Blinded versus unblinded review: A field study comparing the equity of peer-review

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Author Note

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Abstract

Blinded review is often seen as a solution to inequities that appear to arise in merit-based evaluations where particular individuals or groups are favored. Yet, an equitable merit-based evaluation should also be reliable and valid. We evaluated the equity of blinded and unblinded review in a high-stakes field experiment during peer-review of submissions for an academic conference. In the study, each conference submission ($N = 530$) received both double-blind peer-reviews—both reviewer and author identities were withheld—and single-blind peer-reviews—only reviewer identities were withheld. We found both systems exhibited moderate reliability. Yet, this level of reliability meant that the review systems only agreed on 40% of the top submissions meaning some of the differences observed between review systems comes from noisy human judgment. The comparison also revealed that single-blind reviews favored senior coauthors, while double-blind reviews slightly favored male authors. Neither author characteristics nor review process consistently predicted talk quality or popularity, but single- and double-blind reviews predicted subsequent publication. These results imply any partiality towards particular authors' characteristics during single-blind review was not based on calibrated beliefs, and there was not strong evidence suggesting reviewers need to know the authors' characteristics to judge the merit of the work. The results also suggest that the unfettered use of double-blind review may dismiss a certain perspective or type of work. We discuss ways in which blind review may be adapted to create an equitable merit-based evaluation.

Keywords: peer review, double blind, single blind, field study, metascience

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Introduction

Blind review — be it for job, credit or loan applications, legal procedures, or scientific peer review—is often seen as an effective means to help create an equitable merit-based evaluation system (Robertson & Kesselheim, 2016; MacCoun, 2020). But does blinding actually help achieve this goal? For hiring decisions, blind review sometimes seems to create a more equitable selection process, helping women and minorities advance in the interview process (Åslund & Skans, 2012; Goldin & Rouse, 2000). In terms of peer review, *double-blind review*—where both reviewer and author identities are withheld—has been associated with an increase in the representation of women (Budden et al., 2008) and scientists from less prestigious institutions or organizations (Crane, 1967; Tomkins et al., 2017). Sometimes, however, blinding does not work. In some job selection settings, female applicants fared *worse* with blinded applications compared to non-anonymous applications (Behaghel et al., 2015; Krause et al., 2012). Similarly, in the domain of peer review, double-blind review is not always beneficial (Cox & Montgomerie, 2019; Hammerschmidt et al., 2008; Whittaker, 2008). These mixed results are also present in the very few and limited randomized experiments on blind review (Blank, 1991; Okike et al., 2016).

Yet, the degree to which a merit-based evaluation differentially favors certain groups or individuals is only one part of the equity question. An equitable merit-based evaluation should also be a valid and reliable predictor of merit. Does anonymity come at the cost of being a less accurate predictor of quality? Indeed, in discussions about whether to blind reviewers or not, some will argue that partiality towards specific identities might be justified if author characteristics are valid proxies of merit. Such an argument is consistent with a belief- or statistical-based model of discrimination (Aigner & Cain, 1977; Arrow, 1973; Bohren et al., 2019; H. Fang & Moro, 2011; Phelps, 1972). In this case, if these beliefs reflect accurate statistical associations and are used to make the evaluation, then

blinding judges should result in merit-based evaluations being less valid and potentially less reliable. Alternatively, these beliefs could be inaccurate (Bordalo et al., 2016; Fryer et al., 2008; Judd & Park, 1993). In this case, blinding reviewers should not affect the validity and reliability of the evaluations. In fact, it might even result in blinded evaluations having greater validity and reliability as reviewers might be forced to rely on more accurate cues. A third possibility is that partiality towards particular characteristics is preference-based arising due to unfavorable attitudes towards people with a particular characteristic (Becker, 1957). Here again, blinding—assuming preference is not related to the statistical association—should not affect the validity and reliability of the evaluations. The overall point here is that a complete assessment of the equity of a merit-based evaluation requires understanding the degree to which individuals and groups are treated differently and an assessment of the validity and reliability of the system. In the context of whether to blind reviewers or not, to date, there are no published results on the impact blinding has on the validity and reliability of merit-based evaluations. We set out to address this limitation.

Here we report a unique large-scale preregistered field experiment with conference submissions for the Society for Judgment and Decision Making’s (SJDM) 39th Annual Conference. We compared single- and double-blind review of the submissions in three areas: reliability, the differential impact of author characteristics, and validity. A head-to-head comparison between these different review systems in situ on these three different dimensions is revealing for several reasons. For example, establishing differential impact would suggest that author characteristics potentially influence evaluations directly (in single-blind) or indirectly (in double-blind). The setting also makes available a suite of relevant outcome data, including the quality and popularity of the talk, and if the submission was ultimately published or not. Thus, we can establish how well either review system accurately predicts these different outcomes. Taken together, such a multi-faceted comparison provides a more complete view of the equity of the different review systems. If single-blind review differentially favors a particular author characteristic and is more

accurate in predicting relevant outcomes relative to double-blind review, then this would imply the characteristic is a valid proxy for merit. Such a result would help in establishing why people may favor single-blind review. Alternatively, if a particular characteristic is favored in single-blind compared to double-blind and there is no difference in the accuracy of the two review systems, this would help speak to the inequities of single-blind review. Either of these conclusions or others can be further probed by our ability to assess to what degree any of the author characteristics are predictive of any of the relevant outcomes. If, for instance, none of the author characteristics are predictive of the relevant outcomes, then this would seem to suggest that making individuating information available during the review process is unnecessary. Moreover, it will also help in establishing the degree to which any differential treatment of author characteristics may reflect accurate beliefs about the statistical association between an author characteristic and the merit of the submission.

Another important factor that makes our comparison of single- and double-blind review informative is the setting. The SJDM organization is an international society of about 1,800 psychologists, economists, organizational researchers, decision analysts, and others dedicated to studying judgment and decision making. Thus, the reviewers' expertise and the domain made it a near-ideal area to examine the effect blinding has on judgment. At the time of the study, the conference used single-blind review to select submissions for talks even though many members expressed a preference for double-blind review. We confirmed this preference with a survey of the society (see Supplementary Material for details on the survey). Society members rated their preference for single- vs. double-blind review on a 1 - 7 scale where ratings greater than 4 indicated a preference for double-blind review. The preference for double-blind review was strongest when respondents took the perspective of an author ($M = 5.8$, $[5.5, 6.1]$) vs. a conference attendee ($M = 5.4$, $[5.1, 5.7]$) on a 7-point scale; $\beta = -0.23$, $[-0.36, -0.10]$), and only slightly stronger for an author vs. a reviewer ($M = 5.6$, $[5.3, 5.8]$, $\beta = -0.11$, $[-0.24, 0.02]$) (Table S4). Less experienced reviewers also had a stronger preference for double-blind review ($\beta = -0.21$, $[-0.36,$

-0.05]).¹ Thus, at least for SJDM, there was a practice-preference gap where institutional members expressed a preference for blind review, yet the institution itself continued to practice non-anonymous single-blind review. We suspect a similar gap is present for many other institutions and organizations that use merit-based evaluations. At least in the case of SJDM, part of the reason for the practice-preference gap seemed to be a disagreement as to the effectiveness of double-blind review as compared to single-blind review. As we have discussed, we designed our study to address this specific problem by, for instance, collecting a suite of relevant outcome data and also implementing a method to assess the reliability of the different review systems. But, we also recognize merit-based reviews are used in a host of other managerially relevant contexts. Thus, we designed the current study with an eye toward extracting generalizable principles about the strengths and weaknesses of employing either single- or double-blind review in these other contexts. In the discussion, we review these strengths and weaknesses and make evidence-based recommendations for organizations that want to employ peer review for merit-based evaluations, particularly peer-review of scientific work.

This domain of peer-review for conference submissions is an informative setting to study blinding. One reason this setting is informative is that reviewing is often done under time pressure and with limited relevant information. These limitations are particularly prevalent in our setting. For example, in the current study, each reviewer evaluated approximately thirty 600-word submissions within three weeks. It is under these circumstances that we might expect reviewers to rely on heuristic cues like identities and credentials to infer the quality of the work (Hertwig et al., 2019). Another benefit of the setting is the interdisciplinary nature of the conference. International scholars with

¹ This double-blind review preference is associated with perceived differences in fairness between single- and double-blind review ($\beta = 0.54$, [0.42, 0.65]). Consequently, the relationship between reviewing experience and review-system preference dissipates once fairness perceptions are accounted for ($\beta = -0.09$, [-0.23, 0.05]) (Tables S4 & S5).

backgrounds in economics, management, marketing, psychology, and other related areas participate in the conference. Moreover, some of the conference topics, such as probability theory, utility theory, statistics, and methodology, are mathematically intensive, a characteristic that is often associated with disparities by gender and race (Ceci et al., 2014). Thus, we expect results from our comparison of single- and double-blind review to generalize to a wide range of related domains, particularly in domains that are associated with historical disparities.

The conference setting also created a high-stakes environment. With $N = 530$ submission for only 108 speaking slots (thus a 20% acceptance rate), competition for a talk was tight. Indeed, presenting a paper at a high-impact conference can be associated with an increased chance of publishing the work (Gorodnichenko et al., 2021) and ultimately lead to more citations (de Leon & McQuillin, 2020). Moreover, many of the hopeful presenters were on the job market, and being selected for a talk can be an important signal. Finally, the setting also provided a means to address a key challenge in comparing single- and double-blind review: the variability between submissions. Instead of trying to match submissions between single- and double-blind review conditions as might be done in a typical audit study (Bertrand & Duflo, 2017), we leveraged the fact that each submission was evaluated by multiple reviewers. Thus, we randomly assigned reviewers to either the double-blind or single-blind condition for all of their reviews. We then randomly assigned each submission to at least three single- and three double-blind reviewers. Altogether this approach permitted us to directly control for the heterogeneity of the submissions, and, at the same time, employ random assignment to help isolate the differences between single- and double-blind review.

Methods

The SJDM Executive Board and the XXXX Institutional Review Board approved the study. The preregistration for the study is listed on OSF [here](#). The supplementary

materials (SM) documents the deviations from the preregistration. It also contains a complete listing of all measures and observations. De-identified survey data and analyses are at the Open Science Framework: [Blinded OSF Anonymous Peer Review Link](#). More detailed information on the methods including the measures used and collected and the procedures are in the SM.

Submissions

There were $N = 530$ submissions for possible presentation at the meeting. Submissions had between one and six authors, with an average of 2.8 ($SD = 1.0$). A total of 26 (5%) submissions had one author, while two-author submissions were the most prevalent, at 218 (41%) submissions. Table S1 summarizes the characteristics of submitting authors.

Reviews

We recruited a total of $N = 113$ reviewers for the conference submissions who were representative of the society. One reviewer did not complete their reviews, leaving $N = 112$ reviewers. We sent the standard review invitation, which had no information about the study. Due to the increased need for reviewers, many reviewers had not previously reviewed for the conference ($N = 50$). Prior reviewers had reviewed between 1 and 2 times previously for the conference ($M = 1.5$; $SD = 1.7$). Reviewers were randomly assigned to either the single- or double-blind condition. Each reviewer was asked to review 30 randomly assigned submissions within 3 weeks of assignment. Consistent with precedent at the society, in both conditions, reviewers rated each abstract on a nine-point scale from 1 (Poor) to 9 (Excellent). For all analyses, we standardized ratings within each reviewer.

Talk ratings

We recruited $N = 18$ faculty and $N = 12$ pre- and post-doctoral students (henceforth students) to rate the conference talks. The conference had nine sessions each with three

tracks of four talks. Our goal was to have two faculty and two student raters of each of the talks. To achieve this goal, we randomly assigned faculty to one of the three tracks in three of the nine sessions during the conference. We randomly assigned students to rate one track of talks in either the first five sessions or the last four sessions of the conference.

Procedure

We designed the study to keep the submission process consistent with the typical process for the annual meeting (e.g., same abstract length, call for submissions, and review dimensions) and only include the added step of reviewing all submissions with double-blind review. To maintain the experiment's integrity, only the four authors of this paper, the SJDM executive board, and the NSF grant reviewers were aware of the field experiment. The field experiment was revealed on the last day of the conference during the morning business meeting.

The call for submissions was issued on Monday, June 4, 2018, with a deadline of June 22, 2018. Reviewers were recruited soon after the submission deadline. We assigned submissions to reviewers on July 6 and a deadline of July 26, 2018 to submit reviews. We randomly assigned submissions to reviewers such that at least three double-blind and three single-blind reviewers reviewed each submission. As we sought to assess reliability in the different review processes, we randomly assigned $N = 53$ of the submissions (10%) to three additional double-blind and three additional single-blind reviewers. This design resulted in reviewers rating an average of $N = 31$ ($SD = 1.6$) submissions.

The conference chair (XXXX) selected 108 talks for presentation at the annual conference based primarily on the average of the single- and double-blind ratings. For the subset of submissions with two sets of single- and double-blind reviews, the chair selected one set of single-blind and one set of double-blind reviews to include in the average. Consistent with past conferences, the talks occurred during nine sessions, each consisting of three parallel tracks, composed of four talks each. We assigned two student and two faculty

raters to each talk. They each rated the talks on the significance, methods, results, innovation, and uniqueness, which we, in turn, used to form a composite measure of overall quality.

Analysis

Unless otherwise noted, the predictors and outcome variables used in all the regressions were standardized to facilitate interpretation and comparison between regression coefficients. We used Bayesian estimation methods for data analysis. We report the posterior predicted mean of the parameter of interest and in brackets its 95% Credible Interval (CI). The CI summarizes the posterior distribution excluding the 2.5% of the distribution at each tail. In general, we take a quantitative approach focusing on the size of the effect or association, but use the term *credible* when the 95% CI excludes 0.

For model comparisons, we used leave-one-out cross validation (LOO) to compare models based on the expected log pointwise predictive density for a new dataset ($elpd_{loo}$), which quantifies the difference in predictive accuracy between them. In general, we consider $|\Delta elpd_{loo}| < 1 SE$ to be weak evidence for a particular model.

In all cases, we used the default priors, which were set to be weakly informative providing moderate regularization to the estimates (i.e., priors that are skeptical of extreme parameter values). We inspected MCMC chains for representation and accuracy, and we sought to have all reported parameters based on an effective sample size of 10,000. Posterior distributions do not change based on the number of planned or unplanned tests. Thus, there is no correction for the number of tests as statistics and inferences from them are based on the posterior distribution (Gelman et al., 2012; Kruschke & Liddell, 2018).

Results

Of the 530 submissions, the first author was also the corresponding author for $N = 456$ of those. Because for many of the variables including nationality and area of Ph.D. we only have data about the corresponding author, in all of our reported analyses we

Figure 1. A: Correlation between ratings from the two review processes. B: Relationship between the reviews for the subset of 53 submissions that were reviewed by two teams of reviewers in the single-blind condition (inter-rater reliability). C: Relationship between the reviews for the subset of 53 submissions (same set as in B) that were reviewed by two teams of reviewers in the double-blind condition (inter-rater reliability). There is no credible difference between the two conditions.

focus only on submissions where the first author was the corresponding author. Table S1 lists summary statistics of the authors. Next, we compare single- and double-blind review in terms of their review rating reliability, differential impact of personal and submission characteristics, and predictive validity of relevant outcomes including talk/presentation quality and popularity and subsequent publication.

Reliability

Our first analysis focused on the submission level asking how much agreement there was between single- and double-blind review ratings, and how much agreement there was within each review system. To conduct the analysis, for each review system we averaged the review ratings given to each submission forming an average overall rating for each submission. Figure 1A reveals a moderate level of agreement between the two review processes across all 530 submissions. However, the level of agreement depended on the quality of the submission. A median split by the single-blind rating reveals more agreement between single- and double-blind review for the bottom half of the submissions ($r = 0.45$, $[0.35, 0.54]$) than the top half ($r = 0.19$, $[0.07, 0.29]$; $\beta = -0.40$, $[-0.65, -0.16]$; see Table S6). This lack of agreement at the top is consequential. Among the top 108 submissions (i.e., the number accepted for talks) only 43 submissions (40%, $[31, 49]$) make the cut under both single- and double-blind review. In other words, the conference program would feature quite a different talk line-up with different review systems. In comparison, if we examine the bottom 108 submissions, there was more agreement (58 submissions, 54%, $[44, 63]$; $M_{\text{diff}} = 14\%$ $[1, 27]$) about what constitutes a weak submission, than a strong one.

Although some studies have documented poor reliability of peer-reviews (Bornmann et al., 2010; Fiske & Fogg, 1992; Pier et al., 2018; Lawrence, 2015), our study found moderate reliability within each review condition. Recall, we randomly selected 10% of the submissions ($N = 53$) for review by six single-blind reviewers and six double-blind reviewers (whereas the other 90% were reviewed by three single-blind and three double-blind reviewers. For this subset of submissions for both single- and double-blind review, we divided the six reviews into two set of three reviews (Set A and Set B). For each set of three reviews we calculated the average rating. Figures 1B and C plots the relationship between the average ratings given to these submissions between the sets of reviewers. Regressing the average reviews for each submission onto the review condition (single or double), set (A or B), and the interaction between these two revealed a small but

non-credible interaction ($\beta = 0.20, [-0.06, 0.45]$). This result implies the two review processes do not credibly differ in reliability.

Crucially, just as the moderate level of agreement between review systems means that fewer than half of the submissions chosen for a talk with one review system would be selected with a different review system, the moderate level of agreement within review systems means the same is true if the same review system was used but we just had a different set of reviewers. To see this we simulated 530 pairs of 530 normally distributed random variables that were correlated at the level of agreement we observed within review the systems. Then we calculated the proportion of times the same pair was in the top 108 values for each variable. We repeated this simulation 10,000 times. This simulation showed that a correlation of $r = .64$ (the level of agreement within single-blind) resulted in on average 49% of the pairs being in the top 108 values for both variables. When the correlation was $r = 0.58$ (the level of agreement within double-blind), this value was 46%. That is, the moderate level of agreement within review systems also means that the conference program would also feature quite different talks if selected from two different sets of single-blind reviews, or two different sets of double-blind reviews. We discuss the implications of this moderate level of agreement further in the discussion.

Differential impact of author characteristics

Our next set of analyses examined the degree to which author characteristics differentially impacted review ratings. This analysis is, perhaps, the area most people think about in terms of the equity of the different review processes. Do women score better in single-blind or in double-blind? How does author seniority impact the different review processes? To answer these questions, for each submission, we had data for up to eleven different characteristics (Table 1). One set of characteristics consisted of information related to author identities: the authors' gender, position, institution; first author nationality, years since Ph.D., Ph.D. area.

Table 1

Predictors used in the comparison between single- vs. double-blind review.

Characteristic Variable		Description
Condition	Single- or double-blind review	A binary variable indicating single- (0) or double-blind (1) review.
First Author	Gender of first author	Binary variable indicating whether first author was female (0) or male (1).
	Years since Ph.D.	Years from first author's Ph.D. to 2018.
	Domestic or international	Whether the first author was a U.S. citizen (0) or not (1).
	Ave. number of citations for JDM-relevant departments at first author's institutions	Average number of citations for top papers from Psychology, Economics and Business, and Social Science departments at the institution of the focal author as determined by the Web of Science (August 29, 2019). We use this variable as a proxy for institutional prestige.
	Ph.D. area of the first author	Ph.D. area of the first author (Economics, Management, Marketing, Other, Psychology).
	Position of the first author	Position of the first author (student, undergraduate student, master's student, Ph.D. student, Post-doc, research scientist, practitioner, assistant professor, associate professor, full professor).
Coauthors	Proportion of coauthors who were men*	Proportion of coauthors excluding first author who were male.
	Ave. number of citations for JDM-relevant departments at coauthors' institutions*	Average number of citations for top papers from Psychology, Economics and Business, and Social Science departments at the institution of the coauthors. See ave. number of citations JDM-relevant departments at first author's institutions.
	Ave. position rank of coauthor(s)*	Average position rank of coauthor(s) excluding focal author where there are 10 positions (see Position of first author).
Text	Topic	Topic was calculated from a topic model of the 35 chapter Blackwell-Wiley Handbook of Judgment and Decision Making Keren & Wu (2015). There were three core topics that emerged from the handbook: theories of judgment and decision making, empirical phenomena of judgment and decision making, and psychology of judgment and decision making.
	Sentiment	Sentiment score was estimated from a sentiment classifier where sentiment ranged from -1 (negative) to 1 (positive).
Reviewer	Reviewer gender	Binary variable indicating whether reviewer was female (0) or male (1).
	Reviewer years since Ph.D.	Years since 2018 that reviewer obtained Ph.D.
	Ave. number of citations JDM-relevant departments at reviewer's institutions	The average number of citations for top papers from Psychology, Economics and Business, and Social Science departments at the institution of the coauthors. See ave. number of citations JDM-relevant departments at first author's institutions.
	Ph.D. area of the reviewer	Ph.D. area of the reviewer (Economics, Management, Marketing, Other, Psychology).
	Position of the reviewer	Position of the reviewer (research scientist, practitioner, assistant professor, associate professor, full professor).
	Reviewer experience past 7 years	Number of times reviewed for the SJDM Annual Meeting in the past 7 years.

* In the regressions this statistic was sometimes expanded to include all authors so as to not exclude single author submissions. See Footnote 3.

The second set of characteristics was focused on the characteristics of the submitted abstract themselves. One reason we included these characteristics was that we reasoned that perhaps without personal characteristics, double-blind reviewers may focus more on the submission itself. If so, perhaps topic might be more strongly associated with the review in the double-blind than in single-blind. Moreover, by including these variables, we

Figure 2. A. Intercorrelations between author and text characteristics and single- and double-blind review ratings. B. Correlation between author and text characteristics and relevant outcomes. *Note:* The central value is the mean posterior estimate. The values in the upper and lower right-hand corners are the estimates of the upper and lower bounds of the 95% credible interval. Starred values indicate the credible interval excludes 0. The correlations with overall talk rating, attendance, and total potential questions were corrected for indirect restriction of range (Mendoza & Mumford, 1987). Journal impact factor was log-transformed before computing the correlation. Position was treated as a numerical variable in these correlations, but as a categorical variable in the regressions. Area of Ph.D. and topic from a topic model analyses are categorical variables and are not in these matrices, but were entered into the regressions. Table 1 describes each of these characteristics. Figure S5 lists the intercorrelations between the outcome variables. See also Tables S8-S12.

were also able to control for differences in topic and sentiment.² These variables consisted

² Our preregistrated plan was to include submitted keywords representing submission characteristics.

of information extracted from the submission text via natural language processing tools. See the supplementary material for more details on estimating these submission characteristics. Briefly, one characteristic was the sentiment (-1 (negative) to 1 (positive)) estimated using sentiment analysis. The other characteristic was the topic of the text estimated via a topic model from the extensive *Wiley-Blackwell Handbook of Judgment and Decision Making* (Keren & Wu, 2015). The topic model identified three topics: theories, empirical phenomena, and psychology of judgment and decision making. We assigned each abstract the topic with the highest posterior probability.

Intercorrelations between author characteristics and review ratings.

Figure 2A lists the intercorrelations between the (noncategorical) characteristics and the review ratings.³ Inspecting the bottom two rows of Figure 2A reveals a similar correlational pattern between the review ratings and the individual characteristics for the two review systems. The only credible difference between the two rests with the correlation between the review ratings and coauthor seniority: the correlation between the average coauthor rank and single-blind ratings was credibly higher than the corresponding correlation with double-blind ($\text{diff} = 0.19 [0.07, 0.33]$). This pattern suggests that single-blind reviewers based their evaluations in part on coauthor seniority whereas double-blind reviewers did not have access to that cue.

Simultaneous regression analyses. To further assess the degree to which the characteristics differentially impacted single- and double-blind review we entered review type (single vs. double), all eleven submission characteristics, and the interaction between each characteristic and review type simultaneously in a Bayesian hierarchical regression model, with the rating of each submission by each reviewer as the outcome variable. The

However, the variability in the keywords proved extensive and we had more confidence in the topic modeling and estimated sentiment. See Supplementary Material for details on the Preregistration and deviations from the Preregistered plan (??)

³ Race was not included as a predictor as the society is relatively homogeneous on this dimension (Table S1).

regressions modeled the variability between submission and reviewers as random intercepts. We also controlled for differences between reviewers by including six relevant reviewer characteristics (e.g., gender, position, and experience) in the regressions as covariates (Table 1).⁴ In total, 394 submissions had a complete set of characteristics for the analysis. By definition, the $N = 26$ single-author submissions did not have characteristics for coauthors. Therefore to include them in our analyses, for all the submissions, we replaced the coauthor variables with variables for all authors (e.g., the proportion of male authors instead of male coauthors).

Evidence for any differential impact across author characteristics. Our first question with the regressions, was how much evidence across all the characteristics was there for differential impact of author characteristics in the two review systems? To answer that question, we compared a model with the interaction terms between each of the eleven characteristics (Differential Impact Model; DI Model) and the review condition to a model without these interaction terms (No Differential Impact Model; No DI Model. As the LOO statistic was not larger than the standard error associated it, this comparison showed weak evidence in favor of the No DI Model ($\Delta elpd_{loo} = 3.4$; $SE = 6.2$; S6.1). Thus, across all the characteristics there is little support for the differential impact of personal and submission characteristics between single- and double-blind review

Differential impact of specific author characteristics. Our second question turned to each individual characteristic asking if there was evidence for any differential impact of any specific individual or submission characteristics after controlling for the other characteristics as revealed by the interaction between the review condition and the individual characteristic? In this regression, the interaction, between review condition and

⁴ We tested whether the effects of review type differed by reviewer characteristics. None of the reviewer characteristics showed credible interactions with the review condition (Table S10). Moreover, including these interaction as well as potential three-way interactions with author specific characteristics led to a substantially worse prediction by the regression model (via leave-one-out cross-validation) (Table S7).

first author gender ($\beta = 0.211$, $[0.025, 0.396]$) was credible (Tables S8 & S9). To better appreciate the strength of this interaction we conducted a model comparison between the No DI Model where only submission characteristics were entered as predictors and a second model that added (in a stepwise manner) the first-author gender by review condition interaction term to the No DI Model. This model comparison revealed that including first-author gender only provided at-best weak improvement in the model’s predictive accuracy ($\Delta elpd_{loo} = 0.085$; $SE = 1.711$; Table S8). Nevertheless, to better understand this weak interaction, we regressed first-author gender onto review ratings separately for single- and double-blind review (Tables S10). These regressions revealed that male first-authors received a 16.3% $[3.5, 28.6]$ higher rating than those with female first-authors in the double-blind condition, as compared to a weaker, non-credible 9.4% $[-4.6, 23.0]$ higher rating for submissions with male first-authors in the single-blind condition (Figure 2A, Tables S10 & S12). This pattern is also present in the correlations shown in Figure 2A where there was a credible correlation between first-author gender and double-blind reviews, but not in the single-blind condition.⁵ The regression analyses suggest these differences in review ratings are unlikely to be due to differences in submission sentiment, research topic, or any other author characteristic that might be correlated with author gender, as these are controlled for in the analysis. Moreover, in other follow-up analyses, we confirmed that this interaction between first-author gender and review system is present when controlling for reviewer characteristics (e.g., male reviewers showing a preference for male submissions) suggesting reviewer characteristics cannot explain these results. We did not anticipate this slight boost in ratings for male-authored submissions in double-blind

⁵ We examined if this gender differential was present in the top 108 submissions (the number of submissions selected for a talk) for single- and double-blind review. For both review systems there was a gender difference with less representation of women in the top 108 submissions, but if anything the gender difference was slightly stronger for single-blind review. This difference reinforces the fact that the difference between single- and double-blind in terms of gender is subtle and should be interpreted with caution. See Supplementary Material S7.

reviews and return to it in the discussion. An important question to ask, which we do in the next section, is to what degree and how gender is related to any of the relevant outcomes we measured.

Before we turn to predictive validity, we evaluate one remaining issue with regard to the differential impact of author characteristics. Recall in terms of zero-order correlations with submissions, there was a credible difference between single- and double-blind review with coauthor seniority (Figure 2A). However, this result did not materialize in the regressions in which single-author submissions were included. Recall that by definition single-author submissions did not have characteristics for coauthors so to include them in the regressions analyses, for all the submissions, we replaced the coauthor variables with variables for all authors (e.g., the proportion of male authors instead of male coauthors). Therefore, in another set of regressions, we focused solely on multiple-author submissions using the coauthor variables. This full regression model also regressed review type (single vs. double), all eleven submission characteristics, and the interaction between each characteristic and review type onto the review rating (with submission and reviewer as random intercepts and reviewer characteristics were entered as covariates). This full regression with multi-author submissions revealed a credible interaction between the review condition and the average seniority of coauthors ($\beta = -0.093$, $[-0.017, -0.016]$) (Table S9). Model comparisons via the stepwise addition of this interaction term onto the No DI Model where only submission characteristics were entered as predictors revealed that including this term improved the model’s predictive accuracy ($\Delta elpd_{loo} = 6.930$; $SE = 4.052$; Table S9). To better understand this interaction we regressed coauthor seniority on review ratings separately for single- and double-blind review. These regressions revealed that in single-blind review, for every position increase in average coauthor rank (e.g., from associate to full professor), there was an 8.1% $[4.5, 11.8]$ increase in the review rating. However, there was no credible comparable change for double-blind review ($M = 0.4\%$, $[-3.2, 4.0]$) (based on a 1.91 standard deviation of

Table 2

Coefficients from regressing submission outcomes onto single- and double-blind ratings.

	Single (Alone)	Double (Alone)	Rating x Condition
Talk Rating	0.05 [-0.08, 0.18]	-0.02 [-0.14, 0.10]	-0.07 [-0.31, 0.17]
Attendance	-0.11 [-0.42, 0.21]	-0.11 [-0.39, 0.17]	-0.04 [-0.61, 0.52]
Num. Questions	-0.01 [-0.36, 0.34]	0.16 [-0.15, 0.47]	0.11 [-0.53, 0.75]
Talk/Poster Rating	0.35 [0.14, 0.56]	0.23 [0.01, 0.43]	-0.18 [-0.75, 0.41]
Published	0.29 [0.08, 0.52]	0.42 [0.19, 0.66]	0.28 [-1.60, 2.21]
Impact Factor	0.24 [0.04, 0.43]	0.19 [-0.01, 0.40]	-0.03 [-0.36, 0.29]

Bolded values indicated that credible intervals exclude 0. Num. Questions is number of hands raised for questions. All continuous variables were standardized and impact factor was log transformed. When analyzing conference outcomes, conference session was entered as a covariate. When analyzing publication outcomes, conference presentation (1 or 0) was entered as a covariate. The coefficient for the Rating $\times$ Condition Interaction is from a model where the outcome was regressed onto the review rating, the condition, and the interaction. The regressions using “published” as an outcome are logistic regressions, while all other regressions use a normal link function.

coauthor rank; see Table S10; see also Figure 2A & Table S13). These differences in review ratings are unlikely due to differences in other author characteristics, submission sentiment, research topic, or reviewer characteristics, which are controlled for in the analysis. We return to this result in the discussion as well, but the favoritism of submissions with senior coauthors in the single-blind review suggests reviewers were potentially using this characteristic as a cue. Next, we ask the degree to which this characteristic and others were related to outcomes like talk quality and popularity.

Validity

Predictive validity of review ratings. Our final set of analyses focused on predicting a suite of outcome data for the submissions that proxy for the quality and future potential of the work: attendance, number of questions asked, expert quality judgments of

the conference talk, and publication status of the submissions two years later. Our first analysis tested whether the submission reviews themselves were predictive of these outcomes. Submission review ratings (single or double) did not credibly discriminate between higher and lower quality talks in terms of expert judgments, attendance, or the number of potential questions (see Table 2 and the bottom two rows of Figure 2B). However, the selection of talks for the conference based primarily on the review ratings creates a restriction of range problem, limiting our ability to assess the predictive validity of the reviews properly. Notably the correlations in Figure 2 account for range restriction thus suggesting range restriction does not account for the lack of predictive validity. To address this issue with data, we extended our analyses to include additional submissions ($N = 57$) that were not accepted as talks but were instead presented as posters and judged by experts in a student-poster competition. Combining the posters' expert judgments with the spoken presentations' expert judgments revealed that the single- and double-blind ratings credibly predicted these judgments. Notably, the validity did not differ by review type (Table 2).

We also assessed the submissions' publication status two years after the conference. We identified 184 of the 530 submissions (35%) as published in a peer-reviewed journal. Controlling for presentation at the conference, the review ratings from single- and double-blind reviews credibly predicted the submissions' publication status. Still, validity relative to future publication did not differ by review type (Table 2). Moreover, the single-blind reviews rating credibly predicted Web of Science's (logged) journal impact factors of the published submissions. There was also a smaller, non-credible relationship between double-blind ratings and impact factors. Again, there was no credible difference between single- and double-blind in predicting the impact factor for published work.

Predictive validity of author characteristics. A second analysis with the outcome data asked if any of the authors' characteristics and credentials predicted the outcomes. A common argument for single-blind review is that author identities or

credentials may provide valuable predictive information. Perhaps, for instance, having coauthors with more seniority may yield better research and give better talks, and therefore selecting this characteristic improves conference quality. No single author characteristic showed a strong consistent predictive relationship across the measured outcomes (see top 9 rows of Figure 2B and Table S16).⁶

However, there were some author characteristics that did have a relationship with some specific outcomes. Three are worth highlighting. The first relationship was an association between the prestige of the first author’s institution, as indexed by the average number of citations for JDM-relevant departments at the first author’s institute, and the talk rating. In particular, for every additional citation to the average number of citations for JDM-relevant departments, there was on average a 6.4% [0.3,12.4] increase in the talk rating (based on a 3.56 standard deviation in the average number of citations to papers in JDM-relevant departments). The prestige of the first author’s institution was also associated with the attendance such that for every additional citation to the average number of citations for JDM-relevant departments, there was on average 22.4 [8, 36.8] more attendees. However, this apparent predictive validity of the prestige of the first author’s institution did not translate to an increased likelihood of being published or being published in high-impact journals.

The second author characteristic was author seniority. For every increase in the average coauthor rank (e.g., associate to full professor), there were 5.9 [1.7, 10.2] *fewer* attendees (based on a 1.91 standard deviation in coauthor rank; see Table S18). This decrease in attendance for talks with more senior coauthors is notable given that single-blind review favored submissions with more senior coauthors.

⁶ Talk quality, as judged by experts on-site was credibly associated with estimated attendance ($\beta = 0.188$, [0.015, 0.363]), after controlling for the conference session: for every one standard deviation increase in the quality rating, there were 6.5 [.3, 12.6] more attendees (on average, there were 93.9 ($SD = 34.9$) attendees at each talk). Such a relationship does suggest there was some signal in the quality of the talks.

The third characteristic was the gender of the authors. Presentations with male first-authors tended to have lower attendance. Though not credible, there were on average 18.1 fewer attendees $[-1.0, 36.8]$ for men compared to women (Table S15). At the same time, the proportion of male authors predicted publication status such that for every 33% increase in the proportion of male authors, the submission was 1.62 $[1.14, 2.34]$ times more likely to be published. As we will explain further in the discussion, these last two effects are notable in light of our finding that in double-blind review male first authors received a higher rating than in single-blind. Altogether these results might suggest that there might be advantages associated with gender (thus higher ratings in double-blind and ultimately a greater likelihood of publication), but reviewers and conference participants may be actively working to counteract these potentially unwelcome advantages.

Discussion

Blind review is often discussed as a mechanism to level the playing ground creating a more equitable merit-based evaluation in a range of different domains, including employment, legal cases, and in science (Robertson & Kesselheim, 2016). Past studies that have examined the effectiveness of blind review in achieving this goal have yielded mixed results including the few and limited randomized experiments on the topic. Moreover, none of these studies examined the impact blinding has on the validity and reliability of merit-based evaluations. Our high-stakes field experiment addressed these shortcomings by comparing single- and double-blind review head-to-head in the context they were implemented. Doing so provided a unique opportunity to evaluate submissions under both review systems and randomly assign reviewers to the different systems and submissions. This structure allowed us to control for the heterogeneity between submissions that plague past comparisons and isolate similarities and differences between the two review processes in situ.

Similarities and differences between single- and double-blind review

Overall, our field study revealed that single- and double-blind review were similar in many respects. Ratings from both review systems were similarly valid, predicting some quality-related outcomes. Although some studies have documented poor reliability of peer-reviews (Bornmann et al., 2010; Fiske & Fogg, 1992; Pier et al., 2018; Lawrence, 2015), we found the review systems had similar levels of moderate-to-low reliability. Even so, the levels of reliability we observed have consequences. Recall that in terms of the agreement, single- and double-blind review were moderately correlated ($r = 0.52$), but this translated into them only agreeing on 40% of the submissions that would have been selected for a talk under either review system. The agreement within review systems was a little higher ($r = .58$ to $r = .64$). Yet, as we also showed this level of agreement also has important consequences. If we simply reran the review process with the same review system (e.g., single-blind review), between 46% to 49% of the same submissions would be selected again for presentation. We know noise impacts many aspects of human judgment (Kahneman et al., 2021). Sometimes the direct consequences of this noise are difficult to appreciate. But, in terms of merit-based evaluations we can see the consequences. Due to moderate-to-low reliability (i.e., noise) in human judgment if we switched to double-blind or even if we used the same system and just reran the review process, over half the talks would be different and likely lead to a fairly different conference program.

There was some evidence for systematic differences between single- and double-blind review. These differences came in how individual characteristics were used or associated with the reviews. These differences taken together with an understanding of the relationship of these characteristics to relevant outcomes help identify the limitations of each system and some of the causes of these limitations. In terms of single-blind review, we found that as average coauthor seniority increased so did the review rating (on average an 8% increase in the rating for each 1 rank increase in average rank). This relationship was not credibly present in double-blind review. Notably, talks with senior coauthors had lower

attendance, were not judged as better talks, and were not more likely to be published. Together these results imply that in terms author seniority, single-blind review does help perpetuate inequities. Moreover, given conference goers actually veered away from these talks it would seem that this partiality among reviewers is not necessarily preference-based, but due to some miscalibrated belief about the quality of the submission and the presence of more senior coauthors. Regardless, these results suggest that single-blind review may help advance a rich-get-richer dynamic known as a *Matthew Effect* for coauthors: submissions with more eminent scientists receive more credit relative to an unknown researcher (Merton, 1968). This favoritism towards established scholars may help contribute to demographic inertia of less diverse, more senior scholars (Hargens & Long, 2002) and impede steps to foster diversity without improving conference talk quality.

Our results also suggest the anonymity of double-blind review is not a cure-all for the potential inequities in merit-based evaluations. We found that double-blind reviews had a small tendency to give male first-authors higher ratings than females (about 16% higher). In single-blind review this tendency was smaller, with males receiving ratings that were about 9% higher than females (this result was not credibly different from 0). We did not anticipate this specific difference between single- and double-blind review and, as we established, it is a small effect. Nevertheless, it is notable that a similar pattern has been reported where women actually fair worse when employers use anonymous review of job applicants' résumés (Behaghel et al., 2015; Krause et al., 2012). This potential for male submissions to score higher in double-blind review suggests that potential gender differences, at least in the fields related to judgment and decision making, may be due to something other than belief- or preference-based discrimination. Because double-blind reviewers do not have access to author characteristics, we know that they are not using author gender as an explicit cue. Instead, they must be using a cue present in the abstract that is correlated with author's gender. Notably our analyses control for a number of factors including submission sentiment, research topic, and reviewer characteristics. Thus,

a number of potential cues and contributing factors would seem to be ruled out. Moreover, as we established submissions with male first authors were also more likely to be published, which seems consistent with review ratings. One possibility is that gender differences in personal and professional resources could lead to differences in the judged quality of the work (Ceci & Peters, 1984). For instance, there is evidence that gender asymmetries exist in institutional resources (Duch et al., 2012), time commitments and requests at work (Xie & Shauman, 2003), and personal resources as a result of family obligations (Ginther & Kahn, 2009). Another possibility may be that, although our analyses attempted to control for topic and some aspects of language, there may be different writing styles for male and female authors, with reviewers preferring the styles used by men. Regardless, these results highlight a potential limitation of double-blind review in that it could result in an inclination to dismiss a certain perspective or type of work. Such a result could be quite harmful in advancing equity. But, our results are also informative on how to design and use review systems to minimize these and other limitations, a topic we turn to next.

Evidence-based recommendations for blinding merit-based evaluations

The results from our comparison of single- and double-blind review do have implications for the design and use of peer review in merit-based evaluations. The results are probably most informative in the peer-review of scientific work, but they also likely speak to many organizational contexts that rely on merit-based evaluations including employment, consumer purchases, and legal cases (Robertson & Kesselheim, 2016). There were two sets of results that we were most surprised with. First, we did not expect single- and double-blind review to be so similar in terms of their validity and reliability. Second, we also did not anticipate that double-blind reviews would give a slight edge to male-authored submissions. These results would suggest that a call for implementing blind-review needs to be more measured. One might argue that perhaps these results are sufficient evidence to warrant the use (or continued use) of non-anonymous (single-blind)

review. Not only are single- and double-blind similar, but it seems anonymous review may impede reviewers' ability to regulate and counteract potential partiality towards submissions written by particular groups of people during merit-based evaluations, such as what appears to be a slight favoritism towards submissions written by men in our study. We are skeptical for four reasons. First, there is some evidence to suggest that the ability for reviewers to adjust for or counteract a particular partiality towards a characteristic may not occur when a particular characteristic is believed to be a valid predictor (e.g., coauthor seniority and merit), as correcting would seem counterintuitive (Rabinovitch et al., 2020). Second, even if single-blind review is used, an overwhelming majority of members of the society reported that single-blind review was unfair. We believe it is quite likely that a similar perception exists in other implementations of nonanonymous review. This perception of unfairness can have detrimental effects on organizational satisfaction, commitment, and citizenship behaviors (Konovsky, 2000). Third, and related to this concept of procedural fairness, if the justification for continuing to use single-blind review is its ability to allow reviewers to better regulate for some unwanted partiality towards particular groups, it seems there may be better methods than to allow reviewers to implement ad-hoc adjustments. For instance, a more transparent process such as invited submissions or speakers can create gender balance in a conference program. Finally, as we showed the information available during single-blind review did not show a strong consistent predictive relationship across the measured outcomes. Thus, it is not clear why it needs to be included to evaluate merit. One might even speculate that the added individuating details only create an opportunity for stereotypes or deference to eminence to enter the judgment (Biernat et al., 1991).

But, our results also do not support the unfettered use of double-blind review. The tendency for male-authored submissions to score slightly higher with anonymous review illustrates the potential that double-blind processes can leave systemic hurdles unaddressed and thus open the potential for an unnoticed inclination to dismiss a certain perspective or

type of work. This suggests that at the very least organizations that implement blind review should continue to collect and monitor demographic data and even relevant outcome data. But, our data also suggest further steps may need to be taken. For instance, one solution might be to use an “adjusted” double-blind procedure. In this scenario, merit-based evaluations are done via double-blinding. But, procedures are implemented to bump up particular individuals or groups who may be disadvantaged by more systemic factors.

A different approach to implementing double-blind would be to use it in a way that reflects the reliability of the information in the merit-based evaluation itself. If the review systems exhibited no reliability, then it would seem justified to do away with peer review entirely and simply use a lottery to select submissions for scientific conferences (Thorngate et al., 2010). However, we found low-to-moderate reliability, which translated into the ability of the ratings to predict publication three years out. Moreover, we found that there is more agreement about what constitutes a weak submission than a strong one (see also Cortes & Lawrence, 2021). This pattern of results imply that there may be a way to blend double-blind peer review with lotteries: an *informed lottery*. In this approach, double-blind review would be used to separate between meritorious and non-meritorious submissions. This would leverage double-blind reviews’ capability to distinguish the top from the bottom-half of the submissions while weeding out uninformative details like personal characteristics and credentials. Acceptances would then be randomly selected from this meritorious set (for a similar suggestion see also F. C. Fang & Casadevall, 2016). However, the selected submissions would still represent the pool from which they were drawn, allowing bias to creep in. The criterion used to split the submissions can be adjusted to address this bias-creep. In our study, for example, a median split largely minimized any advantage for male first authors. We contend that an informed lottery for scientific conferences 1) recognizes that reviews are most diagnostic for identifying weaker research, 2) creates a more equitable and fair playing field for scholars, and 3) perhaps even

fosters the evolution of science (Hull, 1988).

Conclusion

Adjusted double-blind review and informed lottery are not the best and certainly not the only selection mechanism for all uses of merit-based reviews. Other selection processes may move more to statistical models or integrate human judgment with statistical models via hybrid modeling (Dawes et al., 1989). Regardless, we believe our study illustrates the value of moving away from default selection practices. Instead, the selection and design of merit-based evaluation should be evidence-based, using a head-to-head comparison of the alternatives in the context in which they are implemented (Goswami & Urminsky, 2020), and considering the validity, reliability, and differential impact of different characteristics of the evaluation to fully remove unjustified impediments to advancing equity.

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Supplementary Material for “Blinded versus unblinded review: A field study comparing the equity and fairness of review processes”

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S1 Preregistration

The study was preregistered. It can be found at the OSF at this link: [OSF Peer Review Link](#). There are four deviations from the pre-registration. The first deviation was in the analysis of the reviewer ratings. Our plan was to use the following abstract characteristics in the analyses: disciplinary area, number of studies included, word count, and keywords. We deviated from the plan as disciplinary area was not asked and it was not feasible to classify authors ex post. The number of studies was not a useful statistic as some studies had 0 and some had many and some abstracts were not empirical studies. In terms of word count, nearly all the abstracts were 600 words. Finally, in terms of keywords, although authors were given a list of keywords, authors often chose their own unique set of keywords. Moreover, to make use of the keywords we needed a method to group and classify them. To do this, we turned to methods from Natural Language Processing and once we did this it seemed a better measure of the topics was to model the text of the long abstract directly. Thus, we used the topics model of the abstract as an indicator of key topics (Section S3). We also included a measure of the sentiment of the abstract. The results reported in the paper are unchanged with the sentiment variable excluded from the models.

The second deviation was in the measure of the talk quality. Our initial plan was to have the talks rated on importance, methodological quality, persuasiveness, originality, organization, and degree of match between short and long abstract. As we finalized the talk rating instrument we modified the dimensions to the following set of dimensions: significance, methods, results, conclusion, innovation, and uniqueness. We found these dimensions to be more straightforward and easier to rate. Moreover, in the analysis we averaged across these ratings and across all the raters to achieve a reliable measure of talk quality. By collapsing across raters we did not include rater characteristics into the ratings. But, all ratings were standardized within raters, which should help minimize differences.

A third deviation was to use Pearson correlations as a measure of reliability instead of a rank order correlation. As the ratings were standardized within each reviewer it made little difference to use a rank order correlation or the Pearson correlation. We chose the latter as it was mathematically and statistically more feasible to work with.

A fourth deviation was to use Bayesian regression models with weakly informative priors. As our primary focus was on quantifying effect sizes this Bayesian approach facilitates this better providing moderate regularization to the estimates and helping reduce errant estimates. In general, we report credible intervals around mean posterior estimates instead of maximum likelihood estimate effects with confidence intervals. Posterior distributions do not change based on the number of planned or unplanned tests. Thus, there is no correction for number of tests as the statistics and inferences from them are based on the posterior distribution Gelman et al. (2012a); Kruschke & Liddell (2018a). Another reason we adopted a Bayesian approach as it permitted a more rigorous model comparison approach based on leave-one-out cross validation (Vehtari et al., 2017). Note the posted primary regression analyses on [OSF](#) have a frequentist version of the multi-level model posted for the key analyses in terms of bias. The conclusions remain the same with conventional p-values based on our planned comparisons, but if we include corrections for multiple comparisons the interaction between gender and single or double-blind review condition as well as the interaction between senior coauthorship and review condition would not remain significant.

S2 Methods

S2.1 Conference Materials

The call for conference submission is available at this link <http://www.sjdm.org/programs/2018-cfp.html>. The program for the conference is available at this link <https://sjdm.org/programs/2018-program.pdf>.

S2.2 Submission Characteristics

A summary of the characteristics of the submitting authors is listed in Table S1.

Table S1: Characteristics of authors and reviewers.

		First Author	coauthors	Reviewers
Gender	Female	237 (45%)	355 (38%)	50 (44%)
	Male	288 (54%)	571 (61%)	63 (56%)
	Not reported	5 (1%)	13 (1%)	-
Race/Ethnicity	Arab	-	-	1 (0.9%)
	Arab, Caucasian, White or European	1 (0.1%)	-	-
	Asian	109 (20.6%)	-	12 (10.6%)
	Asian, Caucasian, White or European	3 (0.6%)	-	1 (0.9%)
	Asian, Caucasian, White or European, Other	3 (0.6%)	-	-
	Asian, Other	1 (0.2%)	-	-
	Black, African, or African American	4 (0.8%)	-	-
	Caucasian, White or European	325 (61.3%)	-	57 (50.4%)
	Caucasian, White or European, Other	1 (0.2%)	-	-
	Hispanic or Latino origin	6 (1.1%)	-	-
	Hispanic or Latino origin, Caucasian, White or European	7 (1.3%)	-	3 (2.7%)
	Native American or Alaska Native, Caucasian, White or European	1 (0.2%)	-	-
	Other	12 (2.3%)	-	1 (0.9%)
	Not reported	57 (11%)	-	38 (45.5%)
Citizenship	U.S.	241 (45%)	-	56 (50.0%)
	Non-U.S.	289 (55%)	-	27 (23.9%)
	Not reported	-	-	30 (26.5%)
Ave. Year of Ph.D. (SD)		2013 (8)	-	2008 (7)
Area of Ph.D.	Economics	39 (7.4%)	-	14 (12.4%)
	Management	57 (10.8%)	-	13 (11.5%)
	Marketing	121 (22.8%)	-	25 (22.1%)
	Psychology	253 (47.7%)	-	52 (46.0%)
	Other	60 (11.3%)	-	8 (7.1%)
	Not reported	-	-	1 (0.9%)
Position	Student	0	2 (0.2%)	-
	Undergraduate	1 (0.2%)	17 (1.8%)	-
	Masters Student	8 (1.5%)	20 (2.2%)	-
	Doctoral Student	196 (37.0%)	96 (10.3%)	-
	Postdoctoral Researcher	70 (13.2%)	36 (3.9%)	-
	Research Scientist	17 (3.2%)	48 (5.2%)	5 (4.4%)
	Practitioner	12 (2.3%)	27 (2.9%)	2 (1.8%)
	Assistant Professor	133 (25.1%)	217 (23.4%)	48 (42.4%)
	Associate Professor	48 (9.1%)	144 (15.5%)	31 (27.4%)
	Full Professor	41 (7.7%)	321 (34.6%)	27 (23.9%)
	Not reported	4 (0.8%)	-	-

Many people selected multiple race and ethnicity categories and instead of marginalizing across categories we report the joint selections. Except for gender and position, the characteristics of the first author are based on the subset of submissions when the corresponding author was the first author.

S2.3 Materials

S2.3.1 Information collected at submission

The call for submissions for the 2018 Annual Meeting for the Society for Judgment and Decision Making invited members and non-members to submit a 600-word long-abstract to be considered for a spoken presentation. Submissions also included a title, a 100-word short abstract (to be used in the conference program), a listing of the authors, up to 3 keywords, and an indication as to whether the submission should be considered for a poster if it was not selected for a talk. Authors could also request to present a poster in which case they were only asked to submit a title, 100 word abstract for the program, and a list of authors. Here we focus only on the submissions for a spoken presentation.

At the time of submission, we also collected the following information from all authors:

Position Undergraduate student; Masters student; PhD student; Post doctoral researcher; Research scientist; Lecturer; Assistant Professor; Associate Professor; Full Professor; Practitioner; Other; Prefer not to answer

Department Text answer

Institution Text Answer

Gender Female; Male; Other (please specify); Prefer not to answer

The submitting or corresponding author was also asked to report the following information

Highest degree obtained or in progress Bachelors; Masters; Ph.D.; MD; MPH; Other; Prefer not to answer

Primary area of study for highest degree completed or in progress Economics; Marketing; Management; Psychology (Cognitive); Psychology (Social); Psychology (Other); Statistics; Other (Please specify); Prefer not to answer

Department and institution where the degree was obtained Text Answer

Graduation year for this degree Four digit year

Race/ethnic group Arab; Asian; Black, African, or African American; Hispanic or Latino origin; Native American or Alaska Native; Native Hawaiian or Other Pacific Islander; Caucasian, White, or European; Other (please specify); Prefer not to answer

Nationality List of countries

Table S2: Distribution of the number of authors.

Number of Authors	Frequency
1	26
2	218
3	176
4	78
5	26
6	6

S2.3.2 Conflicts of interest and selection process

Across all assignments, we worked to minimize conflicts of interest by ensuring no submission was assigned to a reviewer who shared a common institution with one of the institutions of the submitting authors. In addition, upon sending reviewers their assigned submissions, they were asked to inspect the submissions and identify any conflict so that it could be reassigned. If a conflict became apparent during the review, then reviewers were instructed to leave the abstract unrated if a conflict became apparent during the review. However, no submission was left unrated. The ratings were then standardized within each reviewer and aggregated across all six ratings forming an average reviewer rating for each submission. The Conference Chair (Urminsky) used the average ratings to decide on accepting a submission for presentation. In the case of the 53 submissions that had two sets of reviews from each process, for the purpose of making a decision one set of three double-blind and one set of three single-blind reviews were randomly selected to aggregate across.

S2.3.3 Collected variables on reviewers at agreement

Besides rating each of their assigned submissions on a 1 *poor* to 9 *excellent* point scale and entering any comments they might have, reviewers were also asked a series of questions. At agreeing to review they were asked

Institution Current academic institution

Department Current academic department

Position Current position

Area of study of highest degree Primary area of study for highest degree completed or in progress: (If you have more than one PhD in a JDM-related field, select the area for your first PhD)

Year of highest degree Graduation year for this degree (enter all 4 digits, i.e., 2008)

Department and school where they obtained their highest degree

Reviewing experience How many times they had reviewed for the annual meeting in the past

Gender Female; Male; Other (please specify); Prefer not to answer

Nationality Dropdown list of countries

Race Arab; Asian; Black, African, or African American; Hispanic or Latino origin; Native American or Alaska Native; Native Hawaiian or Other Pacific Islander; Caucasian, White or European; Other (please specify); Prefer not to answer

S2.3.4 Collected variables from reviewers during and after completing reviews

During review, reviewers were asked to rate each abstract on a nine-point scale ranging from 1 (Poor) to 9 (Excellent). There was also a field to enter any submission comments.

After their reviews, these questions asked them the following items.

Overall confidence How confident are you that your evaluations of the abstracts are an accurate rating of their actual quality? 0 = 0% confident; 10 = 100% confident

How did you complete the reviews? To what extent did you evaluate the abstracts? 1 = Fully on paper; 6 = Fully on screen

When did they complete the reviews? To what extent did you evaluate the abstracts: 1 = Within 1-2 days; 6 = Over several weeks

Did you revise while you reviewed? To what extent did you evaluate the abstracts: 1 = Without any revisions to ratings; 6 = With significant revisions to ratings

Did you consult with colleagues? Did you consult with any colleagues while you were reviewing because you had questions about the process? Yes; No

Comments Text

S2.3.5 Intercorrelations between reviewer characteristics

Figure S1: Intercorrelations between reviewer characteristics. Values in the center of each cell are posterior estimates of the Pearson correlations and values in the upper and lower right-hand corner are the corresponding credible intervals. Starred values indicate credible interval excludes 0.

S2.4 Talk evaluation and statistics

Each faculty member and graduate student rated the talks along the following dimensions:

S2.4.1 Characteristics of raters

Table S3: Distribution of rater characteristics.

		Pre- and Post- doctoral Students	Faculty	Total
Gender	Female	7	7	14
	Male	5	11	12
Ethnicity	White	9	15	24
	Not White	2	2	4
	No Response	1	1	2
Country of Home Institution (Nationality)				
	US	7	14	21
	International	4	3	7
	No Response	1	1	2
Area of Specialty	Psychology	2	12	14
	Marketing	5	1	6
	Economics	1	1	2
	Other	4	4	8

S2.4.2 Rated dimensions

Each faculty member and graduate student rated the talks along the following dimensions:

Significance Is the topic of the talk significant? Does it concern a scientifically important subject or is it relevant for policy or other applications?

Methods Are the methods scientifically sound?

Results Are results presented in enough detail and in an understandable way?

Conclusion Do the conclusions follow from the results? Are they justified? Are the results generalizable?

Innovation Is there something innovative about the presented material?

Uniqueness Is this talk different from other talks typically at SJDM?

S2.4.3 Overall rating

For each rater, we standardized the ratings across all dimensions and all talks they rated. Then for each rater, and each talk we averaged across the ratings to form an overall rating. Then for each talk we averaged across the student faculty ratings giving them equal weight.

S2.4.4 Collected talk statistics

Each research assistant tracked the following statistics:

Attendance Estimated the attendance at the talk 5 minutes into the talk.

Potential questions Estimated the number of potential questions for each talk, where potential questions were indicated by a count of raised hands throughout the talk.

Number of questions answered The number of questions answered for each talk.

Duration of talk The length of the talk.

Duration of Q & A The length of the question and answer period.

S2.5 Poster ratings

There were a total of $N = 96$ posters that were submitted for the student-poster competition during the conference and judged on a similar set of dimensions as those used to judge the quality of the talks. A subset of these posters ($N = 57$) had been originally submitted for talks to the conference had single- and double-blind abstract evaluation scores. Thus, we took the poster ratings, standardized them across each judge, averaged them across the dimensions to arrive at an overall rating for each poster, and integrated these ratings with the ratings for the submissions given as a talk, creating a new talk/poster rating.

S2.6 Preference for review process survey items

Shortly before the conference, we surveyed members of the Society for Judgment and Decision Making listserv, asking them to report their preference between single- vs. double-blind review processes and their judged fairness of each review process. We sent the request for participation out on October 25, 2019. We sent a reminder on November 1, 2019, and we stopped data collection on November 7, 2019. There were $N = 173$ responses to the survey.

The survey asked the following questions.

Author characteristics predictions Indicate the extent to which they believed that specific author characteristics (e.g. gender, proportion of male co-authors, institution, etc.) would increase versus decrease the chances a talk would be accepted as a talk at the conference if using single- vs. double-blind review on a 7-point scale ranging from significantly decreases to significant increases.

Unfair vs. fair to use author characteristics Rate [7-point scale] the extent to which they believed it was very unfair to very fair for reviewers to take into account each of the above author characteristics when judging abstracts.

Preference for review process Rate preferences for single- versus double-blind review as an author v. author v. conference attendee v. overall (1 = definitely prefer single-blind, 7 = definitely prefer double-blind).

Fairness of review process Rate each review process according to its fairness (1 = very unfair, 7 = very fair).

Agreement Rate the degree of agreement between the two review processes.

Validity Rate which review process would better predict the aspects of talk quality (1 = much better predicted by single-blind review, 7 = much better predicted by double-blind review).

Demographics Demographics were collected.

Knowledge of study Yes/No you had heard about the current blind-review study being conducted within the society.

S2.7 Journal publications

Two years after the conference, we sought to identify submissions that were published. To do so, we searched Google Scholar using as a search term the first author's last name and the title of the submission. In total, $N = 130$ submissions were identified as published in a peer-reviewed journal. Then we contacted via email all of the corresponding authors of the remaining submissions and asked if their submission had been published in a peer-reviewed journal and what the journal was. The initial email was sent in October 2020 and we collected emails up until December 18, 2020. We also separately identified the impact factor of the journal via Web of Science and Google Scholar. Responses to the email identified an additional $N = 54$ submissions that had been published. We used the (logged) impact factor from Web of Science as a metric of impact.

S2.8 Analyses

We used Bayesian estimation methods for data analysis. Statistics were conducted using R 3.6.2 (R Core Team, 2019), the `rstanarm` package (v2.19.3; Goodrich et al., 2020), and the `BayesFactor` package (0.9.12-4.2; Morey & Rouder, 2018). We report the posterior predicted mean of the parameter of interest and in brackets its 95% Credible Interval (CI). The CI summarizes the posterior distribution excluding the 2.5% of the distribution at each tail. We use the term *credible* when the 95% CI excludes 0. For model comparisons, we used leave-one-out cross validation (LOO) to compare models based on the expected log pointwise predictive density for a new dataset (elpd_{loo}). The difference between models on elpd_{loo} quantifies the difference in predictive accuracy between them. The standard error (SE) captures the uncertainty around each elpd_{loo} . In general, we consider $|\Delta \text{elpd}_{\text{loo}}| < 1 \text{ SE}$ to be weak evidence for a particular model. In all cases, we used the default priors, which were set to be weakly informative providing moderate regularization to the estimates (i.e., priors that are skeptical of extreme parameter values). We inspected MCMC chains for representation and accuracy, and we sought to have all reported parameters based on an effective sample size of 10,000. Posterior distributions do not change based on the number of planned or unplanned tests. Thus, there is no correction for the number of tests as statistics and inferences from them are based on the posterior distribution (Gelman et al., 2012b; Kruschke & Liddell, 2018b).

S3 Modeling the text of the long abstracts

S3.1 Text Corpus

The text corpus was the *Wiley Blackwell Handbook of Judgment and Decision Making* edited by Keren and Wu published in 2015. This two volume handbook has 35 chapters that provides a comprehensive, examination of the field of judgment and decision making. The handbook has authors from across the discipline including psychology, economics, marketing, finance, public policy, sociology, and philosophy. The review covered traditional topics, controversies, new topics, as well as applications. Therefore, the text provides a good representation of the field. We obtained the text from all 35 chapters and prepared it to model by removing

- Front and back matter
- Titles
- Author names, and cited authors
- Page numbers
- Equations, numbers, and mathematical notation
- Figure and figure caption
- Table and table captions

In the end, we created a .txt file where each line was a chapter. Then we applied the following pre-processing steps in Matlab. See [OSF](#)

- Converted all the text to lower-case.
- Removed hyphens
- Removed numbers
- Made a second pass to remove authors using the author index as a reference.
- Removed punctuation
- Removed stop words like "a", "and", "to", and "the".
- Removed words 2 letters or shorter.

Figure S3: Topic distribution across the 530 long abstracts. The topic model came from the best fitting LDA topic model of the 2015 *Wiley Blackwell Handbook of Judgment and Decision Making* (see Figure S2).

These labels correspond well to the chapters. For instance, for Chapter 2 Topic 1 had the greatest probability. It focused on the theory of how people make decisions under risk, a core topic of judgment and decision making. For Chapter 6 Topic 2 had the greatest probability and it focused on the empirical phenomena of overconfidence in judgment. And for Chapter 22 Topic 3 had the greatest probability and it focused on learning processes during decision making.

We then used the model to calculate the posterior probability that each long abstract belonged to each of these three topics and assigned each submission the topic with the greatest posterior probability. Figure S3 shows the distribution of topics across the 530 long abstracts. The code and output for the topic modeling is available on [OSF](#).

S3.3 Sentiment Analysis

The sentiment analysis assigned a score to each long abstract according to whether it had on average a positive or negative sentiment. The score was based on a sentiment analysis conducted by training a support vector machine classifier on a subset of 6,800 positive and negative words from Hu & Liu (2004). Then after validating the classifier on the hold-out set, we predicted the sentiment of the words in the long abstract with the classifier. Note both the positive and negative words and the abstract words were represented by 300 dimensional numerical vectors via a pre-trained word embedding of 1 million English words available in Matlab. Figure S4 shows the word clouds of the words with the strongest negative and positive sentiment in the abstracts. The sentiment of the abstract was determined by averaging across the sentiment scores of each word in the abstract. The average sentiment is shown in the bottom panel of Figure S4. The code and output for the sentiment analysis is available on [OSF](#).

Figure S4: Sentiment analysis of the long abstracts. The word clouds show the words with the strongest negative and positive sentiments in the abstracts. The bottom plot is the average sentiment of each of the 530 abstracts.

S4 Analyses of survey data

S4.1 Preference Ratings

S4.1.1 Regressing perspective and reviewing experience on double-blind vs. single-blind preference

Table S4: Coefficients from regressing perspective, reviewing experience, and fairness on double-blind vs. single-blind preference.

	w/o Fairness		w Fairness	
	M	95% CI	M	95% CI
Intercept	0.139	[-0.025, 0.298]	0.125	[-0.011, 0.261]
Reviewer vs. Author	-0.112	[-0.24, 0.012]	-0.113	[-0.242, 0.017]
Attendee vs Author	-0.225	[-0.353, -0.1]	-0.229	[-0.36, -0.098]
Reviewing Experience (z)	-0.206	[-0.364, -0.049]	-0.091	[-0.231, 0.047]
Reviewer vs. Author x Reviewing Experience	-0.042	[-0.17, 0.082]	-0.043	[-0.165, 0.084]
Attendee vs. Author x Reviewing Experience	-0.008	[-0.135, 0.119]	-0.008	[-0.135, 0.117]
Fairness of Double- vs. Single-Blind (z)	-	-	0.538	[0.422, 0.652]

Bolded values indicated credible interval excludes 0. Preference and reviewing experience were standardized in the model. Respondent id was a random intercept in the regression model.

S4.2 Fairness perceptions

S4.2.1 Regressing reviewing type and reviewing experience on fairness

Table S5: Coefficients from regressing perspective, reviewing experience, and fairness.

	M	95% CI
Double (1) or Single (0)	1.31	[1.14 , 1.48]
Reviewing Experience (z)	0.20	[0.08 , 0.32]
Double or Single x Reviewer Experience (z)	-0.24	[-0.41 , -0.07]

Bolded values indicated credible interval excludes 0. Fairness ratings and reviewing experience were standardized in the model. Respondent id was a random intercept in the regression model.

S5 Reliability of review systems

S5.1 Bottom vs. top half

As reported in the main paper, median split by the single-blind rating reveals more agreement between single- and double blind review for the bottom half of the submissions ($r = 0.45$, $[0.35, 0.54]$) compared to the top half ($r = 0.19$, $[0.07, 0.29]$). To establish if this degree of agreement was different between the bottom vs. top half, we regressed the double-blind rating onto the single-blind rating, a dummy variable for bottom-vs. top-half, and the interaction. The interaction was credible (Table S6) indicating a credible difference between bottom and top-half in terms of agreement.

Table S6: Regressing double-blind review rating onto single-blind review rating, whether the submission was in the bottom vs. top half of the median split, and the interaction.

	M	95% CI
Intercept	0.098	[-0.013, 0.209]
Single-blind Review	0.686	[0.534 , 0.84]
Bottom (0) vs. Top (1) Half	0.035	[-0.136, 0.206]
Single-blind x Bottom vs. Top	-0.400	[-0.645 , -0.162]
sigma	0.578	[0.545, 0.614]

Bolded values indicated credible intervals exclude 0.

S6 Analyses examining differential use between single and double-blind review

S6.1 Model comparison

S6.1.1 Evidence for differential effect of submission characteristics

Our first step was to assess the overall evidence for submission characteristics like the author’s identity being used differently between single- and double-blind using a model comparison. We compared a model that had an interaction terms between each of the eleven characteristics and the condition (*Differential Use (DU) Model*) to a model that did not have these interaction terms (*No Differential Use (NoDU) Model*) using leave-one-out cross validation. The difference between the two models in terms of the expected log-pointwise predictive density was $\Delta elpd_{loo} = 3.4$ favoring the simpler NoDU model without the interaction terms, but

this difference was well within the margin of error of $SE = 6.2$ indicating very weak evidence against an omnibus differential use of submission characteristics during single-blind review.

S6.1.2 Evidence for differential effect of reviewer characteristics

Our main analysis entered all eleven characteristics (Table 1) simultaneously in a multilevel regression model with the ratings for the single- and double-blind conditions as the outcome variables. Though reviewers were randomly assigned to conditions and submission, we also included the six reviewer characteristics listed in Table 1 as predictors. In the analyses reported in the manuscript the reviewer characteristics were entered alone. We also explored whether there were potential interactions between the review condition and reviewer characteristics. None of the reviewer characteristics showed credible interactions with the review condition (Table S10). Moreover, in a model comparison between the Differential Use Model (DUM) and the model including an interaction between reviewer characteristics and condition as well as potential three-way interactions with author specific author characteristics led to a substantially worse fit of the regression model (Table S7).

Table S7: Model comparison between models with interactions between reviewer characteristics and review condition.

	Δelpd	$\text{se}(\Delta\text{elpd})$	$\text{elpd}_{\text{l}_{\text{oo}}}$	$\text{se}(\text{elpd}_{\text{l}_{\text{oo}}})$
Differential Use Model	0	0	-3320.181	32.782
Differential Use Model + Reviewer x Condition	-7.742	2.321	-3327.923	32.831
Differential Use Model + Reviewer x Condition + Reviewer x Submission x Condition	-31.942	10.558	-3352.122	33.203

The comparisons were made with the expected log pointwise predictive density for a new dataset estimated from the leave-one-out cross validation ($\text{elpd}_{\text{l}_{\text{oo}}}$) for each model. The difference between two models with this statistic ($\Delta \text{elpd}_{\text{l}_{\text{oo}}}$) quantifies the difference in predictive accuracy between the two and offers a measure of the relative support for either model. There is uncertainty around each $\text{elpd}_{\text{l}_{\text{oo}}}$ and this is captured by the standard error (SE) around each estimate.

S6.2 Coefficients from regression with all characteristics entered simultaneously.

Table S8: Coefficients from regressing single- and double-blind ratings onto submission characteristics.

		M [95% CI]		Δ ELPD _{loo} (SE)
Characteristic		Predictor	Predictor x Condition	Interaction - No DUM
Intercept Condition; Single (0) or Double (1)		-0.017 [-0.483, 0.443] 0.235 [-0.215, 0.69]		
First Author Characteristic	Female (0) or Male (1)	0.14 [-0.041, 0.322]	0.211 [0.025, 0.396]	0.085 (1.711)
	Years Since Ph.D.	-0.131 [-0.263, 0.001]	-0.016 [-0.148, 0.115]	3.122 (2.944)
	Domestic (0) or International (1)	0.033 [-0.11, 0.175]	-0.074 [-0.221, 0.071]	-0.478 (1.157)
	Ave. Citations of 1st Author's Institute	0.025 [-0.124, 0.174]	0.004 [-0.146, 0.154]	1.398 (2.235)
	Economics Ph.D. vs. Psychology	0.084 [-0.209, 0.375]	0.042 [-0.253, 0.336]	-2.124 (2.185)
	Management Ph.D. vs. Psychology	0.104 [-0.131, 0.344]	0.095 [-0.15, 0.339]	"
	Marketing Ph.D. vs. Psychology	0.027 [-0.157, 0.213]	-0.012 [-0.199, 0.178]	"
	Other Ph.D. vs. Psychology	0.103 [-0.117, 0.325]	-0.089 [-0.314, 0.136]	"
	Undergraduate vs. Full	-0.026 [-1.367, 1.308]	-0.951 [-2.339, 0.449]	1.447 (3.997)
	Masters vs. Full	-0.182 [-0.861, 0.501]	-0.153 [-0.849, 0.547]	"
	Ph.D. vs. Full	-0.03 [-0.523, 0.467]	-0.496 [-1.004, 0.006]	"
	Post Doc vs. Full	-0.094 [-0.568, 0.38]	-0.352 [-0.834, 0.128]	"
	Research Scientist vs. Full	0.082 [-0.525, 0.688]	-0.577 [-1.202, 0.05]	"
	Practitioner vs. Full	-0.474 [-1.216, 0.261]	-0.217 [-0.939, 0.501]	"
	Assistant vs. Full	0.052 [-0.373, 0.481]	-0.299 [-0.738, 0.136]	"
	Associate vs. Full	-0.114 [-0.512, 0.29]	-0.167 [-0.579, 0.24]	"
All Authors	Proportion Male Authors	0.016 [-0.078, 0.11]	-0.095 [-0.19, 0.002]	-0.332 (0.979)
	Ave. Citations of Authors' Institutes	0.127 [-0.022, 0.277]	-0.045 [-0.196, 0.106]	2.610 (2.665)
	Ave. Seniority of Authors	0.128 [0.049, 0.208]	-0.071 [-0.151, 0.008]	-0.606 (0.935)
Text	Empirical Studies vs. Traditional Topic	-0.002 [-0.16, 0.158]	0.065 [-0.094, 0.224]	-1.642 (1.339)
	Psychology of JDM vs. Traditional Topic	-0.033 [-0.245, 0.176]	0.067 [-0.144, 0.279]	"
	Sentiment	-0.064 [-0.133, 0.005]	0.048 [-0.022, 0.118]	-0.730 (0.991)
Reviewer	Reviewer Female (0) or Male (1)	-0.026 [-0.105, 0.053]		
	Reviewer Years Since Ph.D.	-0.021 [-0.081, 0.039]		
	Reviewer Ave. Citations of 1st Author's Institute	0.026 [-0.012, 0.063]		
	Economics Ph.D. vs. Psychology	0.026 [-0.099, 0.151]		
	Management Ph.D. vs. Psychology	-0.004 [-0.123, 0.113]		
	Marketing Ph.D. vs. Psychology	-0.031 [-0.131, 0.069]		
	Other Ph.D. vs. Psychology	0.021 [-0.135, 0.178]		
	Research Scientist vs. Full	-0.143 [-0.336, 0.051]		
	Practitioner vs. Full	-0.173 [-0.585, 0.236]		
	Assistant vs. Full	-0.038 [-0.182, 0.105]		
	Associate vs. Full	-0.017 [-0.135, 0.102]		
	Reviewer # Times Review Past 7 Years	-0.012 [-0.053, 0.028]		

Bolded values indicate credible intervals exclude 0. All coauthor characteristic characteristics were represented by the statistics based on all the authors (e.g., proportion of male authors instead of male coauthors) so that single-author submissions were included in the analysis. Thus, the regression coefficients for the first author variables represent incremental change for the variables in which there are corresponding coauthor characteristics. Review ratings and numerical predictors were standardized as indicated by the z. The values in the column under Δ ELPD_{loo} are the differences in the expected log pointwise predictive density for a new dataset between the NoDU model including the interaction between the predictor and condition and the NoDU model.

S6.3 Coefficients from regression with all characteristics entered simultaneously for multiauthor submissions.

Table S9: Coefficients from regressing single- and double-blind ratings onto submission characteristics for multi-authored submissions.

		M [95% CI]		Δ ELPD _{loo} (SE)
Characteristic		Predictor	Predictor x Condition	Interaction - No DUM
	Intercept	0.077 [-0.377, 0.525]		
	Condition; Single (0) or Double (1)	0.172 [-0.271, 0.62]		
First Author Characteristic	Female (0) or Male (1)	0.182 [0.044, 0.32]	0.101 [-0.041, 0.243]	0.548 (1.725)
	Years Since Ph.D.	-0.126 [-0.269, 0.018]	-0.026 [-0.167, 0.114]	2.659 (2.732)
	Domestic (0) or International (1)	0.067 [-0.078, 0.211]	-0.088 [-0.238, 0.061]	0.011 (1.400)
	Ave. Citations of 1st Author's Institute	0.06 [-0.037, 0.156]	-0.011 [-0.112, 0.09]	2.020 (2.391)
	Economics Ph.D. vs. Psychology	0.172 [-0.125, 0.467]	0.022 [-0.285, 0.33]	-1.285 (2.353)
	Management Ph.D. vs. Psychology	0.172 [-0.075, 0.417]	0.071 [-0.187, 0.327]	"
	Marketing Ph.D. vs. Psychology	0.042 [-0.148, 0.23]	0.013 [-0.184, 0.21]	"
	Other Ph.D. vs. Psychology	0.162 [-0.063, 0.388]	-0.122 [-0.358, 0.112]	"
	Undergraduate vs. Full	-0.43 [-1.743, 0.883]	-0.751 [-2.138, 0.626]	0.178 (3.790)
	Masters vs. Full	-0.436 [-1.101, 0.229]	-0.016 [-0.706, 0.677]	"
	Ph.D. vs. Full	-0.255 [-0.737, 0.233]	-0.342 [-0.841, 0.149]	"
	Post Doc vs. Full	-0.305 [-0.764, 0.161]	-0.225 [-0.7, 0.248]	"
	Research Scientist vs. Full	-0.108 [-0.71, 0.499]	-0.453 [-1.083, 0.171]	"
	Practitioner vs. Full	-0.63 [-1.359, 0.097]	-0.14 [-0.859, 0.578]	"
	Assistant vs. Full	-0.057 [-0.487, 0.379]	-0.243 [-0.695, 0.201]	"
	Associate vs. Full	-0.139 [-0.547, 0.269]	-0.185 [-0.608, 0.239]	"
Coauthors	Proportion Male Coauthors	0.033 [-0.038, 0.102]	-0.065 [-0.137, 0.007]	2.735 (2.605)
	Ave. Citations of Coauthors' Institutes	0.092 [-0.003, 0.188]	-0.035 [-0.133, 0.064]	3.101 (2.956)
	Ave. Seniority of Coauthors	0.101 [0.024, 0.178]	-0.093 [-0.17, -0.016]	6.930 (4.052)
Text	Empirical Studies vs. Traditional Topic	-0.005 [-0.166, 0.153]	0.103 [-0.061, 0.268]	-0.372 (1.751)
	Psychology of JDM vs. Traditional Topic	-0.033 [-0.245, 0.178]	0.123 [-0.096, 0.344]	"
	Sentiment	-0.065 [-0.135, 0.006]	0.038 [-0.035, 0.109]	-0.869 (0.630)
Reviewer	Reviewer Female (0) or Male (1)	-0.03 [-0.112, 0.051]		
	Reviewer Years Since Ph.D.	-0.019 [-0.081, 0.042]		
	Reviewer Ave. Citations of 1st Author's Institute	0.032 [-0.007, 0.071]		
	Economics Ph.D. vs. Psychology	0.028 [-0.102, 0.157]		
	Management Ph.D. vs. Psychology	-0.021 [-0.142, 0.099]		
	Marketing Ph.D. vs. Psychology	-0.028 [-0.133, 0.076]		
	Other Ph.D. vs. Psychology	0.045 [-0.116, 0.207]		
	Research Scientist vs. Full	-0.116 [-0.319, 0.086]		
	Practitioner vs. Full	-0.162 [-0.584, 0.261]		
	Assistant vs. Full	-0.007 [-0.156, 0.14]		
	Associate vs. Full	-0.002 [-0.124, 0.12]		
	Reviewer # Times Review Past 7 Years	-0.009 [-0.051, 0.031]		

Bolded values indicated credible intervals exclude 0. Review ratings and numerical predictors were standardized. The data were subsetted to only include multi-author submissions. ELPD stands for the expected log pointwise predictive density for a new dataset calculated with leave one out cross validation (loo) indicating the predictive accuracy of the respective model. The values in the column under Δ ELPD_{loo} indicate the difference between the NoDU model for multiauthor submissions including the interaction between the predictor and condition and the NoDU model for multiauthor submissions.

S6.4 Coefficients from regression with each variable entered alone.

Table S10: Coefficients from regression with each variable entered alone.

Category	Variable	Single Blind Coef (Alone)		Double Blind Coef (Alone)	
		M	95% CI	M	95% CI
First Author	Female (0) or Male (1)	0.094	[-0.046, 0.230]	0.163	[0.035, 0.286]
	Years Since Ph.D.*	-0.102	[-0.172, -0.032]	-0.03	[-0.099, 0.037]
	International (0) or Domestic (1)	0.172	[0.034, 0.307]	0.151	[0.023, 0.276]
	Ave. Citations of 1st Author's Institute	0.156	[0.090, 0.224]	0.095	[0.032, 0.160]
	Economics Ph.D. vs. Psychology	0.092	[-0.174, 0.363]	0.157	[-0.113, 0.416]
	Management Ph.D. vs. Psychology	0.245	[0.022, 0.474]	0.300	[0.083, 0.513]
	Marketing Ph.D. vs. Psychology	0.222	[0.050, 0.389]	0.191	[0.031, 0.353]
	Other Ph.D. vs. Psychology	0.360	[0.137, 0.580]	0.220	[0.015, 0.429]
	Undergraduate vs. Full	0.232	[-1.056, 1.543]	-0.401	[-1.606, 0.904]
	Masters vs. Full*	-0.206	[-0.722, 0.370]	-0.196	[-0.694, 0.378]
	Ph.D. vs. Full*	0.342	[0.072, 0.592]	-0.007	[-0.264, 0.254]
	Post Doc vs. Full	0.267	[-0.046, 0.552]	0.073	[-0.221, 0.375]
	Research Scientist vs. Full	0.340	[-0.085, 0.757]	-0.089	[-0.509, 0.321]
	Practitioner vs. Full	-0.031	[-0.683, 0.520]	-0.172	[-0.788, 0.404]
	Assistant vs. Full	0.372	[0.131, 0.645]	0.168	[-0.097, 0.426]
	Associate vs. Full	0.053	[-0.274, 0.382]	-0.038	[-0.356, 0.280]
Authors & Co-Authors	Proportion Male Coauthors*	0.041	[-0.027, 0.110]	-0.034	[-0.100, 0.031]
	Proportion Male Authors	0.051	[-0.018, 0.118]	0.018	[-0.047, 0.84]
	Ave. Citations of Co-Authors' Institutes*	0.196	[0.129, 0.262]	0.118	[0.053, 0.183]
	Ave. Citations of Authors' Institutes*	0.192	[0.128, 0.254]	0.125	[0.060, 0.188]
	Ave. Seniority of Coauthors*	0.157	[0.087, 0.227]	0.005	[-0.061, 0.077]
	Ave. Seniority of Authors	0.112	[0.047, 0.179]	0.063	[0.001, 0.126]
Text	Empirical Studies vs. Traditional Topic	0.013	[-0.146, 0.168]	0.045	[-0.105, 0.199]
	Psychology of JDM vs. Traditional Topic	-0.123	[-0.322, 0.079]	-0.092	[-0.286, 0.108]
	Sentiment	-0.012	[-0.079, 0.055]	0.017	[-0.044, 0.081]
Reviewer	Female (0) or Male (1)	-0.009	[-0.105, 0.086]	-0.010	[-0.109, 0.091]
	Years Since Ph.D.	-0.001	[-0.008, 0.006]	-0.003	[-0.011, 0.004]
	Ave. Citatiton of Institution	0.007	[-0.036, 0.051]	0.017	[-0.036, 0.069]
	Economics Ph.D. vs. Psychology	0.041	[-0.113, 0.201]	0.028	[-0.131, 0.183]
	Management Ph.D. vs. Psychology	-0.022	[-0.187, 0.135]	0.040	[-0.117, 0.197]
	Marketing Ph.D. vs. Psychology	0.002	[-0.125, 0.130]	-0.008	[-0.134, 0.119]
	Other Ph.D. vs. Psychology	-	-	0.022	[-0.133, 0.172]
	Research Scientist vs. Full	-0.077	[-0.302, 0.146]	-0.078	[-0.337, 0.176]
	Practitioner vs. Full	-	-	-0.037	[-0.3000, 0.221]
	Assistant vs. Full	0.051	[-0.078, 0.179]	-0.031	[-0.146, 0.089]
	Associate vs. Full	0.028	[-0.097, 0.160]	-0.042	[-0.188, 0.099]
	Experience reviewing past 7 years	-0.012	[-0.044, 0.018]	0.003	[-0.024, 0.030]

Bolded values indicated credible interval excludes 0. Starred variables (*) indicate a credible interaction between the variable and the condition in Table S12. Review ratings and numerical predictors were standardized. The coefficients in the single- and double-blind were entered alone.

Table S11: Coefficients from regression with each variable entered alone along with the review condition.

Category	Variable	M [95% CI]				Δ ELPD _{loo} (SE)	
		Intercept	Condition (Coef)	Predictor Coef	Single x Double Coef		
First Author	Female (0) or Male (1)	-0.065 [-0.160, 0.031]	-0.036 [-0.128, 0.053]	0.092 [-0.039, 0.223]	0.081 [-0.041, 0.204]	0.208 (1.395)	
	Years Since Ph.D.	-0.029 [-0.097, 0.038]	0.009 [-0.052, 0.071]	-0.103 [-0.172, -0.035]	0.073 [0.012, 0.134]	2.014 (2.498)	
	International (0) or Domestic (1)	-0.097 [-0.185, -0.009]	0.016 [-0.067, 0.099]	0.173 [0.043, 0.303]	-0.023 [-0.146, 0.101]	-1.240 (0.489)	
	Ave. Citations of 1st Author's Institute	0.044 [-0.021, 0.109]	-0.003 [-0.067, 0.060]	0.154 [0.090, 0.220]	-0.059 [-0.124, 0.007]	0.553 (1.935)	
	Economics Ph.D. vs. Psychology	-0.14 [-0.266, -0.051]	0.020 [-0.065, 0.106]	0.108 [-0.155, 0.370]	0.034 [-0.208, 0.276]	-2.186 (1.770)	
	Management Ph.D. vs. Psychology	"	"	0.243 [0.023, 0.464]	0.06 [-0.150, 0.268]	"	
	Marketing Ph.D. vs. Psychology	"	"	0.219 [0.055, 0.385]	-0.033 [-0.187, 0.122]	"	
	Other Ph.D. vs. Psychology	"	"	0.352 [0.141, 0.561]	-0.138 [-0.336, 0.064]	"	
	Undergraduate vs. Full	-0.287 [-0.523, -0.052]	0.238 [0.029, 0.449]	0.19 [-1.159, 1.569]	-0.628 [-1.953, 0.689]	0.628 (3.723)	
	Masters vs. Full	"	"	-0.177 [-0.714, 0.359]	-0.017 [-0.508, -0.472]	"	
	Ph.D. vs. Full*	"	"	0.332 [0.078, 0.585]	-0.333 [-0.566, -0.104]	"	
	Post Doc vs. Full	"	"	0.267 [-0.033, 0.565]	-0.205 [-0.479, 0.062]	"	
	Research Scientist vs. Full	"	"	0.346 [-0.073, 0.754]	-0.442 [-0.820, 0.063]	"	
	Practitioner vs. Full	"	"	-0.032 [-0.631, 0.555]	-0.148 [-0.669, 0.374]	"	
	Assistant vs. Full	"	"	0.369 [0.100, 0.642]	-0.205 [-0.449, 0.033]	"	
	Associate vs. Full	"	"	0.057 [-0.266, 0.388]	-0.097 [-0.390, 0.193]	"	
Authors & Co-Authors	Proportion Male Coauthors	0.005 [-0.061, 0.072]	0.002 [-0.061, 0.063]	0.042 [-0.026, 0.109]	-0.075 [-0.139, -0.012]	1.809 (2.458)	
	Proportion Male Authors	-0.021 [-0.054, 0.066]	0.006 [-0.54, 0.066]	0.051 [-0.014, 0.166]	-0.03 [-0.090, 0.031]	-0.939 (1.048)	
	Ave. Citations of Co-Authors' Institutes	0.044 [-0.022, 0.108]	-0.013 [-0.078, 0.051]	0.195 [0.129, 0.259]	-0.076 [-0.141, -0.011]	2.007 (2.550)	
	Ave. Citations of Authors' Institutes	0.023 [-0.041, 0.088]	-0.008 [-0.069, 0.053]	0.191 [0.128, 0.255]	-0.067 [-0.127, -0.007]	0.658 (2.315)	
	Ave. Seniority of Coauthors	-0.007 [-0.072, 0.060]	0.018 [-0.046, 0.081]	0.151 [0.084, 0.219]	-0.141 [-0.204, -0.078]	9.632 (4.555)	
	Ave. Seniority of Authors	-0.020 [-0.084, 0.045]	0.006 [-0.054, 0.066]	0.11 [0.047, 0.173]	-0.047 [-0.105, 0.012]	0.263 (1.662)	
Text	Empirical Studies vs. Traditional Topic	-0.010 [-0.141, 0.119]	-0.017 [-0.135, 0.100]	0.021 [-0.136, 0.179]	0.030 [-0.114, 0.175]	-1.939 (0.543)	
	Psychology of JDM vs. Traditional Topic	"	"	-0.114 [-0.316, 0.087]	0.032 [-0.152, 0.220]	"	
	Sentiment	-0.020 [-0.085, 0.045]	-0.006 [-0.054, 0.067]	0.011 [-0.077, 0.054]	0.026 [-0.033, 0.086]	0.051 (0.957)	
Reviewer	Female (0) or Male (1)	-0.008 [-0.088, 0.070]	-0.012 [-0.111, 0.086]	-0.024 [-0.114, 0.068]	0.034 [-0.100, 0.167]	-0.577 (0.747)	
	Years Since Ph.D.	-0.014 [-0.109, 0.084]	0.033 [-0.084, 0.146]	-0.001 [-0.008, 0.007]	-0.003 [-0.013, 0.008]	-0.809 (0.776)	
	Ave. Citatiton of Institution	-0.020 [-0.086, 0.044]	0.004 [-0.055, 0.063]	0.015 [-0.028, 0.056]	0.008 [-0.057, 0.073]	0.314 (0.608)	
	Economics Ph.D. vs. Psychology	-0.027 [-0.105, 0.050]	0.013 [-0.081, 0.110]	0.074 [-0.74, 0.220]	-0.063 [-0.279, 0.150]	-3.549 (1.026)	
	Management Ph.D. vs. Psychology	"	"	-0.016 [-0.167, 0.134]	0.055 [-0.161, 0.271]	"	
	Marketing Ph.D. vs. Psychology	"	"	-0.001 [-0.123, 0.119]	-0.018 [-0.190, 0.157]	"	
	Other Ph.D. vs. Psychology	"	"	-0.004 [-0.144, 0.137]	-	"	
	Research Scientist vs. Full	-0.043 [-0.146, 0.062]	0.070 [-0.065, 0.200]	-0.052 [-0.260, 0.162]	-0.082 [-0.404, 0.237]	-0.745 (1.384)	
	Practitioner vs. Full	"	"	-0.073 [-0.332, 0.179]	-	"	
	Assistant vs. Full	"	"	0.035 [-0.086, 0.158]	-0.073 [-0.237, 0.092]	"	
	Associate vs. Full	"	"	0.038 [-0.086, 0.162]	-0.114 [-0.297, 0.079]	"	
	Experience reviewing past 7 years	-0.006 [-0.083, 0.067]	-0.012 [-0.094, 0.071]	-0.009 [-0.037, 0.019]	0.013 [-0.025, 0.050]	-0.595 (0.861)	

Bolded values indicated credible interval excludes 0. Review ratings and numerical predictors were standardized. The interaction term was run entering the variable predicting both single- and double-blind ratings together with condition dummy coded (0: single-blind; 1: double-blind). ELPD stands for the expected log pointwise predictive density for a new dataset calculated with leave one out cross validation (loo) indicating the predictive accuracy of the respective model (Vehtari et al., 2017). The values in the column under Δ ELPD_{loo} indicate the difference between model where the interaction between the predictor and condition was in and the model without the interaction and only the predictor. Positive values of Δ ELPD_{loo} indicate more predictive accuracy for the model with the interaction indicating differential use of that predictor between conditions. Negative values indicate more predictive accuracy for the model without the interaction term. The standard error is the variability associated the difference and indexes the uncertainty around the difference in predictive accuracy of the model.

S6.5 Coefficients from regressions entering all variables simultaneously separately for single- and double-blind.

Table S12: Coefficients from regressing submission characteristics onto single- or double-blind review ratings separately.

		Single		Double	
		M	95% CI	M	95% CI
Intercept		-0.135	[-0.613, 0.351]	0.267	[-0.222, 0.759]
First Author	Female (0) or Male (1)	0.151	[-0.032, 0.334]	0.336	[0.151, 0.522]
	Years Since Ph.D.	-0.120	[-0.252, 0.013]	-0.145	[-0.278, -0.01]
	Domestic (0) or International (1)	0.029	[-0.116, 0.174]	-0.037	[-0.178, 0.106]
	Ave. Citations of 1st Author's Institute	0.027	[-0.123, 0.176]	0.029	[-0.125, 0.182]
	Economics Ph.D. vs. Psychology	0.085	[-0.203, 0.374]	0.137	[-0.154, 0.431]
	Management Ph.D. vs Psychology	0.105	[-0.135, 0.345]	0.195	[-0.048, 0.439]
	Marketing Ph.D. vs. Psychology	0.032	[-0.156, 0.22]	0.023	[-0.166, 0.212]
	Other Ph.D. vs. Psychology	0.114	[-0.109, 0.338]	0.014	[-0.21, 0.238]
	Undergraduate vs. Full	0.041	[-1.329, 1.415]	-0.949	[-2.333, 0.433]
	Masters vs. Full	-0.128	[-0.819, 0.558]	-0.318	[-1.015, 0.371]
	Ph.D. vs. Full	0.021	[-0.479, 0.514]	-0.53	[-1.034, -0.025]
	Post Doc vs. Full	-0.062	[-0.534, 0.405]	-0.438	[-0.919, 0.044]
	Research Scientist vs. Full	0.099	[-0.522, 0.712]	-0.481	[-1.108, 0.146]
	Practitioner vs. Full	-0.442	[-1.188, 0.301]	-0.691	[-1.443, 0.06]
	Assistant vs. Full	0.089	[-0.345, 0.514]	-0.246	[-0.679, 0.19]
	Associate vs. Full	-0.102	[-0.509, 0.301]	-0.268	[-0.675, 0.139]
All Authors	Proportion Male Authors	0.014	[-0.079, 0.109]	-0.075	[-0.171, 0.02]
	Ave. Citations of Authors' Institutes	0.127	[-0.022, 0.277]	0.079	[-0.072, 0.232]
	Ave. Seniority of Authors	0.135	[0.052, 0.215]	0.057	[-0.023, 0.137]
Text	Empirical Studies vs. Traditional Topic	-0.007	[-0.167, 0.155]	0.055	[-0.105, 0.217]
	Psychology of JDM vs. Traditional Topic	-0.033	[-0.244, 0.179]	0.02	[-0.192, 0.232]
	Sentiment	-0.067	[-0.136, 0.003]	-0.018	[-0.087, 0.051]
Reviewer	Reviewer Female (0) or Male (1)	-0.011	[-0.128, 0.107]	-0.01	[-0.143, 0.124]
	Reviewer Years Since Ph.D.	0.039	[-0.055, 0.131]	-0.077	[-0.166, 0.012]
	Reviewer Ave. Citations of 1st Author's Institute	0.019	[-0.033, 0.072]	0.019	[-0.045, 0.084]
	Economics Ph.D. vs. Psychology	-0.005	[-0.19, 0.178]	0.031	[-0.161, 0.223]
	Management Ph.D. vs Psychology	-0.007	[-0.182, 0.167]	0.037	[-0.142, 0.216]
	Marketing Ph.D. vs. Psychology	-0.008	[-0.152, 0.138]	-0.029	[-0.19, 0.135]
	Other Ph.D. vs. Psychology	-	-	0.046	[-0.143, 0.237]
	Research Scientist vs. Full	-0.07	[-0.35, 0.209]	-0.161	[-0.471, 0.146]
	Practitioner vs. Full	-	-	-0.203	[-0.642, 0.239]
	Assistant vs. Full	0.092	[-0.137, 0.32]	-0.134	[-0.345, 0.078]
	Associate vs. Full	0.051	[-0.13, 0.232]	-0.076	[-0.293, 0.136]
	Reviewer # Times Review Past 7 Years	-0.031	[-0.098, 0.035]	0.011	[-0.052, 0.075]

Bolded values indicated credible interval excludes 0. All co-author characteristic characteristics were represented by the statistics based on all the authors (e.g., proportion of male authors instead of male coauthors) so that single-author submissions were included in the analysis. Thus, the regression coefficients for the first author variables represent incremental change for the variables in which there are corresponding coauthor characteristics. Review ratings and numerical predictors were standardized. The z indicates when the variables were standardized. Review ratings and numerical predictors were standardized. The characteristics were entered simultaneously for both regression models.

Table S13: Coefficients from regressing submission characteristics onto single- or double-blind review ratings separately for multi-author submissions.

		Single		Double	
		M	95% CI	M	95% CI
Intercept		-0.019	[-0.5, 0.456]	0.262	[-0.219, 0.751]
First Author	Female (0) or Male (1)	0.191	[0.055, 0.327]	0.271	[0.131, 0.411]
	Years Since Ph.D.	-0.109	[-0.255, 0.035]	-0.151	[-0.298, -0.007]
	Domestic (0) or International (1)	0.064	[-0.081, 0.21]	-0.017	[-0.165, 0.132]
	Ave. Citations of 1st Author's Institute	0.061	[-0.036, 0.158]	0.047	[-0.053, 0.148]
	Economics Ph.D. vs. Psychology	0.167	[-0.128, 0.464]	0.211	[-0.09, 0.512]
	Management Ph.D. vs Psychology	0.176	[-0.069, 0.424]	0.235	[-0.016, 0.488]
	Marketing Ph.D. vs. Psychology	0.048	[-0.14, 0.237]	0.064	[-0.133, 0.258]
	Other Ph.D. vs. Psychology	0.173	[-0.054, 0.4]	0.043	[-0.186, 0.273]
	Undergraduate vs. Full	-0.375	[-1.689, 0.952]	-1.131	[-2.48, 0.234]
	Masters vs. Full	-0.391	[-1.061, 0.276]	-0.427	[-1.111, 0.258]
	Ph.D. vs. Full	-0.211	[-0.698, 0.277]	-0.597	[-1.101, -0.098]
	Post Doc vs. Full	-0.279	[-0.745, 0.182]	-0.516	[-0.997, -0.042]
	Research Scientist vs. Full	-0.09	[-0.69, 0.515]	-0.537	[-1.165, 0.087]
	Practitioner vs. Full	-0.601	[-1.34, 0.125]	-0.76	[-1.505, -0.024]
	Assistant vs. Full	-0.021	[-0.458, 0.413]	-0.295	[-0.749, 0.147]
	Associate vs. Full	-0.13	[-0.54, 0.283]	-0.308	[-0.727, 0.112]
Co-Authors	Proportion Male Coauthors	0.033	[-0.037, 0.103]	-0.031	[-0.103, 0.04]
	Ave. Citations of Coauthors' Institutes	0.092	[-0.002, 0.186]	0.052	[-0.045, 0.149]
	Ave. Seniority of Coauthors	0.106	[0.029, 0.181]	0.006	[-0.074, 0.085]
Text	Empirical Studies vs. Traditional Topic	-0.015	[-0.175, 0.144]	0.088	[-0.074, 0.252]
	Psychology of JDM vs. Traditional Topic	-0.038	[-0.25, 0.173]	0.077	[-0.136, 0.291]
	Sentiment	-0.066	[-0.136, 0.004]	-0.03	[-0.102, 0.041]
Reviewers	Reviewer Female (0) or Male (1)	-0.022	[-0.143, 0.098]	-0.024	[-0.161, 0.113]
	Reviewer Years Since Ph.D.	0.049	[-0.048, 0.144]	-0.066	[-0.158, 0.026]
	Reviewer Ave. Citations of 1st Author's Institute	0.034	[-0.02, 0.089]	0.028	[-0.041, 0.095]
	Economics Ph.D. vs. Psychology	-0.042	[-0.229, 0.147]	0.074	[-0.127, 0.272]
	Management Ph.D. vs Psychology	-0.046	[-0.231, 0.137]	0.051	[-0.132, 0.235]
	Marketing Ph.D. vs. Psychology	-0.037	[-0.186, 0.111]	0.009	[-0.161, 0.18]
	Other Ph.D. vs. Psychology			0.091	[-0.107, 0.289]
	Research Scientist vs. Full	-0.085	[-0.377, 0.208]	-0.065	[-0.394, 0.261]
	Practitioner vs. Full			-0.199	[-0.663, 0.267]
	Assistant vs. Full	0.124	[-0.109, 0.357]	-0.077	[-0.296, 0.138]
	Associate vs. Full	0.082	[-0.102, 0.268]	-0.069	[-0.289, 0.150]
	Reviewer # Times Review Past 7 Years	-0.032	[-0.1, 0.037]	0.016	[-0.050, 0.082]

Bolded values indicated credible interval excludes 0. Review ratings and numerical predictors were standardized. The characteristics in the single- and double-blind were simultaneously for both regressions. The data were subsetting to only include multi-author submissions.

S7 Comparing single- vs. double-blind in the top 108

The comparison between single- and double-blind review in terms of bias revealed that in double-blind review there was a Matilda effect where male first-author submissions are evaluated to have greater scientific merit than female first-author submissions. In single-blind review this effect was mitigated. At the same time, there was a Matthew Effect in single-blind review more eminent coauthors got more credit than a comparatively unknown researcher. We were curious how these effects would be realized if the top 108 submissions were identified by single-blind or double-blind reviews. In terms of the Matilda Effect, if we look at the top 108 as specified by the single-blind review ratings and do the same for double-blind review, then double-blind review has less of a Matilda effect than single-blind. In the top 108 submission

according to single-blind review there are 35 submissions (32%) with female first authors while according to double-blind review there were 39 submissions (36%). Note across all 530 submissions there were 246 female first authors (46%). Thus, for both review systems there would be a Matilda Effect with less representation of women in the hypothetical conference, but if anything the effect would be slightly stronger for single-blind review. This difference reinforces the fact that the difference between single- and double-blind in terms of the Matilda Effect is subtle and should be interpreted with caution.

In terms of the Matthew Effect in single-blind review, we can do the same analysis and ask how the representation of senior coauthorship would change if the selection was done with single-blind review or double-blind review. If the top 108 submissions were identified by the single-blind review ratings the mean coauthor rank would be 8.3 ($SD = 1.7$) (i.e., between an Associate and a Full Professor). In contrast, if the top 108 was identified by double-blind review then the mean coauthor rank would be 8.0 ($SD = 1.9$) (i.e., an Associate Professor). Across all 530 submissions the mean coauthor rank excluding the first author was 7.9 ($SD = 1.9$) (i.e., just below Associate Professor). Thus, from the perspective of the conference threshold there is a Matthew Effect in single-blind, but not in double-blind.

S8 Analyses examining the predictive validity of review ratings and submission characteristics

S8.1 Summary of Talk Outcomes Across Sessions

Table S14: Mean (M) and standard deviation (SD) of talk ratings, attendance, and total potential questions

Session	Overall Rating (Std.)		Attendance		Potential Questions	
	M	SD	M	SD	M	SD
1	-0.13	0.45	99.2	23.8	3.3	1.5
2	-0.04	0.31	117.3	21.4	3.3	2.0
3	0.09	0.40	102.8	30.3	2.5	1.6
4	0.07	0.39	89.5	20.9	2.0	1.1
5	0.20	0.40	100.6	37.6	3.4	1.3
6	-0.08	0.29	106.7	43.0	2.5	1.9
7	0.14	0.43	102.4	44.7	3.1	1.8
8	0.05	0.39	62.6	28.8	2.8	1.3
9	0.19	0.27	65.1	17.1	1.9	1.8

S8.2 Intercorrelations between outcomes

Figure S5: Intercorrelations between outcome data. *Note:* The central value is the mean posterior estimate. The values in the upper and lower right-hand corners are the estimates of the upper and lower bounds of the 95% credible interval. Starred values indicate the credible interval excludes 0. Intercorrelations between talk rating and talk/poster rating and published and journal impact factor are not informative and are thus excluded. Journal impact factor was log-transformed before computing the correlation.

S8.3 Regression of outcomes onto single- and double-blind review ratings.

Table S15: Coefficients from regressing conference outcomes onto single- and double-blind review ratings simultaneously.

	Single		Double	
	M	95% CI	M	95% CI
Talk Rating (z)	0.048	[-0.092, 0.190]	-0.018	[-0.139, 0.106]
Attendance (z)	-0.119	[-0.438, 0.207]	-0.117	[-0.397, 0.166]
Total Potential Questions (z)	0.017	[-0.326, 0.368]	0.164	[-0.158, 0.495]
Talk & Poster Rating (z)	0.326	[0.112, 0.536]	0.191	[-0.022, 0.400]
Published	0.184	[-0.049, 0.410]	0.368	[0.132, 0.604]
Journal Impact Factor (z)	0.204	[0.001, 0.409]	0.131	[-0.075, 0.342]

Bolded values indicated credible interval excludes 0. All regressions included a dummy variable indicating whether the submission was presented at the conference or not. The z indicates that the variables were standardized.

S8.4 Regression of outcomes onto author and submission characteristics

S8.4.1 Regression with standardized outcome values

Table S16: Coefficients from regressing conference outcomes onto submission characteristics.

		M [95% CI]						
Characteristic		Talk Rating (z)	Attendance (z)	Total Potential Questions (z)	Talk/Poster Rating (z)	Published Dec 2020	Impact Factor of Journal Published	
(Intercept)		-0.077 [-0.712, 0.539]	0.356 [-0.918, 1.619]	0.583 [-0.882, 2.033]	-0.802 [-2.228, 0.614]	-0.005 [-1.346, 1.324]	-0.126 [-1.294, 1.045]	
First Authors	Female (0) or Male (1)	-0.058 [-0.338, 0.225]	-0.518 [-1.059, 0.023]	-0.24 [-0.899, 0.418]	0.281 [-0.282, 0.834]	-0.027 [-0.695, 0.639]	0.076 [-0.322, 0.473]	
	Years Since Ph.D.	-0.124 [-0.375, 0.138]	0.37 [-0.134, 0.881]	-0.22 [-0.817, 0.377]	-0.142 [-0.748, 0.455]	-0.233 [-0.655, 0.177]	-0.086 [-0.693, 0.512]	
	Domestic (0) or International (1)	0.052 [-0.201, 0.303]	-0.188 [-0.667, 0.287]	-0.272 [-0.861, 0.317]	0.05 [-0.405, 0.51]	0.113 [-0.428, 0.657]	-0.143 [-0.59, 0.302]	
	Ave. Citations of 1st Author's Institute	0.228 [0.011, 0.444]	0.644 [0.233, 1.054]	-0.109 [-0.625, 0.407]	0.4 [-0.131, 0.936]	-0.312 [-0.851, 0.221]	0.168 [-0.089, 0.428]	
	Economics Ph.D. vs. Psychology	0.197 [-0.197, 0.707]	-0.197 [-0.707, 0.313]	0.225 [-0.819, 1.271]	0.42 [-0.621, 1.453]	-1.294 [-2.449, -0.228]	0.69 [-0.276, 1.654]	
	Marketing Ph.D. vs. Psychology	0.054 [-0.224, 0.331]	-0.026 [-0.54, 0.477]	0.386 [-0.248, 1.009]	0.217 [-0.321, 0.749]	-1.425 [-2.159, -0.717]	0.206 [-0.409, 0.819]	
	Other Ph.D. vs. Psychology	0.201 [-0.103, 0.502]	0.669 [0.1, 1.225]	0.674 [-0.037, 1.38]	0.318 [-0.337, 0.98]	-0.245 [-0.98, 0.481]	0.198 [-0.365, 0.75]	
	Undergraduate vs. Full	-	-	-	-2.239 [-4.62, 0.193]	-1.332 [-5.548, 2.407]	-	
	Masters vs. Full	-0.36 [-1.176, 0.465]	0.479 [-1.17, 2.101]	-0.365 [-2.21, 1.517]	-0.942 [-2.647, 0.787]	-0.938 [-3.162, 1.161]	0.047 [-1.739, 1.855]	
	Ph.D. vs. Full	-0.337 [-1.005, 0.352]	-0.773 [-2.163, 0.612]	-0.847 [-2.434, 0.744]	-0.534 [-2.025, 1.002]	-0.486 [-1.934, 0.938]	-0.207 [-1.655, 1.201]	
	Post Doc vs. Full	-0.275 [-0.889, 0.357]	-0.376 [-1.643, 0.879]	-0.406 [-1.854, 1.061]	-0.302 [-1.749, 1.167]	-0.156 [-1.522, 1.228]	0.004 [-1.245, 1.224]	
	Research Scientist vs. Full	0.083 [-0.849, 1.018]	-0.364 [-2.244, 1.498]	-0.796 [-2.946, 1.431]	0.504 [-1.768, 2.792]	-3.49 [-6.688, -0.94]	-	
	Practitioner vs. Full	-0.108 [-1.006, 0.802]	0.293 [-1.489, 2.087]	0.871 [-1.243, 2.934]	-0.099 [-2.359, 2.127]	-2.702 [-6.2, 0.198]	-	
	Assistant vs. Full	-0.22 [-0.768, 0.364]	-0.168 [-1.327, 0.976]	-0.362 [-1.699, 0.975]	-0.085 [-1.347, 1.179]	-0.223 [-1.453, 1.004]	-0.046 [-1.117, 1.017]	
	Associate vs. Full	-0.225 [-0.775, 0.328]	-0.619 [-1.695, 0.461]	-0.698 [-1.962, 0.601]	-0.245 [-1.6, 1.101]	-0.433 [-1.676, 0.788]	0.124 [-0.88, 1.129]	
	All Authors	Proportion Male Authors	0.017 [-0.127, 0.164]	0.156 [-0.123, 0.428]	0.251 [-0.093, 0.601]	-0.172 [-0.462, 0.12]	0.488 [0.132, 0.852]	0.125 [-0.084, 0.337]
		Ave. Citations of Authors' Institutes	-0.17 [-0.41, 0.069]	-0.331 [-0.778, 0.116]	0.146 [-0.402, 0.684]	-0.198 [-0.732, 0.323]	0.262 [-0.284, 0.804]	0.048 [-0.225, 0.315]
		Ave. Seniority of Authors	0.085 [-0.064, 0.238]	-0.315 [-0.596, -0.032]	-0.205 [-0.553, 0.146]	0.099 [-0.2, 0.408]	0.24 [-0.064, 0.547]	-0.022 [-0.227, 0.183]
Submission Text	Empirical Studies vs. Traditional Topic	0.181 [-0.085, 0.446]	0.415 [-0.092, 0.916]	0.437 [-0.196, 1.058]	0.336 [-0.16, 0.835]	0.075 [-0.516, 0.673]	-0.075 [-0.545, 0.388]	
	Psychology of JDM vs. Traditional Topic	0.112 [-0.253, 0.476]	0.499 [-0.206, 1.21]	-0.061 [-0.931, 0.826]	0.176 [-0.528, 0.88]	0.279 [-0.495, 1.036]	-0.024 [-0.59, 0.538]	
	Sentiment	-0.091 [-0.209, 0.026]	-0.058 [-0.28, 0.158]	0.003 [-0.269, 0.274]	-0.219 [-0.469, 0.029]	-0.186 [-0.446, 0.071]	0.055 [-0.148, 0.259]	
Session	Session 2 vs. 1	0.08 [-0.319, 0.49]	1.312 [0.56, 2.066]	-0.182 [-1.109, 0.743]	0.318 [-0.683, 1.334]	-	-	
	Session 3 vs. 1	-0.005 [-0.454, 0.449]	0.369 [-0.464, 1.194]	-0.522 [-1.517, 0.482]	0.121 [-0.959, 1.192]	-	-	
	Session 4 vs. 1	0.145 [-0.266, 0.562]	0.259 [-0.511, 1.047]	-0.449 [-1.374, 0.477]	0.303 [-0.737, 1.327]	-	-	
	Session 5 vs. 1	0.109 [-0.324, 0.528]	-0.591 [-1.385, 0.21]	0.307 [-0.717, 1.354]	0.571 [-0.461, 1.589]	-	-	
	Session 6 vs. 1	0.048 [-0.388, 0.481]	0.168 [-0.64, 0.977]	0.004 [-0.993, 1.013]	0.389 [-0.684, 1.454]	-	-	
	Session 7 vs. 1	0.088 [-0.32, 0.502]	-0.017 [-0.783, 0.77]	-0.106 [-1.055, 0.849]	0.395 [-0.682, 1.44]	-	-	
	Session 8 vs. 1	0.204 [-0.189, 0.606]	-1.105 [-1.852, -0.342]	-0.118 [-1.015, 0.795]	0.733 [-0.255, 1.706]	-	-	
	Session 9 vs. 1	0.189 [-0.207, 0.583]	-0.841 [-1.578, -0.091]	-1.055 [-1.95, -0.14]	0.607 [-0.335, 1.566]	-	-	
	Poster Session vs. 1	-	-	-	1.138 [0.303, 1.963]	-	-	
	Presentation	-	-	-	-	0.223 [-0.408, 0.837]	0.038 [-0.442, 0.519]	
		sigma	0.388 [0.316, 0.482]	0.717 [0.585, 0.888]	0.885 [0.719, 1.098]	0.999 [0.853, 1.176]	-	0.953 [0.828, 1.099]

Bolded values indicated credible intervals exclude 0. As with the regressions comparing single- vs. double-blind reviews, all coauthor characteristic characteristics were represented by the statistics based on all the authors (e.g., proportion of male authors instead of male coauthors) so that single-author submissions were included in the analysis. Thus, the regression coefficients for the first author variables represent incremental change for the variables in which they correspond coauthor characteristics. The z indicates when the variables were standardized. When regressing conference outcomes (talk rating, attendance, questions, and talk/poster rating) conference session was entered as a covariate in the model. When regressing publication outcomes whether the submission was presented at the conference or not was entered as a covariate. Table S18 provides the regression coefficients when subsetting the data on multiple author submissions.

S8.4.2 Regression with raw outcome values

Table S17: Coefficients from regressing conference outcomes onto single- and double-blind review ratings simultaneously.

		Attendance		Total Potential Questions	
		M	CI	M	CI
(Intercept)		106.4	[62.7, 150.6]	3.7	[1.3, 6.1]
First Authors	Female (0) or Male (1)	-18.1	[-36.8, 1]	-0.4	[-1.5, 0.7]
	Years Since Ph.D.	12.9	[-4.7, 30.6]	-0.4	[-1.3, 0.6]
	Domestic (0) or International (1)	-6.4	[-22.7, 10]	-0.5	[-1.4, 0.5]
	Ave. Citations of 1st Author's Institute	22.4	[8, 36.8]	-0.2	[-1, 0.7]
	Economics Ph.D. vs. Psychology	-21	[-50.9, 9.1]	0.4	[-1.3, 2.1]
	Marketing Ph.D. vs. Psychology	-1	[-18.8, 16.8]	0.6	[-0.4, 1.7]
	Other Ph.D. vs. Psychology	23.3	[3.4, 42.8]	1.1	[0, 2.3]
	Masters vs. Full	16.6	[-40.5, 74]	-0.6	[-3.8, 2.6]
	Ph.D. vs. Full	-26.9	[-75.5, 22]	-1.4	[-4.1, 1.2]
	Post Doc vs. Full	-13	[-56.9, 31.4]	-0.7	[-3.1, 1.7]
	Research Scientist vs. Full	-12.8	[-78.9, 53.7]	-1.3	[-4.8, 2.4]
	Practitioner vs. Full	10.3	[-52.2, 72.6]	1.5	[-2.1, 4.9]
	Assistant vs. Full	-6	[-46.1, 33.7]	-0.6	[-2.8, 1.6]
	Associate vs. Full	-21.4	[-58.5, 16.6]	-1.1	[-3.3, 1]
All Authors	Proportion Male Authors	5.4	[-4.2, 15]	0.4	[-0.2, 1]
	Ave. Citations of Authors' Institutes	-11.4	[-26.9, 4.2]	0.2	[-0.7, 1.1]
	Ave. Seniority of Authors	-11	[-20.8, -0.9]	-0.3	[-0.9, 0.2]
Submission Text	Empirical Studies vs. Traditional Topic	14.3	[-3.4, 31.8]	0.7	[-0.3, 1.8]
	Psychology of JDM vs. Traditional Topic	17.1	[-8, 42.4]	-0.1	[-1.6, 1.3]
	Sentiment	-2	[-9.7, 5.6]	0	[-0.4, 0.4]
Session	Session 2 vs. 1	45.8	[19.6, 71.3]	-0.3	[-1.8, 1.2]
	Session 3 vs. 1	13.1	[-16.3, 41.9]	-0.9	[-2.5, 0.8]
	Session 4 vs. 1	9.1	[-17.7, 36]	-0.8	[-2.3, 0.8]
	Session 5 vs. 1	-20.4	[-47.9, 7.2]	0.5	[-1.2, 2.2]
	Session 6 vs. 1	6	[-22.6, 34.1]	0	[-1.7, 1.7]
	Session 7 vs. 1	-0.3	[-27.8, 27.6]	-0.2	[-1.7, 1.4]
	Session 8 vs. 1	-38.2	[-64.5, -12.2]	-0.2	[-1.7, 1.3]
	Session 9 vs. 1	-29.1	[-54.9, -2.9]	-1.7	[-3.2, -0.2]
sigma		25	[20.3, 31.1]	1.5	[1.2, 1.8]

Bolded values indicated credible interval excludes 0. All regressions included a dummy variable indicating whether the submission was presented at the conference or not. The z indicates when the variables were standardized.

S8.4.3 Regression with multi-author submissions

Table S18: Coefficients from regressing conference outcomes onto submission characteristics for multiple author papers.

		Talk Rating		Attendance (z)		Questions (z)		Talk/Poster (z)		Published		Impact Factor	
		M	95% CI	M	95% CI	M	95% CI	M	95% CI	M	95% CI	M	95% CI
(Intercept)		-0.162	[-0.803, 0.459]	0.182	[-1.096, 1.429]	0.017	[-1.492, 1.479]	-0.883	[-2.285, 0.509]	0.048	[-1.279, 1.352]	-0.126	[-1.294, 1.045]
First Authors	Female (0) or Male (1)	-0.011	[-0.254, 0.234]	-0.518	[-0.957, -0.086]	0.002	[-0.587, 0.58]	0.141	[-0.32, 0.603]	0.579	[0.058, 1.095]	0.076	[-0.322, 0.473]
	Years Since Ph.D. (z)	-0.064	[-0.333, 0.21]	0.242	[-0.29, 0.788]	-0.248	[-0.885, 0.397]	-0.078	[-0.703, 0.556]	-0.42	[-0.927, 0.05]	-0.086	[-0.693, 0.512]
	Domestic (0) or International (1)	0.069	[-0.186, 0.327]	-0.241	[-0.708, 0.229]	0.270	[-0.359, 0.893]	-0.007	[-0.456, 0.435]	0.175	[-0.391, 0.751]	-0.143	[-0.59, 0.302]
	Ave. Cites of 1st Auth. Inst. (z)	0.106	[-0.066, 0.278]	0.480	[0.168, 0.795]	-0.039	[-0.444, 0.367]	0.154	[-0.217, 0.524]	-0.177	[-0.551, 0.184]	0.168	[-0.089, 0.428]
	Economics Ph.D. vs. Psychology	0.364	[-0.114, 0.846]	-0.942	[-1.822, -0.05]	0.096	[-1.042, 1.241]	0.647	[-0.399, 1.704]	-1.252	[-2.426, -0.181]	0.69	[-0.276, 1.654]
	Marketing Ph.D. vs. Psychology	0.118	[-0.172, 0.408]	-0.167	[-0.7, 0.364]	0.294	[-0.383, 0.987]	0.334	[-0.212, 0.878]	-1.413	[-2.144, -0.698]	0.206	[-0.409, 0.819]
	Other Ph.D. vs. Psychology	0.216	[-0.089, 0.517]	0.681	[0.124, 1.236]	0.668	[-0.058, 1.391]	0.396	[-0.265, 1.049]	-0.276	[-1.044, 0.47]	0.198	[-0.365, 0.75]
	Undergraduate vs. Full	-	-	-	-	-	-	-2.336	[-4.623, -0.063]	-1.533	[-5.585, 2.105]	-	-
	Masters vs. Full	-0.366	[-1.164, 0.456]	0.568	[-1.021, 2.204]	-0.125	[-2.015, 1.841]	-1.069	[-2.734, 0.597]	-1.436	[-3.552, 0.597]	0.047	[-1.739, 1.855]
	Ph.D. vs. Full	-0.313	[-0.963, 0.351]	-0.660	[-1.984, 0.707]	-0.610	[-2.176, 0.946]	-0.36	[-1.857, 1.147]	-0.97	[-2.41, 0.457]	-0.207	[-1.655, 1.201]
	Post Doc vs. Full	-0.187	[-0.817, 0.446]	-0.196	[-1.456, 1.093]	-0.257	[-1.757, 1.258]	-0.064	[-1.514, 1.403]	-0.59	[-1.966, 0.8]	0.004	[-1.245, 1.224]
	Research Scientist vs. Full	0.044	[-0.888, 0.982]	-0.370	[-2.221, 1.462]	-0.721	[-2.987, 1.585]	0.65	[-1.539, 2.918]	-3.714	[-6.833, -1.144]	-	-
	Practitioner vs. Full	-0.005	[-0.925, 0.924]	0.234	[-1.607, 2.103]	0.813	[-1.363, 3.019]	0.062	[-2.174, 2.351]	-2.862	[-6.36, 0.007]	-	-
	Assistant vs. Full	-0.098	[-0.685, 0.497]	-0.247	[-1.435, 0.97]	-0.392	[-1.786, 1.025]	0.202	[-1.097, 1.512]	-0.216	[-1.516, 1.073]	-0.046	[-1.117, 1.017]
	Associate vs. Full	-0.336	[-0.904, 0.239]	-0.199	[-1.28, 0.877]	-0.423	[-1.753, 0.921]	-0.665	[-2.046, 0.719]	-0.466	[-1.773, 0.814]	0.124	[-0.88, 1.129]
Coauthors	Proportion Male Coauthors (z)	-0.016	[-0.131, 0.099]	0.065	[-0.147, 0.278]	0.172	[-0.105, 0.452]	-0.121	[-0.338, 0.1]	0.375	[0.098, 0.659]	0.125	[-0.084, 0.337]
	Ave. Cites Coauthors' Inst. (z)	-0.093	[-0.256, 0.071]	-0.152	[-0.448, 0.139]	0.126	[-0.265, 0.514]	-0.124	[-0.469, 0.22]	0.139	[-0.233, 0.51]	0.048	[-0.225, 0.315]
	Ave. Seniority of Coauthors (z)	0.052	[-0.075, 0.178]	-0.325	[-0.556, -0.091]	-0.102	[-0.399, 0.199]	-0.007	[-0.26, 0.245]	0.036	[-0.234, 0.316]	-0.022	[-0.227, 0.183]
Submission Text	Emp. Studies vs. Traditional	0.133	[-0.147, 0.417]	0.435	[-0.078, 0.936]	0.413	[-0.242, 1.057]	0.159	[-0.338, 0.668]	-0.012	[-0.611, 0.591]	-0.075	[-0.545, 0.388]
	Psych. of JDM vs. Traditional	0.125	[-0.256, 0.499]	0.428	[-0.277, 1.121]	-0.155	[-1.061, 0.744]	0.075	[-0.627, 0.786]	0.249	[-0.525, 1.024]	-0.024	[-0.59, 0.538]
	Sentiment (z)	-0.106	[-0.227, 0.016]	-0.012	[-0.238, 0.21]	0.003	[-0.282, 0.286]	-0.268	[-0.51, -0.021]	-0.222	[-0.49, 0.049]	0.055	[-0.148, 0.259]
Session	Session 2 vs. 1	0.091	[-0.31, 0.49]	1.470	[0.718, 2.214]	-0.216	[-1.163, 0.755]	0.32	[-0.665, 1.296]	-	-	-	-
	Session 3 vs. 1	0.008	[-0.456, 0.462]	0.637	[-0.217, 1.503]	-0.525	[-1.601, 0.55]	0.195	[-0.904, 1.262]	-	-	-	-
	Session 4 vs. 1	0.072	[-0.364, 0.504]	0.513	[-0.299, 1.327]	-0.440	[-1.467, 0.602]	0.195	[-0.857, 1.218]	-	-	-	-
	Session 5 vs. 1	0.235	[-0.213, 0.678]	-0.274	[-1.091, 0.569]	0.305	[-0.738, 1.368]	0.883	[-0.184, 1.925]	-	-	-	-
	Session 6 vs. 1	0.097	[-0.349, 0.553]	0.505	[-0.313, 1.338]	0.055	[-1.002, 1.1]	0.606	[-0.462, 1.641]	-	-	-	-
	Session 7 vs. 1	0.12	[-0.298, 0.532]	0.059	[-0.71, 0.833]	-0.078	[-1.061, 0.9]	0.383	[-0.67, 1.413]	-	-	-	-
	Session 8 vs. 1	0.232	[-0.16, 0.625]	-0.862	[-1.602, -0.131]	-0.059	[-0.991, 0.891]	0.772	[-0.198, 1.746]	-	-	-	-
	Session 9 vs. 1	0.215	[-0.194, 0.63]	-0.666	[-1.414, 0.086]	-1.034	[-1.986, -0.054]	0.816	[-0.166, 1.762]	-	-	-	-
	Poster Session vs. 1	-	-	-	-	-	-	1.231	[0.39, 2.065]	-	-	-	-
	Presentation	-	-	-	-	-	-	-	-	0.248	[-0.38, 0.87]	0.038	[-0.442, 0.519]
	sigma	0.39	[0.318, 0.483]	0.704	[0.57, 0.874]	0.914	[0.74, 1.138]	0.972	[0.831, 1.144]	-	-	0.953	[0.828, 1.099]

Bolded values indicated credible interval excludes 0. The z indicates when the variables were standardized. The data were subsetted to only include multi-author submissions. When regressing conference outcomes (talk rating, attendance, questions, and talk/poster rating) conference session was entered as a covariate in the model. When regressing publication outcomes whether the submission was presented at the conference or not was entered as a covariate.

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