat to the almost trivial yet difficult to attack descriptive finding (the motte)” (p.9). In this case, the stated purpose of the study (perhaps even in the title) is prediction, but the theoretical and applied issues around which the study is framed depend on the assumption that causal information is conveyed by the findings. Importantly, neither Grosz and colleagues nor we assume that researchers deliberately mislead readers by using causally ambiguous statistical language. The use of causally informative statistical language is likely a reaction to both the norm against straightforward causal interpretations of nonexperimental research and researchers’ beliefs that their work is causally relevant in some way. Still, there is a contradiction between denying causal informativeness of some statistical predictor and arguing for intervention on the same variable based on its predictive power. Regardless of the origins of the use of causally ambiguous statistical language, it may allow authors to avoid punishment for violating the norm against straightforward causal language while still arguing for the policy-relevance of their claims.

Current Study

The goal of the current study is to test whether describing nonexperimental psychological research findings using causally ambiguous statistical language influences perceptions of the quality and policy-relevance of the research. We hypothesize that the motte-and-bailey strategy is effective in raising judgments of study quality. Further, because the motte-and-bailey strategy emphasizes policy-relevance without violating the norm against straightforward causal language,

we hypothesize that the strategy increases receptivity towards policy-relevant conclusions that are based on causal interpretations of the results. Such findings would imply that the status quo limits incentives for psychologists analyzing nonexperimental data to aspire to causal estimation: In addition to the burden of motivating the estimation of more complicated models to obtain smaller estimates, a straightforward causal framing of the results of nonexperimental psychological research may be detrimental for the perceived quality and policy-relevance of one's work.

The study focused on potential reviewers, editors, and citers of nonexperimental psychological research—namely, graduate students, postdoctoral researchers, and faculty in psychology. If causally ambiguous statistical language raises perceived study quality to these readers without reducing perceived policy-relevance, this practice may increase the frequency of nonexperimental research studies interpreted causally without increasing the quality of methods for causal inference within psychology.

Method

This study was exempt by the University of California, Irvine institutional review board for human research protections as we conducted an anonymous survey that did not collect personal identifiers or identifiable information. The experiment was pre-registered at <https://osf.io/2v8mg/> before data collection began. We describe the method and deviations from the pre-registered design below.

Participants

Based on the power analysis described in the preregistration, we planned to recruit 100 Ph.D. students, postdoctoral scholars, and faculty in psychology, education, and human development and family studies departments by posting a link on social media sites frequented

by psychologists and via Twitter¹. Colleagues posted a link to the website, so that the involvement of the last author (who has previously posted about possible costs of the norm against using causal language in nonexperimental psychology on Twitter) would be less obvious to participants. In all, 142 individuals were recruited via Twitter, the Psychological Methods Discussion Facebook page, and the Cognitive Development Society listserv.

Descriptive statistics for the full sample of participants are shown in Tables 1 and 2. The full sample included participants who reported being 7 to 67 years old ($M = 32.98$, $SD = 9.23$). On average, the participants had completed 4.13 statistics courses ($SD = 2.74$). Most participants were recruited from the Cognitive Development Society listserv (47%), followed by the Psychological Methods Discussion Facebook group (28%), and Twitter (24%). Most participants were female (54%) and work in the United States of America (58%). Our participants consisted of academic faculty (32%), post-doctoral researchers (20%), PhD students (33%), Masters students (1%), and undergraduates (1%). Most were from psychology (80%) encompassing a variety of interdisciplinary subfields, as shown in Table 1.

We preregistered that we would attempt to recruit 100 participants and exclude participants who were younger than 18 years old, responded to the first two questions about one of the abstracts in under 30 seconds, responded incorrectly to the question of how many abstracts were causally worded (our manipulation check), were not in a field related to psychology, and were not (1) enrolled in a psychology, education, or human development Ph.D. program, (2) a

¹ Laypeople were not included in the study for two reasons. First, the public likely consumes psychological research findings primarily via the media, which often does not respect the norm against use of causal language to describe results of nonexperimental studies (Buhse et al., 2018). Second, among lay adults, the tendency to infer causation from psychological research findings does not appear to be strongly influenced by the strength of the research design (Bleske-Rechek et al., 2015).

postdoctoral researcher in psychology, or (3) a psychology faculty member. Descriptive statistics for the 39 participants who met these criteria are shown in Tables S1 and S2.

Materials

We created abstracts describing two fictional nonexperimental studies, one about scientific reasoning and the other about reading achievement. For each study, we created two abstracts, one using causal wording and one using causally ambiguous wording, resulting in four abstracts. The full abstracts appear in the preregistration document, Appendix A. The causally-worded abstracts described the studies' purpose and findings using causal language: for example, "children's scientific reasoning scores **causes** a 7-percentage point increase ($p < .0001$) in the probability a child would attend a four-year college or university by age 21" for the scientific reasoning study, and "a standard deviation increase in children's grade 3 reading achievement scores **causes** a .4 standard deviation increase ($p < .0001$) in children's grade 11 PSAT Verbal score" for the reading achievement study. The causally ambiguous abstracts were identical to the causally worded abstracts except that causal language was replaced by causally ambiguous language; for example, the word "causes" was replaced by "predicts." For each abstract, causal wording was replaced with causally ambiguous statistical wording in 3 instances: once when the purpose of the study was described, once when the purpose of the analysis was described, and once when describing the results of the study.

The abstracts concluded with policy-relevant conclusions that relied on causal interpretations of the results. These conclusions did not differ between the causal and causally ambiguous abstracts. For the scientific reasoning study, the conclusion was "We conclude that raising the quantity and quality of early science instruction is an important way to raise children's educational prospects in the 21st century." For the reading achievement study, the

conclusion was “We conclude that extra resources for third grade reading instruction are likely to improve children’s college readiness and propose this as a useful intervention.”

After participants read each abstract, they were asked the two questions. Question 1 asked “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?”. Participants answered using the following scale: 5 = *Very high quality*, 4 = *High quality*, 3 = *Moderate quality*, 2 = *Low quality*, 1 = *Very low quality*. Question 2 asked “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: ”. Participants responded to question 2 using the following scale: 5 = *Very strongly*, 4 = *Strongly*, 3 = *Moderately*, 2 = *Weakly*, 1 = *Very Weakly/Not at all*. The abstract and questions were shown on the same page, allowing participants to refer to the abstract as they evaluated it.

After participants read both abstracts they were asked the following question as a manipulation check: “How many of the two abstracts you just read employed explicitly causal language in their description of the results?” which participants answered on a scale of 0 = *Neither*, 1 = *Only one*, and 2 = *Both*. Lastly, participants were given a brief demographic questionnaire about academic status, field of study, and psychology subfield of study followed by six optional questions about personal background characteristics such as age, sex, and English language learner status. All questions are provided as they were asked verbatim in the preregistration document, Appendix B.

Procedure

Each participant received two of the four abstracts—the causally-worded abstract for one study (e.g., scientific reasoning study) and the causally ambiguous abstract for the other study (e.g., reading achievement study). We randomized which study was presented in its causal

version and whether the causal or causally ambiguous abstract was presented first, resulting in four conditions (see Tables 1 and S1). Participants read the first abstract and answered Questions 1 and 2 for that abstract, then did the same for the second abstract. Next, participants answered the manipulation check, followed by the demographic questionnaire, which was labeled “optional”. We did not predict any effects involving the demographic questionnaire variables.

Analysis

As pre-registered, we estimated random intercept models, with responses nested within participants, using maximum likelihood estimation. To estimate the effect of causally ambiguous statistical language wording on the key outcome measures², we regressed responses to the questions about study quality and policy relevance on an indicator of whether the abstract was causally worded, along with indicators for the order in which the abstract was seen, and which hypothetical study was described in the abstract.

For each rating question—perceived quality and perceived support for policy conclusions—we estimated the effect of causally ambiguous statistical language in a series of four models. Model 1 included the full study sample ($n = 142$) but only included data from the first abstract viewed by each participant. This model was included to test whether results were sensitive to testing effects. Because in the real world, readers may not usually judge the merits of two abstracts that contrast in their use of causal language one after the other, the estimate based on participants’ ratings of the first abstract only is plausibly the most externally valid estimate. However, it is less precise because it uses only half the available data. Thus, Model 2 included the full study sample and both abstracts. Model 3 included the first 100 participants regardless of

² Our preregistered hypotheses pertained to the effect of causal (vs. causally ambiguous statistical) language. However, for clarity, we present the impacts of the reverse-coded treatment, causally ambiguous statistical (vs. causal) language.

whether they met the inclusion criteria ($n = 100$). Finally, Model 4 included only the preregistered sample, namely those of the first 100 participants who met all inclusion criteria ($n = 39$).

Results

The Effects of Causally Ambiguous Statistical Language on Perceived Quality

We estimated the impact of causal framing on participants' ratings of study quality. Table 3 indicates that results for the key parameter estimate, "causally ambiguous statistical language", were quite similar and highly significant across the four models. Participants reliably rated abstracts worded in causally ambiguous statistical language as of higher quality than those worded in causal language, with estimates of the difference ranging from .34 to .48 points on the 5-point Likert scale. Expressed in standard deviations, these estimates range from .48 to .59 *SD*.

For the full sample, results were similar when only the first abstract response was included (Model 1) as to when both responses were included (Model 2), suggesting that the within-participants design did not elicit a contrast effect that exaggerated these estimates.

Results using all available observations (Model 2) are displayed in panel A of Figure 1. As can be seen in the figure, most participants gave a different response in the two conditions, with the most common response patterns being a 4 or a 3 when studies were described in causally ambiguous statistical language, with a rating of 2 or 3 when studies were described in causal language. The higher amount of area shaded in red indicates that the most common pattern was to rate causally worded abstracts as of lower quality.

The Effects of Causally Ambiguous Statistical Language on Perceived Support for Policy

Conclusions

We estimated the impact of causal framing on participants' ratings of strength of support for policy conclusions. Table 4 indicates that results for the key parameter estimate, again “causally ambiguous statistical language”, were similar across the four models. Participants rated causally worded abstracts as of similar or higher quality than causally ambiguous abstracts, with estimates of the difference ranging from .16 to .25 points on the 1-5 Likert scale. Expressed in standard deviations, these estimates range from .16 to .26 *SD*. The estimate was significantly greater than 0 in the full sample using all available observations (Model 2). The estimate in the pre-registered sample (Model 4) was larger but fell short of statistical significance because of a larger standard error. Panel B of Figure 1 shows that more participants gave lower ratings to causally worded abstracts than to statistically worded abstracts, but many participants shifted in both directions.

For the full study sample, the estimate was the same whether only the first abstract response was included (Model 1) compared to when both responses were included (Model 2), suggesting that testing effects did not affect the magnitude of the estimate.

Exploratory Subgroup Analyses

Because we used a convenience sample, external validity was a major concern. We thus estimated the effects of causally ambiguous statistical language for two kinds of subgroups: 1) the source from which an individual accessed the survey and 2) occupation (Tables S3-S6). Estimated effects of causally ambiguous statistical language on study quality went in the same direction across source subgroups, although were larger in the PsychMD and cogdevsoc subgroups than in the Twitter subgroup (Table S3). The effect of causally ambiguous statistical language on ratings of policy relevance was only statistically significant in the cogdevsoc

subgroup and was close to 0 in the other groups (Table S4). Estimates for both questions were similar for psychology faculty, postdocs, and Ph.D. students (Tables S5 and S6).

Discussion

As hypothesized, participants rated studies described with causally ambiguous statistical language as of higher quality (by .48-.59 *SD*), and as similarly supportive or more supportive (by .16-.26 *SD*) of policy recommendations relying implicitly on causal interpretations of research results. Thus, under some circumstances, causally ambiguous statistical language may allow authors to communicate causal interpretations without being punished for violating the norm against straightforward causal language.

Effects on perceived support for policy recommendations were smaller and less robust than the effects on perceived study quality. However, to reach the eyes of the public and policymakers, a study must be published, and publication likely depends on evaluations of study quality. By increasing the chance of publication, causally ambiguous language could increase the chance of policy recommendations being widely disseminated.

Implications: Should We Encourage Causal Language?

Perhaps a useful practice for improving causally informative statistical analysis in psychology would be to encourage psychologists testing causal theories to use causal language throughout their manuscripts. Pearl and Mackenzie (2018) asserted that statisticians' reluctance to incorporate causal language into their work limited the types of questions they could answer, and resulted in longstanding apparent paradoxes (see also Hernán, 2018a, 2018b). Likewise, one may argue that psychologists' reluctance to explicitly talk about causality limits the questions they can address directly, and results in seemingly contradictory findings (similar claims have been made by Foster, 2010; Grosz et al., 2020; Rutter, 2007; and Watts & Duncan, 2019).

The possible benefits of encouraging psychologists to specify their causal theories explicitly include clarity to readers and clarity to writers. In particular, causal language can make the link between research methods and theory more transparent. Most findings in nonexperimental psychology are consistent with multiple possible theories (Brick & Bailey, 2020; Meehl, 1971, 1990; Tomarken & Waller, 2003), often with different policy implications. Encouraging researchers testing causal theories to use causal language throughout the manuscript can help clarify the assumptions, which, along with these findings, led the writer to a particular set of theoretical and policy conclusions. Further, use of causal language could make both writers and readers more alert to potential biases in estimates of causal effects (e.g., over-estimation of effect size due to the presence of unobserved confounding variables).

Although we find these arguments compelling, it does not necessarily follow that causal language will influence psychologists' judgements of study quality or policy-relevance. For the benefits of more causal language to outweigh the costs, using causal language must cause researchers to *think* differently. Without stronger norms around causal inference (e.g., training, longer manuscripts with more robustness checks and falsification tests), dissolving the norm against straightforward causal language in psychology could backfire, resulting in stronger claims *without* stronger evidence. Top journals might consider policies that combine incentives for researchers *attempting* causal inference with methodologically rigorous norms (e.g., badges for papers reviewed by experts in causal inference).

Limitations

The generalizability of these results is limited in two ways. First, our convenience sample is not representative of psychological researchers in general or in any subfield. While subgroup analyses suggested that participants from different recruiting sources as well as participants in

different research stages reacted similarly, it is possible that certain subfields have different norms (indeed, exploratory subgroup analyses suggested that ratings of policy relevance were only affected within participants recruited from one of the three sources).

Second, we only tested two different types of abstracts. While these were written to be realistic, they cannot exhaustively represent nonexperimental psychological research. It is entirely possible that, for example, studies with strong quasi-experimental designs popular in the economics literature (Angrist & Pischke, 2010) would not be penalized for using causal language.

Conclusion

Participants reliably rated abstracts worded in causally ambiguous statistical language as of higher quality. Furthermore, they thought that policy recommendations were better supported when causally ambiguous statistical language was used, although such recommendations are only justified in the presence of a causal effect. Thus, the ambiguous language did not prevent participants from indirectly endorsing causal conclusions. We hope psychologists will consider adopting Hernán's (2018b) recommendations: to articulate clear causal questions, distinguish them from the procedure used to emulate the causal question in the study, and pinpoint or bound estimates by triangulating results from different studies.

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Table 1*Descriptive Statistics for the Full Survey Sample Categorical Variables*

Variable	Proportion
Condition	1 st Science study ambiguous language, 2 nd reading study causal language
	25%
	1 st Science study causal language, 2 nd reading study ambiguous language
	25%
Source	1 st Reading study causal language, 2 nd science study ambiguous language
	24%
	1 st Reading study ambiguous language, 2 nd science study causal language
	25%
Sex	cogdevsoc listserv
	47%
	PsychMD
Country Academic Career	Twitter
	24%
	Male
	30%
Age Learned English	Female
	54%
	Non-binary
	2%
Career Status	Prefer not to answer / Do not answer
	13%
	United States
	58%
Academic Field	Canada
	7%
	Other / Did not respond
	35%
Psychology Subfield	Native Speaker
	58%
	Before Age 6
	9%
Career Status	Between Ages 7-10
	11%
	Between Ages 11-14
	8%
Academic Field	Between Ages 15-18
	1%
	Prefer not to answer / Do not answer
	12%
Psychology Subfield	Faculty
	32%
	Postdoctoral Researcher
	20%
Psychology Subfield	PhD Student
	33%
	Masters Student
	1%
Psychology Subfield	Undergraduate
	1%
	Other / Did not respond
	13%
Psychology Subfield	Medical & Health Sciences
	1%
	Psychology
	80%
Psychology Subfield	Natural Sciences
	1%
	Mathematics
	1%
Psychology Subfield	Other / Did not respond
	17%
	Clinical
	8%
Psychology Subfield	Cognitive
	23%
	Neuroscience
	9%
Psychology Subfield	Developmental
	46%
	Quantitative
	8%
Psychology Subfield	Social/Personality
	11%
	Educational
	6%
Psychology Subfield	Other / Did not respond
	25%

Note. $n = 142$. PsychMD = Psychological Methods Discussion Facebook group. Participants that preferred not to answer questions or did not answer were reported together to prevent any possibility of identification. Some academic fields categorized as other included 6 areas that were included in the analyses as psychological subfields.

Table 2*Descriptive Statistics for the Full Survey Sample Continuous Variables*

Variable	N	Mean	SD	Min	Max
Age	120	32.98	9.23	7	67
Statistics Courses Taken	127	4.13	2.74	0	20
Survey Duration	142	481	1211	1	12828
Abstract 1 Statistical Question Duration	65	77	39	19	256
Q1:Quality of design & analysis	65	3.29	0.8	1	5
Q2: Information supports conclusion	65	2.31	1.01	1	5
Abstract 1 Causal Language Duration	64	64	27	3	141
Q1:Quality of design & analysis	64	2.73	0.82	1	4
Q2: Information supports conclusion	64	1.94	0.85	1	4
Abstract 2 Statistical Question Duration	66	166	453	4	2992
Q1:Quality of design & analysis	66	3.18	0.74	1	5
Q2: Information supports conclusion	66	2.18	0.96	1	4
Abstract 2 Causal Language Duration	65	189	887	12	7230
Q1:Quality of design & analysis	65	2.86	0.77	1	4
Q2: Information supports conclusion	65	2.2	1.11	1	5
Passed Manipulation Check	63				
Participants Excluded	82				

Note. $n = 142$. Participants excluded are still included in this descriptive analysis, and later excluded in the pre-registered analytic sample. 82 cases were excluded because participants answered first two questions in under 30 seconds ($n=11$), participants were not in a field related to psychology ($n=5$), they failed the manipulation check ($n=64$), were not enrolled in a PhD program, post-doctoral position, or a faculty position ($n = 1$), or they were not at least 18 years-old ($n=1$). Question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?” is answered on a scale from 1 – 5 where 5 =Very high quality, 4 = High quality , 3 = Moderate quality , 2 = Low quality, and 1= Very low quality . Question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: “We conclude that raising the quantity and quality of (resources for third grade reading OR early science instruction) is an important way to raise children’s educational prospects in the 21st century.” Is answered on a scale from 5 = Very strongly, 4 = Strongly, 3 = Moderately, 2= Weakly, 1 = Very Weakly/Not at all. Duration shown in seconds.

Table 3*Participant Ratings of Quality of Design and Study*

Model	1			2			3			4		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.48***	0.14	0.82	0.45***	0.07	0.81	0.34***	0.08	0.71	0.38**	0.12	0.61
Abstract	0.01	0.14		-0.004	0.07		0.09	0.08		0.22	0.12	
Order				0.21**	0.07		0.17*	0.08		0.16	0.12	
Intercept	2.67***	0.23		2.50***	0.16		2.49***	0.18		2.34***	0.25	
Participants	124			132			90			39		
Observations	124			260			177			78		
R ₂	0.08			0.07			0.08			0.16		
Model Specifications												
First abstract only	X											
Both abstracts				X			X			X		
Passed Manipulation check										X		
First 100 participants							X			X		
Passed exclusionary criteria										X		

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. PsychMD = Psychological Methods Discussion Facebook group. The dependent variable is Question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?” is answered on a scale from 1 – 5 where 5 = *Very high quality*, 4 = *High quality*, 3 = *Moderate quality*, 2 = *Low quality*, and 1 = *Very low quality*. Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on quality rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on quality rating. Model 1 is an ordinary least squares model using only the quality response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in quality rating within-person since all participants saw two abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. *R*² reflects the pseudo r-squared for fixed effects.

Table 4
Participant Ratings of *Perceived Support for Policy Conclusion*

Model	1			2			3			4		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.20	0.16	0.88	0.20*	0.08	0.99	0.16	0.10	1.00	0.25	0.14	0.96
Abstract	-0.08	0.16		0.03	0.08		0.11	0.10		0.14	0.15	
Order				0.49***	0.08		0.45***	0.10		0.32*	0.15	
Intercept	1.95***	0.25		1.30***	0.19		1.28***	0.23		1.51***	0.31	
Participants	124			132			90			39		
Observations	124			260			177			78		
R^2	0.02			0.07			0.06			0.05		
Model Specifications												
First abstract only		X										
Both abstracts				X				X			X	
Passed Manipulation check											X	
First 100 participants								X			X	
Passed exclusionary criteria											X	

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The dependent variable is Question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: We conclude that raising the quantity and quality of early science instruction is an important way to raise children’s educational prospects in the 21st century” OR “We conclude that extra resources for third grade reading instruction are likely to improve children’s college readiness, and propose this as a useful intervention”, is answered on a scale from 5 = *Very strongly*, 4 = *Strongly*, 3 = *Moderately*, 2 = *Weakly*, 1 = *Very Weakly/Not at all*. Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on support rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on support rating. Model 1 is an ordinary least squares model using only the support response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in support rating within-person since all participants saw to abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. R^2 reflects the pseudo r-squared for fixed effects.

Figure 1

Changes in Ratings by Condition for Questions 1 and 2

Note. The left panel compares ratings from question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described? “. The right panel compares ratings from question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: “We conclude that raising the quantity and quality of (resources for third grade reading OR early science instruction) is an important way to raise children’s educational prospects in the 21st century. “. Lines represent differences in participant rating of quality between abstracts that has statistical language and causal language. Gray lines indicate the number of participants that rated abstracts with different languages the same. Blue lines indicate the number of participants that rated abstracts with causal language higher than abstracts with statistical language. Red lines indicate the number of participants that rated abstracts with statistical language higher than abstracts with causal language.

Online Supplementary Materials

Table S1

Descriptive Statistics for the Pre-Registered Survey Sample Categorical Variables

Variable	Proportion
Condition	1 st Science study ambiguous language, 2 nd reading study causal language 31%
	1 st Science study causal language, 2 nd reading study ambiguous language 31%
	1 st Reading study causal language, 2 nd science study ambiguous language 15%
	1 st Reading study ambiguous language, 2 nd science study causal language 23%
Source	cogdevsoc listserv 26%
	PsychMD 41%
	Twitter 33%
Sex	Male 46%
	Female 54%
	Non-binary 0%
Country Academic Career	United States 62%
	Canada 15%
	Other / Did not answer 23%
Age Learned English	Native Speaker 59%
	Before Age 6 13%
	Between Ages 7-10 13%
	Between Ages 11-14 15%
	Between Ages 15-18 0%
	Prefer not to answer / Did not answer 0%
Career Status	Faculty 33%
	Postdoctoral Researcher 23%
	PhD Student 41%
	Masters Student 3%
	Undergraduate 0%
	Other / Did not answer 0%
Academic Field	Psychology 100%
	Other / Did not answer 0%
Psychology Subfield	Clinical 5%
	Cognitive 28%
	Neuroscience 8%
	Developmental 33%
	Quantitative 15%
	Social/Personality 21%
	Educational 5%
	Other / Did not answer 10%

Note. $n = 39$. PsychMD = Psychological Methods Discussion Facebook group. Descriptive statistics of full pre-registered analytic sample after cases that met exclusionary criteria were removed. Participants that preferred not to answer questions or did not answer were reported together to prevent any possibility of identification. Some academic fields categorized as other included 6 areas that were included in the analyses as psychological subfields.

Table S2*Descriptive Statistics for the Pre-Registered Survey Sample Continuous Variables*

Variable	N	Mean	SD	Min	Max
Age	37	33.57	9.44	22	67
Statistics Courses Taken	39	4.97	3.54	0	20
Survey Duration	39	322	110	181	623
Abstract 1 Statistical Question Duration	18	92	35	45	161
Q1: Quality of design & analysis	18	3.11	0.47	2	4
Q2: Information supports conclusion	18	2.50	0.79	1	4
Abstract 1 Causal Language Duration	21	68	27	33	142
Q1: Quality of design & analysis	21	2.81	0.60	2	4
Q2: Information supports conclusion	21	1.95	0.86	1	4
Abstract 2 Statistical Question Duration	21	83	43	30	173
Q1: Quality of design & analysis	21	3.43	0.51	3	4
Q2: Information supports conclusion	21	2.38	1.02	1	4
Abstract 2 Causal Language Duration	18	86	42	35	205
Q1: Quality of design & analysis	18	3.00	0.69	2	4
Q2: Information supports conclusion	18	2.50	1.10	1	4
Passed Manipulation Check	63				
Participants Excluded	103				

Note. $n = 39$. Descriptive statistics of full pre-registered analytic sample after cases that met exclusionary criteria were removed. 103 cases were excluded because the participants answered first two questions in under 30 seconds ($n=15$), participants reported being younger than 18 years old ($n = 2$), participants were not in a field related to psychology ($n=5$), they failed the manipulation check ($n=63$), they were not enrolled in a PhD program, post-doctoral position, or a faculty position ($n = 2$), and they were not the first 100 survey respondents ($n = 16$). Question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?” is answered on a scale from 1 – 5 where 5 = Very high quality, 4 = High quality, 3 = Moderate quality, 2 = Low quality, and 1 = Very low quality. Question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: “We conclude that raising the quantity and quality of (resources for third grade reading OR early science instruction) is an important way to raise children’s educational prospects in the 21st century.” Is answered on a scale from 5 = Very strongly, 4 = Strongly, 3 = Moderately, 2 = Weakly, 1 = Very Weakly/Not at all. Duration shown in seconds.

Table S3*Participant Ratings of Quality of Design and Study Split by Survey Media Source*

Model	Twitter			PsychMD			Cogdevsoc		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.21	0.15	0.7	0.58***	0.13	0.77	0.45**	0.11	0.88
Abstract	0.2	0.15		0.08	0.13		-0.11	0.1	
Order	0.03	0.15		0.29*	0.13		0.23*	0.1	
Intercept	2.55***	0.31		2.22***	0.3		2.60***	0.24	
Participants	31			34			67		
Observations	61			65			134		
<i>R</i> ²	0.05			0.18			0.06		

Model Specification

Both abstracts	X	X	X
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Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. PsychMD = Psychological Methods Discussion Facebook group. The dependent variable Question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?” is answered on a scale from 1 – 5 where 5 = Very high quality, 4 = High quality, 3 = Moderate quality, 2 = Low quality, and 1 = Very low quality Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on support rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on support rating. Model 1 is an ordinary least squares model using only the support response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in support rating within-person since all participants saw to abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. *R*² reflects the pseudo r-squared for fixed effects.

Table S4*Participant Ratings of Perceived Support for Policy Conclusion Split by Survey Media Source*

Model	Twitter			PsychMD			Cogdevsoc		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.04	0.16	1	0.05	0.17	1.06	0.32**	0.11	0.96
Abstract	0.4*	0.16		-0.1	0.17		-0.07	0.11	
Order	0.54**	0.15		0.27	0.17		0.55***	0.11	
Intercept	0.7	0.35		1.89***	0.4		1.31	0.25	
Participants	31			34			67		
Observations	61			65			134		
<i>R</i> ²	0.12			0.02			0.11		
Model Specifications									
Both abstracts		X			X			X	

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. PsychMD = Psychological Methods Discussion Facebook group. The dependent variable Question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: We conclude that raising the quantity and quality of early science instruction is an important way to raise children’s educational prospects in the 21st century” OR “We conclude that extra resources for third grade reading instruction are likely to improve children’s college readiness, and propose this as a useful intervention”, is answered on a scale from 5 = *Very strongly*, 4 = *Strongly*, 3 = *Moderately*, 2 = *Weakly*, 1 = *Very Weakly/Not at all*. Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on support rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on support rating. Model 1 is an ordinary least squares model using only the support response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in support rating within-person since all participants saw to abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. *R*² reflects the pseudo r-squared for fixed effects.

Table S5*Participant Ratings of Quality of Design and Study Split by Participant Professional Status*

Model	Faculty			Post-Doctoral Research			PhD Students		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.49***	0.11	0.73	0.58**	0.16	0.8	0.36**	0.11	0.8
Abstract	-0.12	0.11		0.15	0.16		0.05	0.11	
Order	0.14	0.11		0.4	0.16		0.15	0.11	
Intercept	2.78	0.24		1.92***	0.43		2.48***	0.23	
Participants	46			28			47		
Observations	92			56			94		
R ²	0.11			0.15			0.07		
Model Specifications									
Both abstracts		X			X			X	

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The dependent variable is Question 1: “Based on the limited information available in this abstract, how would you rate the quality of the design and analysis of the study described?” is answered on a scale from 1 – 5 where 5 = Very high quality, 4 = High quality, 3 = Moderate quality, 2 = Low quality, and 1 = Very low quality. Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on support rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on support rating. Model 1 is an ordinary least squares model using only the support response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in support rating within-person since all participants saw two abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. R² reflects the pseudo r-squared for fixed effects.

Table S6*Participant Ratings of Perceived Support for Policy Conclusion Split by Participant Professional Status*

Model	Faculty			Post-Doctoral Researchers			PhD Students		
	Estimate	SE	SD	Estimate	SE	SD	Estimate	SE	SD
Causally Ambiguous Statistical Language	0.24*	0.12	0.94	0.18	0.19	0.95	0.21	0.13	0.96
Abstract	-0.07	0.12		-0.15	0.18		0.24	0.13	
Order	0.32**	0.12		0.66**	0.18		0.41**	0.13	
Intercept	1.69***	0.27		1.15*	0.49		1.04***	0.27	
Participants	46			28			47		
Observations	92			56			94		
R ²	0.04			0.14			0.09		
Model Specifications									
Both abstracts		X			X			X	

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The dependent variable Question 2: “Based on the limited information available in this abstract, how strongly does the study support the conclusion in the final sentence, quoted below: We conclude that raising the quantity and quality of early science instruction is an important way to raise children’s educational prospects in the 21st century” OR “We conclude that extra resources for third grade reading instruction are likely to improve children’s college readiness, and propose this as a useful intervention”, is answered on a scale from 5 = Very strongly, 4 = Strongly, 3 = Moderately, 2 = Weakly, 1 = Very Weakly/Not at all. Causally Ambiguous Statistical Language is a dummy variable in which causal language used in the abstract = 0 and Causally Ambiguous Statistical Language = 1. The abstract variable is coded as 1 = abstract 1 and 2 = abstract 2 to indicate effects of abstract used on support rating. Order indicates which abstract was seen first (1) or second (2) to measure the effects of abstract order on support rating. Model 1 is an ordinary least squares model using only the support response from the first abstract seen by the participants. All other models use individual random effects to estimate the effect of the independent variables on changes in support rating within-person since all participants saw to abstracts and provided two quality ratings. SD indicates one standard deviation for the outcome variable for each analysis sample. An effect size can be calculated by dividing regression estimates by the outcome standard deviation. R² reflects the pseudo r-squared for fixed effects.