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The False Balance Effect: Exploring Partition Dependence as a Potential Explanation

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ABSTRACT

False balance arises when opposing viewpoints about a scientific issue are portrayed as more evenly matched than what the empirical evidence demonstrates. We examined the extent to which partition dependence is the psychological mechanism underlying the false balance effect. Participants ($N=360$) read a statement about an interrogation practice (i.e., the use of false evidence ploys) that reached expert consensus, viewed data about the level of the expert consensus, and then assigned randomly to view (a) balanced expert comments in equal proportion on each side (3:3), (b) two-sided comments with more consensus views (5:1), (c) two-sided comments with more contrarian views (1:5), or (d) no comments at all. Results showed that balanced comments distorted perceived expert consensus and that two-sided comments with more consensus views had the largest impact on debiasing perceived expert consensus. We discuss the implications of our findings for science communication efforts.

1 | Introduction

It is not uncommon for propagandists to seek "balance" or appeal to "both sides of an issue" so they can raise doubts about the legitimacy of facts that do not align with their interests. For instance, in response to the deadly Unite the Right rally in 2017, where white supremacists attacked counter-protesters when protesting the city's decision to remove a statue of Robert Lee, the Former US President Donald Trump remarked, "You had some very bad people in that group, but you also had people that were very fine people, on both sides," (Keneally 2018). Even reputable sources sometimes fall prey to the need for balance. For instance, the BBC remarked that the broadcaster's mission was to show "due balance and due impartiality on any subject" after being accused of providing equal attention to economists and lobbyists during the Brexit referendum (Barker 2022; House of Commons of the United Kingdom 2023). However, providing balanced coverage by media outlets is unsurprising, considering that 76% of US adults believe that journalists should always strive to give equal coverage to both sides of an issue (Forman-Katz and Jurkowitz 2022). Communication scientists have suggested that the public wants a balanced presentation of competing views because it aligns with their expectations of a democratic society, which is grounded in the principles of freedom of speech, protecting the voices of minorities, and not being ideologically driven (Boykoff and Boykoff 2004; Taylor and Condit 1988).

However, equally representing two opposing views of an issue when the empirical evidence overwhelmingly favors one side is known as *false balance*. False balance aims to exploit the journalistic norm of balance whereby informed opinions presented by experts are paired with opposing, unsubstantiated opinions by contrarians (Dearing 1995; Cook 2022). Often, media outlets give unjustified contrarian voices equal airtime when reporting on issues that have achieved scientific consensus, thereby manufacturing a sense of "controversy" on important matters (e.g., climate change). False balance can also be present when people knowingly or unknowingly interact with influential science deniers who spread misinformation about scientific facts via their social media posts, comments, podcasts, videos, or even fake accounts, algorithms, and generative AIs.

Content analyses of media sources have indicated that false balance has infiltrated the communication about consequential issues (Merkley 2020) such as climate change (e.g., Petersen, Vincent, and Westerling 2019), vaccine safety (e.g., Thomas, Tandoc Jr, and Hinnant 2017), COVID pandemic (e.g., Zenone et al. 2022), abortion (e.g., Kendall et al. 2023), and elections (e.g., Miro and Anderson 2024). Although journalists have, over time, taken a step back from false balance when reporting stories (McAllister et al. 2021; Merkley 2020), the practice still exists. For example, McAllister et al. (2021) estimated that 1%–10% of the 4856 newspaper articles on climate change they examined, from 2005 to 2019, contained false balance. Moreover, research has found that contrarian perspectives on climate change have gained as much visibility as the consensus perspectives in mainstream media; contrarians were featured nearly 1% more often than scientists in digital and print media articles from 30 mainstream sources (Petersen, Vincent, and Westerling 2019). While researchers have detected false balance and attempted to combat it, contrarian views continue to receive disproportionate media attention (Wetts 2020).

1.1 | The Effect of Falsely Balanced Messages on Perceptions

Empirical evidence has shown that falsely balanced messages have a negative influence on public perceptions of expert opinions and their certainty about scientific facts (Corbett and Durfee 2004; Dixon and Clarke 2013; Dixon et al. 2015; Kohl et al. 2016; Kortenkamp and Basten 2015). Specifically, Dixon and colleagues found that people who read a balanced article on vaccines and autism perceived more divisiveness in the medical community, leading them to perceive less certainty among experts and to feel less sure there is no link between vaccines and autism (cf., one-sided scientific fact or unrelated article; Dixon and Clarke 2013; Dixon et al. 2015). These findings were replicated with the topic of climate change (Cook, Lewandowsky, and Ecker 2017; Imundo and Rapp 2021) and lesser-known topics such as health risks of pollution (Kortenkamp and Basten 2015) and facial recognition (Kohl et al. 2016). These findings suggest that false balance coverage implies the absence of scientific consensus over a target issue.

In testing the bounds of the false balance effect, Imundo and Rapp (2021) revealed that balanced messages decreased the perceived consensus among experts no matter the qualifications of the opposing "experts" (i.e., source expertise). They observed the false balance effect even when the science denier's expertise was irrelevant to global warming (i.e., physics) or did not have a scientific background (i.e., automotive plant manager). Their findings suggest that people may prioritize the mere presence of opposing views over the source expertise, indicating that the false balance effect might stem from a representative heuristic rather than source factors (e.g., expertise, attractiveness, credibility; Chaiken and Maheswaran 1994). False balance may imply to readers that a majority of support for one side of an issue (e.g., 80%) and a minority for the other side (e.g., 20%) should be treated equally in terms of the level of support because there are two sides (i.e., a 50–50 split).

Some journalists have addressed concerns over false balance in reporting by informing their audience about the weight of evidence (WOE) behind competing views (Dunwoody 2005). Research has shown that including WOE information (e.g., the percentage of experts who agree about an issue) alongside balanced messages leads to more accurate perceptions of expert consensus than balanced messages alone. Adding WOE also yielded levels of perceived consensus comparable to hearing only the scientific perspective (e.g., Dixon et al. 2015; Imundo and Rapp 2021). While the provision of WOE information is a promising intervention, such findings suggest that the false balance effect may stem from assigning a disproportionate amount of weight to the contrarian view, as opposed to people learning about the mere existence of a denial (Boudana 2016; Dearing 1995; Schmid, Schwarzer, and Betsch 2020).

Relatedly, and unsurprisingly, Koehler (2016) found that presenting WOE information alongside a balanced message resulted in less accurate assessments of expert consensus than reading only about the WOE information. This finding was especially pronounced when it pertained to a high-consensus issue (i.e., most experts agreed about the target issue). Despite having access to the WOE information, perceptions of the proportion of experts supporting each side of an issue were swayed from the actual data by falsely balanced comments—that is, the presence of balance overshadowed the statistical data (Koehler 2016; Borgida and Nisbett 1977).

Han, Snook, and Day (2024) conceptually replicated Koehler's (2016) study with a police interrogation practice. They examined the extent to which false balance skewed perceived expert consensus about minimization tactics, a technique that aims to elicit a confession by pragmatically implying leniency (Kassin et al. 2018). All participants first read a statement about minimization tactics and were then presented with data on the level of expert consensus about the tactic. Specifically, half the participants read that expert consensus was high (91% agree vs. 9% disagree), and the other half read that consensus was low (62% agree vs. 38% disagree). Further, half of the participants in each consensus condition (high and low) read balanced comments from two opposing experts. In line with Koehler's (2016) findings, when collapsed across all conditions, Han, Snook, and Day (2024) found that the presence of balanced messages decreased the perceptions of expert consensus (vs. only seeing the data). Participants in the high expert consensus conditions experienced more negative effects from balanced messages than those in the low expert consensus conditions. Balanced messages also reduced policy support for expert testimony on minimization tactics.

1.2 | Why Does False Balance Decrease Perceived Expert Consensus?

One potential psychological mechanism underlying how falsely balanced messages affect perceived expert consensus is partition dependence (Koehler 2016). An error in probabilistic reasoning can occur when people assess the probabilities of events based on how options are partitioned (Fox and Rottenstreich 2003). For example, when dividing events into two options, individuals may assign equal probabilities to those two options (Fox and Clemen 2005; Fox and Rottenstreich 2003). In the case of a falsely balanced message, seeing two opposing perspectives might invoke a 50/50 partition that biases judgments toward a midpoint (Koehler 2016). In that case, people may refrain from using the numerical WOE information when rating the level of expert consensus. Invoking a 50/50 partition may cause their ratings of expert consensus to be overly influenced by the representativeness of the balanced presentation (Griffin and Tversky 1992). In short, some people underestimate or neglect the base rates, which may lead them to base their inferences on a sample of expert comments from both sides of an issue (Kahneman and Tversky 1972).

Tversky and Koehler (1994) established the partition dependence account through their Support Theory, which suggested that people tend to assign a higher total probability to an option (A) when there are suboptions and a lower probability to an option (A) when its complement (¬A) has suboptions. For example, Tversky and Koehler (1994) found that participants estimated a 58% chance of death by natural causes (A) but 73% when asked separately about the chance of death by natural causes from three mutually exclusive suboptions (i.e., heart disease, cancer, other natural causes; 22% + 18% + 33%). Similarly, participants estimated a 32% chance of dying by *unnatural* causes (¬A), but 53% when asked separately about three mutually exclusive subcategories of the *unnatural* causes (i.e., accident, homicide, other unnatural causes; 32% + 10% + 11%). However, their estimated chance of natural causes (A) decreased from 68% to 47% in this scenario.

In addition, researchers have found that the impact of a separate evaluation of *subevents* (i.e., explicit disjunction) is more robust than the unpacking of an event into an implicit disjunction of subevents (e.g., Rottenstreich and Tversky 1997; Sloman et al. 2004). For example, Fox and Clemen (2005) asked MBA students to estimate the probability that six different universities would receive the top rank in *Business Week*'s ranking of business schools. They found that the sum of estimated probabilities for *all universities other than Wharton (¬A)* was higher when all six choices were listed separately (i.e., 70% for all options) than when listed as two options (i.e., 40% when the non-Wharton universities were collapsed and all listed on the same line and 40% when the non-Wharton universities were pruned into a single group; see Table 1 for a visualization of the options). Moreover, as suggested by the support theory, the estimated probabilities (40%) for the collapsed and pruned options were below their frequency probability of 50%. The estimated probability (70%) in a condition with six separate options was also below its frequency probability of 5/6 (or 83%; Fox and Clemen 2005).

In sum, the above research on probabilistic reasoning suggests that people tend to judge probabilities by leaning toward 50% when there are two options to be evaluated. In other words, judging an event's probability relies on the options' frequency probabilities, known as *partition dependence* (Fox and Rottenstreich 2003). As for false balance, a balanced message is a two-sided message that presents fact (X) and denial (¬X) equally. The juxtaposition of fact and denial might lead to a binary partition of expert opinions, leading people to adjust their beliefs toward a midpoint. If this happens, this binary partition may mislead people to perceive more controversy than what exists (Koehler 2016).

1.3 | Current Research

Like other scientific disciplines, establishing expert consensus in the field of psychology and law about various issues provides a critical empirical foundation that allows practitioners to apply findings in the real world to ensure that practices are, for instance, ethical, effective, and economical. Unfortunately, findings in the field of psychology and law are not immune from contrarians raising doubts about scientific consensus.

The current study sought to replicate the finding that false balance overshadows the numerical WOE about an interrogation issue. Specifically, we examined the effect of balanced messages (balanced presentation + WOE vs. WOE alone) on perceived expert consensus on using false evidence ploys. In general, several empirical studies have shown that false evidence ploys (e.g., falsely implying/claiming the existence of evidence, bluffing, suggesting hypothetical evidence) can produce false confessions (e.g., Kassin and Kiechel 1996; Luke, Crozier, and Strange 2017; Nash and Wade 2009; Perillo and Kassin 2011; Swanner, Beike, and Cole 2010). Moreover, there is a strong consensus among interrogation experts that false evidence ploys can lead innocent individuals to falsely confess (Kassin et al. 2018). There have been instances, however, where the link between false evidence

TABLE 1 | Visualization of the partitions used in Fox and Clemen (2005).

Separate options (all options)	Two options (collapsed options)	Two options (pruned options)
• Chicago	• Chicago, Harvard, Kellogg, Stanford, or another school other than Wharton (¬A)	• A school other than Wharton (¬A)
• Harvard	• Wharton (A)	• Wharton (A)
• Kellogg		
• Stanford		
• Wharton		
• None of the above		

ploys and false confessions has been challenged (e.g., John E. Reid and Associates 2011, 2021).

Given that no research has examined the potential psychological explanation of the false balance effect, we explored partition dependence as a potential psychological mechanism underlying the distorting effect of false balance (Koehler 2016). We examined the partition account by comparing balanced expert messages in equal proportion on each side (e.g., 3:3) to two-sided expert messages in proportion to their relative prevalence among the expert population (e.g., 5:1, 1:5). We anticipated that exposure to balanced messages from experts would decrease perceptions of expert consensus on a high-consensus issue, even when we provided the numerical WOE information. Additionally, we expected lower perceived expert consensus when expert comments were evenly split (i.e., 3:3) compared to proportionally representative messages (i.e., 5:1).

2 | Materials and Methods

2.1 | Participants

Despite planning and following a Bayesian analytical approach, we conducted a power analysis rooted in NHST assumptions as a compromise for readers interested in this approach and those who view the results of our NHST testing (see https://osf.io/bxf74/). An a priori power analysis using G*Power indicated that 360 participants were required to detect a small effect ($d=0.35$) with an alpha of 0.05 and 80% power for a single-factor between-subjects design with four conditions. We chose to detect an effect of 0.35 based on a previous exploration of the false balance effect in the interrogation context (Han, Snook, and Day 2024). Although the decision was somewhat arbitrary, the chosen effect size was at the lower end of the range of effect sizes found in previous research (Han, Snook, and Day 2024; Koehler 2016) and using that effect size allowed us to have a relatively larger sample size when attempting to replicate Han, Snook, and Day (2024).

We recruited participants ($N=371$) from the general population in Canada through an online survey platform called Prolific, which provides similarly high-quality data to MTurk (Peer et al. 2017). Participants were pre-screened to have English as their first language and compensated £2 ($3.44 Canadian) for their time (the study lasted around 20 min). Eleven participants failed the attention check, resulting in a final sample size of 360. See Table 2 for a breakdown of participants by demographic variables (i.e., gender, age, level of education, ethnicity, income level). There were no differences in demographic characteristics across conditions.

TABLE 2 | Breakdown of participants by demographic variables.

Demographic variable	Percentage
Gender	
Male	45.3
Female	52.5
Other	2.2
Age	
Below 20	1.4
20–29	29.9
30–39	34.1
40–49	18.7
50–59	10.3
60–69	5.3
70–79	0.3
Level of education	
Some high school	0.6
High school graduate	8.9
Some-post secondary	12.3
Diplomatic/certificate	14.2
Bachelor's degree	46.0
Graduate degree	15.0
Professional degree	3.1
Ethnicity	
Asian	20.1
Black/African	5.3
Hispanic/Latino	0.6
Indigenous/Aboriginal	0.8
Middle Eastern	1.7
Pacific Islander	0
White	66.9
Other	3.1
Prefer not to say	1.7
Level of income	
$0–$9999	6.1
$10,000–$24,999	11.4
$25,000–$49,999	15.0
$50,000–$74,999	22.6
$75,000–$99,999	15.6
$100,000–$149,999	16.4
$150,000—higher	6.4
Prefer not to answer	6.4

2.2 | Design

A single-factor between-subject design with four conditions was employed, with the level of balance as the independent variable. Specifically, the conditions were (1) no comment (i.e., the no-balance control condition), (2) an equal number of comments from both sides (i.e., balanced 3:3 condition), (3) more consensus-view comments (i.e., evidentiary balanced 5:1 condition), and (4) more contrarian-view comments (i.e., contrarian balanced 1:5 condition). We measured perceived expert consensus and support for the practice. We preregistered the experiment at https://osf.io/ghb5x. While we preregistered a detailed study design, procedure, and hypotheses, we failed to preregister our analytic plan beyond prescribing that it would be Bayesian. The experiment was conducted online via Qualtrics.

2.3 | Materials

The materials included (a) an informed consent form, (b) two versions of instructions on how to complete the study, (c) a statement about false evidence ploys, (d) a summary table containing the level of expert consensus about false evidence ploys, (e) expert comments (varied by the number of comments from opposing experts), (f) a 10-item questionnaire to measure perceived expert consensus and support for its use (i.e., policy support), (g) a demographic questionnaire, and (h) a debriefing form. All experimental materials are available at https://osf.io/bxf74/. All materials are described below except for the informed consent and debriefing forms.

2.3.1 | Instructions

All participants saw the following instructions:

Please read this information carefully because you will be asked questions about it later. In this study, you will read some results from a survey of experts on the psychology of interrogations and confessions. The experts either hold a PhD in psychology, criminal justice, and other related empirical fields, have published on interrogations and confessions in peer-reviewed journals, or have testified as an expert witness about interrogations and confessions. The experts were invited worldwide by virtue of their research and/or courtroom experience. Specifically, the experts were provided with a statement regarding an interrogation/confession issue and indicated whether they agreed with the statement or not. You will be told the percentage of experts who agreed or disagreed with the statement. You will then evaluate the extent to which the experts agree with each other about that statement.

We also provided the following instructions to participants in the three conditions containing expert comments:

Some experts also provided a brief comment explaining their beliefs. You will be shown some comments from experts who agreed and disagreed with the statement.

2.3.2 | False Evidence Ploy Statement and Summary Table

We selected the statement about false evidence ploy from an online survey of 87 experts (either highly published or with courtroom experience) on 30 issues related to confessions and interrogations (Kassin et al. 2018). As mentioned, we chose the statement about false evidence ploys because it achieved a high level of expert consensus in the survey. Specifically, 94% of the respondents agreed that "Presentations of false incriminating evidence during interrogation increase the risk that an innocent suspect would confess to a crime he or she did not commit." (Kassin et al. 2018). As a result, the data in our summary table indicated that 94% of survey respondents agreed with the statement and that 6% disagreed with the statement. To improve the comprehension of the concept, we adapted the statement to layperson's terms. We presented the statement as follows:

False Evidence Ploy: This involves presenting false incriminating evidence to a suspect during an interrogation. For example, an interrogator tells a suspect that his accomplice had confessed or that he failed a polygraph test, when it never really happened. The use of false evidence ploys will increase the risk that an innocent suspect would confess to a crime he or she did not commit.

2.3.3 | Expert Comments

Except for the control condition, we presented participants with a different number of comments from opposing experts. We used Koehler (2016) and the literature on partition dependence (e.g., Fox and Clemen 2005) to decide the number of expert comments needed to manipulate the level of balanced presentation of expert opinions. As mentioned, we presented participants with either three comments from three experts who agreed with the statement and three comments from three experts who disagreed with the statement (three agree vs. three disagree condition), five comments from five experts who agreed with the statement and one comment from an expert who disagreed with the statement (five agree vs. one disagree condition), or one comment from an expert who agreed with the statement and five comments from five experts who disagreed with the statement (one agree vs. five disagree condition). Based on Fox and Clemen (2005), we listed the expert comments separately and displayed them vertically; this allowed us to create a disjunction of expert comments to operationalize a different ratio of partitions (Fox and Clemen 2005; Koehler 2016). We also used Schmid, Schwarzer, and Betsch's (2020) examination of the efficacy of *outnumbering* (a weight-of-evidence strategy to provide each side of a debating issue with a weight relevant to the amount of evidence the side of view achieved) to guide our decision to unpack the partition of conflicting expert opinions into a disjunction of six subcategories (comments). It is worth noting that the manipulation of the level of balance (i.e., number of comments + sources) in the present study is different from the weight-of-evidence strategies using numeric information or number of sources as the "weight" (e.g., Dixon et al. 2015; Schmid, Schwarzer, and Betsch 2020).

We presented all comments as three double-spaced lines in Qualtrics. The comments were similar in structure and number of words. The comments ranged from 35 to 49 words in length. One part of the comment pertained to the expert's perspective (e.g., "False evidence can substantially change people's emotional and decision-making states"). The other part of the comment pertained to the rationale for the perspective (e.g., "In the face of false evidence, innocent people may feel trapped and under pressure, and therefore decide to confess out of a misplaced confidence that their confession will be later disproved due to their innocence").

We created 10 comments (5 of each on opposing sides) from opinion pieces and research articles and counterarguments to scientific claims. Firstly, we adapted three pairs of equivalent comments for the balance 3:3 condition; this served as the "false balance" condition. Specifically, we took three comments, agreeing that false evidence ploys can cause innocent suspects to confess, from Kassin (2021) and Perillo and Kassin (2011). The three comments opposing the proposition were taken from correspondence by John E. Reid and Associates (2021). One hundred and twenty-nine words comprised the three comments that aligned with the proposition, and 123 words comprised the three comments that opposed the proposition.

We then rephrased the first pair of comments to create an additional two pairs of comments for the remaining two conditions (i.e., 5:1 and 1:5). To increase the salience of the manipulation (i.e., that participants were aware of the ratio of experts who agree and disagree with the proposition), we added a human icon next to each of the comments and highlighted the icons with different colors (blue for the agreed side and orange for the disagreed side). We added the icons to emphasize that a different expert made each comment; that is, independent experts provided the comments.

We randomized the order of the groups of expert comments; specifically, we presented all the comments that agreed with the statement before or after all the comments that disagreed with the statement. We based this decision on Koehler's (2016) finding that support for government policy was stronger when the agreeing comment came before the disagreeing comment. We did not randomize the order of the summary table and the comments—the summary table was always presented first with the comments on a single screen. This decision not to randomize the summary table and comments was based on Koehler's (2016) finding that the order of those variables did not affect the level of perceived expert consensus and policy support. Given our focus on manipulating the level of balance, we did not randomize the order of comments within any partition. All comments that agreed with the false evidence ploy statement were always presented in the same order, as were those that disagreed with the statement. We aimed to ensure all comments were similar in content (see https://osf.io/bxf74/). For the two conditions with a single comment (i.e., 1:5 condition and the balance 5:1 condition), the one (dis)agreed comment was randomly selected from the five comments from that side of the partition to avoid a specific comment from standing out and confounding the partition manipulation.

2.3.4 | Measures of Perceived Expert Consensus and Policy Support

We created a 10-item questionnaire for this study. The first item served as an attention check, asking about the topic of the material participants read (whoever did not select false evidence ploy was excluded from the sample). The 10th item also served as an attention check, asking participants to pick "2" from the choices (no one failed this check). Items 2–4 were about perceived expert consensus on the statement; we adapted them from previous research on the false balance effect (i.e., Dixon and Clarke 2013; Koehler 2016). Specifically, the second item measured the extent to which there was agreement among the surveyed experts about false evidence ploys, using a 7-point scale (1 = *very little*, 7 = *very much*). The third item asked participants to provide the likelihood of two randomly selected experts from the survey sharing the same opinion about the statement of false evidence ploys on a slider scale from 0% to 100%. The fourth item asked about perceptions of consensus in the expert community: "Suppose 100 different confession experts, with similar qualifications, were surveyed about the same false evidence ploy statement. How many of these experts do you think would agree that false evidence can cause an innocent suspect to confess?". Participants recorded their responses on a slider scale that ranged from 0 to 100. Cronbach's α for the items regarding the perception of expert consensus was 0.68.

We also measured participants' views about using false evidence ploys in interrogations and expert testimony on the tactic (i.e., policy support measures). Specifically, we asked participants to rate their level of agreement (1 = *strongly disagree*, 7 = *strongly agree*) with the following three statements about using false evidence ploys in interrogations: "The police should be allowed to use false evidence ploys during an interrogation," "Using false evidence ploys should be considered police misconduct (i.e., improper behaviour that could lead to disciplinary/punishment action)," and "A confession (admission of guilt) given after an interrogator used false evidence ploys should not be used as evidence of guilt in court." To calculate the internal consistency for the above items, we reverse-scored the item "The police should be allowed to use false evidence ploys during an interrogation." Cronbach's α for the three policy support items was 0.86.

We asked participants to rate their level of agreement (1 = *strongly disagree*, 7 = *strongly agree*) with the following two statements about expert testimony on false evidence ploys: "There is enough agreement among experts about false evidence ploys to form the basis of expert testimony in court" and "It is reasonable to believe that expert testimony about false evidence ploys would help judges and juries make decisions about guilt and innocence." We defined expert testimony in the questionnaire. Specifically, we told participants that expert testimony is evidence given in court by an expert on a topic and may include the expert's opinions about specific facts to help the judge and jury understand an issue and help them make a decision.

2.4 | Procedure

Upon consenting to the experiment, all participants read a statement about false evidence ploys and the percentages of the experts who agreed or disagreed with it (i.e., such ploys can lead to false confessions). They were then randomly assigned to one of the four conditions, directed to answer the 10-item question, and debriefed.

2.5 | Statistical Analysis

We used a Bayesian approach to analyze our results to estimate the magnitude of the difference among groups and, most importantly, to assess (un)certainty about the estimated true difference between conditions (Gelman et al. 2014). In particular, the Bayesian approach uses evidence from the data collected to update prior beliefs about the compatible magnitudes of differences between the balance and no balance conditions (e.g., Kruschke 2013). After accounting for the collected data and our prior assumptions, the degree of belief about the true difference is expressed in the posterior probability distribution (Etz and Vandekerckhove 2018). We provided estimated mode and highest density intervals (HDIs) to describe our posterior probability distributions. As a type of posterior interval, HDIs represent a range of parameter values most compatible with the data, summarizing the posterior probability mass rather than accepting or rejecting hypotheses (Gelman et al. 2014; McElreath 2020). For example, a 95% HDI contains 95% of the posterior probabilities, and likewise, an 80% HDI contains 80% of the posterior probabilities. In this way, HDIs describe the different probabilities of the estimated parameter values (e.g., plausible difference scores).

It is worth noting that Bayesian modeling is powerful and robust when analyzing asymmetrical data (i.e., skewed data; Martin and Williams 2017). The current study observed left-skewed data on the perceptions of expert consensus (skewness ranged from −1.21 to −1.89) because participants read a high-consensus statement and responded near boundaries on all measures of perceived expert consensus. Bayesian modeling forgoes the normality assumptions since it is essentially a joint probability distribution specified on the data and the parameters assumed to underlie the data-generating process. Instead of adjusting data to conform to model assumptions, the models can be modified to account for data characteristics and represent a data-generating process that can feasibly produce observations. Moreover, the inferential procedure remains the same regardless of assumptions: we can draw inferences from the posterior distribution rather than a hypothetical sampling distribution (Martin and Williams 2017).

As for the current study, we chose to use skew-normal distributions in Bayesian models to represent the assumed distributions for perceptions of expert consensus, as they add only one more parameter (i.e., the shape parameter α controlling the skewness) than a normal distribution (Martin and Williams 2017). This process allows the skew-normal distributions to capture negatively skewed data ($\alpha < 0$), positively skewed data ($\alpha > 0$), or normally distributed data ($\alpha = 0$).

We carried out the Bayesian parameter estimation using R (version 4.1.1; R Core Team 2020) and the *brms* package (version 2.16.1; Bürkner 2017). The analysis involved fitting a series of skew-normal models to predict the differences in perceptions of expert consensus. The *tidybayes* package was used alongside *brms* to compute the posterior mode for each model (version 3.0.3; Kay 2023; Kurz 2023). The unstandardized difference between the no-balance and the other three conditions was chosen as our parameter of interest, as it intuitively captures the magnitude of differences in perceived expert consensus and policy support. Priors for the mean of the referent condition and residual error were set by default in the *brms* package, using Student-*t* distribution with 3 degrees of freedom to provide better model convergence (Bürkner 2017). For the differences of perceptions on expert consensus, we used weakly informative priors to make our inferences as objective as possible (i.e., perceived expert consensus ~ normal distribution (0, 3), likelihood of consensus among two of the experts randomly selected ~ normal distribution (0, 10), perceived consensus among the science community ~ normal distribution (0, 15), and combined measure ~ normal distribution (0, 0.6)). Since no study has explored this topic, priors were set by default using uniform distributions for policy support items. Details for Bayesian model metrics are available at https://osf.io/bxf74/, including data and R codes. Although we provide means, standard deviations, and Cohen's *d* effect sizes, we recognize that some readers may wish to view our analyses framed in a more familiar light. The results of the NHST analyses are also available at https://osf.io/bxf74/.

3 | Results

Table 3 contains the descriptive statistics for a combination of variables as a function of dependent measures, and Table 4 contains the associated effect sizes (i.e., Cohen's *d*).

3.1 | Perception of Expert Consensus

As seen in Table 4, the effect sizes for the effect of messages with different levels of balance on perceptions of expert consensus (i.e., perceived expert consensus, likelihood of consensus among two experts randomly selected, perceived consensus among the science community) ranged from 0 to 0.77. The presence of an evenly balanced message (three agree vs. three disagree) decreased the perceptions of expert consensus (*ds* = 0.50, 0.29, 0.47). Moreover, an evidentiary balanced message (five agree vs. one disagree) also decreased the perceptions of expert consensus (*ds* = 0.44, 0.06, 0.21). When the level of balance within a message leaned more toward the contrarian view (one agree vs. five disagree), perceptions of expert consensus decreased even more (*ds* = 0.77, 0.42, 0.53).

3.1.1 | Posterior Probability Distributions

As the three key measures were conceptually consistent as well as internally ($\alpha = 0.68$), we combined the measures by first standardizing them via z scores and then taking the mean of the standardized scores. Figure 1a shows the posterior probability distribution of each condition. Figure 1b shows the posterior probability distribution of the mean differences among the conditions. As can be seen in Figure 1b, the best fitting model suggests that there is a 95% chance that an evenly balanced message (i.e., three agree comments vs. three disagree comments) reduces the perception of expert consensus, *HDI* [−0.53, −0.18], *Mode* = −0.35. Our model also suggests a 95% chance that exposure to an evidentiary balanced message (i.e., five agree comments vs. one disagree comment; *HDI* [−0.33, −0.03], *Mode* = −0.18) or a two-sided message with more contrarian comments (i.e., one agree comment vs. five disagree comments; *HDI* [−0.72, −0.33], *Mode* = −0.50) decreases perceptions of expert consensus on the false evidence ploy.

TABLE 3 | Means and standard deviations for dependent measures.

Dependent measures	Level of balance			
	No balance	Balance 3 agree versus 3 disagree	Evidentiary balance 5 agree versus 1 disagree	Contrarian balance 1 agree versus 5 disagree
Perceived expert consensus (1–7)	6.37 (1.07)	5.77 (1.23)	5.77 (1.55)	5.23 (1.75)
Likelihood of two experts surveyed sharing the same opinion (0–100)	84.52 (18.43)	78.90 (20.72)	83.43 (15.35)	75.55 (23.56)
Perceived consensus in the science community (0–100)	84.44 (19.63)	72.56 (29.59)	79.97 (23.81)	71.60 (28.26)
Support for the use of false evidence ploy (1–7, not reverse-scored)	3.00 (1.65)	2.43 (1.54)	2.70 (1.76)	2.86 (1.50)
False evidence ploy is police misconduct (1–7)	4.85 (1.64)	5.08 (1.74)	5.26 (1.70)	4.74 (1.48)
Confession elicited is inadmissible (1–7)	4.91 (1.63)	5.17 (1.47)	5.39 (1.34)	4.86 (1.42)
Sufficient consensus to use expert testimony on false evidence ploy (1–7)	5.15 (1.41)	5.05 (1.47)	5.08 (1.39)	4.84 (1.25)
Helpfulness of expert testimony on false evidence ploy for verdict decisions (1–7)	5.17 (1.40)	5.17 (1.41)	5.37 (1.15)	4.74 (1.33)

TABLE 4 | Effect sizes (Cohen's *d*) for group comparisons by dependent measures.

Cohen's *d*	$d_{3:3\text{ v. nb}}$	$d_{5:1\text{ v. nb}}$	$d_{1:5\text{ v. nb}}$	$d_{3:3\text{ v. }5:1}$	$d_{3:3\text{ v. }1:5}$	$d_{5:1\text{ v.}1:5}$
Perceived expert consensus (1–7)	−0.50	−0.44	−0.77	0	0.36	0.33
Likelihood of two experts surveyed sharing the same opinion (0–100)	−0.29	−0.06	−0.42	−0.25	0.15	0.40
Perceived consensus in the science community (0–100)	−0.47	−0.21	−0.53	−0.30	0.03	0.32
Support for the use of false evidence ploy (1–7, not reverse-scored)	−0.36	−0.18	−0.09	−0.16	−0.28	−0.10
False evidence ploy is police misconduct (1–7)	0.14	0.25	−0.07	−0.11	0.21	0.33
Confession elicited is inadmissible (1–7)	0.17	0.32	−0.03	−0.16	0.22	0.38
Sufficient consensus to use Expert testimony on false evidence ploy (1–7)	−0.07	−0.05	−0.23	−0.02	0.15	0.18
Helpfulness of expert testimony on false evidence ploy for verdict decisions (1–7)	0	0.16	−0.32	−0.16	0.32	0.51

Note: nb = no balance; 3:3 = 3 agree vs. 3 disagree; 5:1 = 5 agree vs. 1 disagree; 1:5 = 1 agree vs. 5 disagree.

More importantly, our model suggests an 80% chance that an evidentiary balanced message (5:1) has a debiasing impact on the perception of expert consensus compared to the presence of an evenly balanced message (3:3; *HDI* [0.05, 0.29], *Mode* = 0.17). In contrast, a two-sided message with more contrarian comments (1:5) biases the perception of expert consensus more than an evenly balanced message (*HDI* [−0.31, −0.02], *Mode* = −0.17). In sum, a two-sided message (regardless of the level of balance) is likely to decrease perceptions of expert consensus. Separate Bayesian analyses for each measure can be found at https://osf.io/bxf74/.

3.2 | Policy Support

As shown in Table 3, the use of false evidence ploys during interrogations was generally not endorsed across the conditions. Specifically, most participants indicated that interrogators should not use the technique, that it constitutes misconduct, and that any evidence collected using it should be ruled inadmissible in court. Further, participants endorsed expert testimony about the tactic. The data in Table 4 show that, compared to the no-balance control condition, the evenly balanced message (3:3) decreased support for using false evidence ploys, increased beliefs

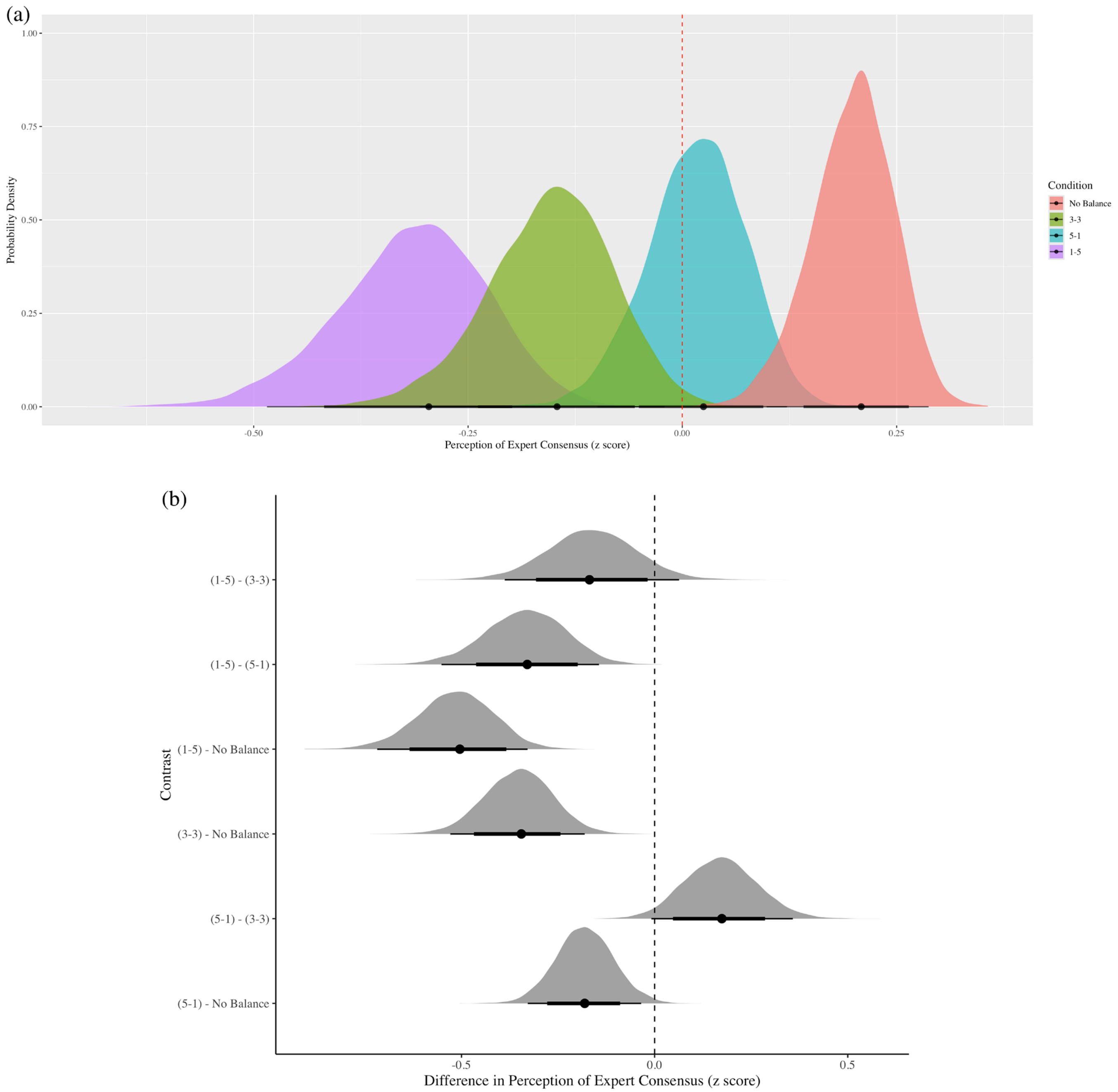


FIGURE 1 | Panel (a) The posterior probability distributions of each condition for the combined standard score of perceptions of expert consensus; panel (b) the posterior probability distribution of the mean differences among the conditions for the combined standard score of perceptions of expert consensus.

that false evidence ploys are police misconduct, and increased beliefs that confessions elicited from its use should be inadmissible ($ds = -0.36$, 0.14 and 0.17); we found similar trends when comparing the evidentiary balanced message (5:1) to the control condition ($ds = -0.18$, 0.25, and 0.32). However, the difference between a two-sided message with more contrarian comments (1:5) and the control condition was negligible for all policy support variables. We also found small to negligible effects of a balanced message (regardless of the level of balance) on the support for expert testimony. That is, the two-sided messages had little effect on their support for expert testimony about false evidence ploys.

3.2.1 | Posterior Probability Distributions

Because the three items for the usefulness of false evidence ploys (i.e., support for the use of false evidence ploys, false evidence ploys as police misconduct, confessions elicited as inadmissible) were consistent ($\alpha = 0.86$; note that the item of the support for false evidence ploys was reverse-scored), we conducted our tests on aggregate data. As shown in Figure 2, the posterior probability mass of the difference between an evenly balanced message and no message moves away from zero; there is approximately 80% chance that an evenly balanced message makes people more eager to oppose the use of false evidence ploys by the police

(80% *HDI* [0.08, 0.62], *Mode* = 0.36). In addition, there is at least an 80% chance that an evidentiary balanced message increases support for a policy banning false evidence ploys (80% *HDI* [0.14, 0.67], *Mode* = 0.41). Separate Bayesian analyses for each item can be found at https://osf.io/bxf74/.

Figure 3 (panel a) shows the posterior probability distributions of the mean differences among the conditions concerning support for expert testimony. As indicated, our model suggests an 80% chance that a two-sided message with more contrarian comments reduces the belief that there was enough expert consensus to support testimony on false evidence ploys (*HDI* [−0.58, −0.05], *Mode* = −0.29). Figure 3 (panel b) shows the posterior probability distributions of the mean differences among the conditions concerning the perceived impact of expert testimony about false evidence ploys on verdict decisions. The figure shows an 80% chance that a two-sided message with more contrarian comments negatively influences the perceived helpfulness of expert testimony on false evidence ploys for verdict decisions (*HDI* [−0.69, −0.19], *Mode* = −0.42). The posterior probability masses of the difference between an evenly balanced message or an evidentiary balanced message and no message contains zero in the middle zone.

4 | Discussion

We found that presenting a balanced message with an equal number of expert comments on each side (i.e., three agree vs. three disagree) decreased perceptions of expert consensus on an issue where there was high expert consensus (i.e., 94% of surveyed experts agreed that false evidence ploys could lead the innocent to confess falsely). In other words, adding balanced commentary alongside data about the WOE was found to distort estimations about the level of expert consensus on this scientific issue. We also found that a two-sided message with more consensus-supporting comments (five agree vs. one disagree) decreased perceptions of expert consensus but less than an evenly balanced message (three agree vs. three disagree). We also found that the presence of a two-sided message with more contrarian comments (one agree vs. five disagree) decreased perceptions of expert consensus and more than evenly balanced messages. Despite the presence of factual data (WOE), any two-sided message (with the ratios of expert comments we explored) will likely cause people to underestimate the true level of expert consensus if the actual level of expert consensus is greater than the ratios explored.

In line with previous research, we replicated the effect of falsely balanced messages on the perceived scientific consensus about an interrogation tactic (i.e., false evidence ploys; Han, Snook, and Day 2024; Koehler 2016). Even when people can access data on the percentages of experts supporting each side, exposure to balanced expert comments appears to decrease public perceptions about the level of agreement among experts. Unlike well-politicized issues such as climate change and vaccines, interrogation practices are less likely to evoke strong prior beliefs from the public regarding perceptions of expert consensus.

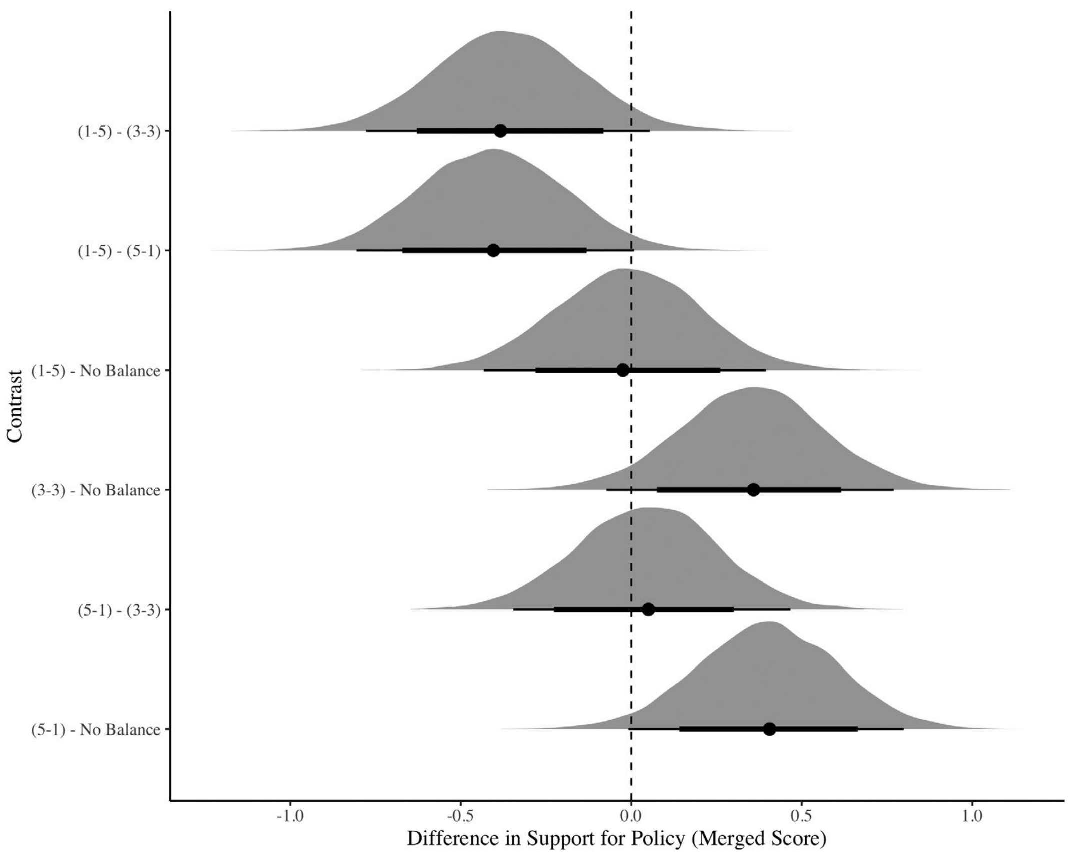
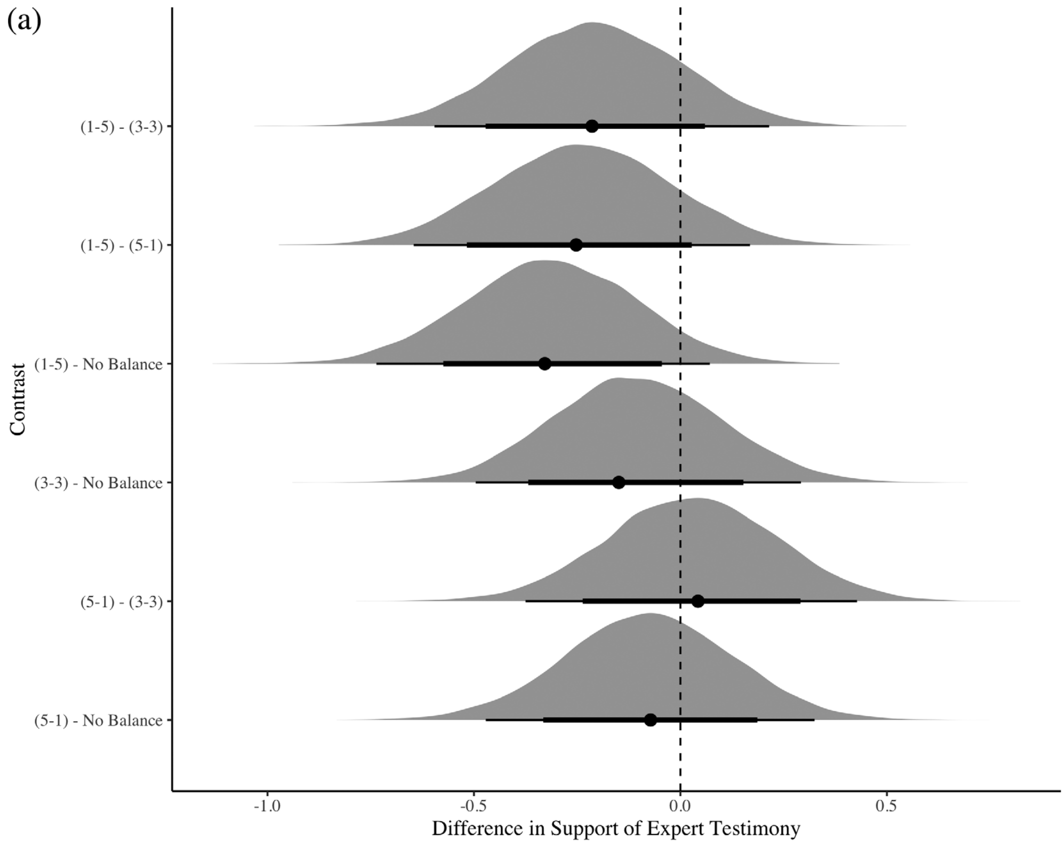


FIGURE 2 | The posterior probability distribution of the mean differences among the conditions for the combined score of policy support against false evidence ploys.



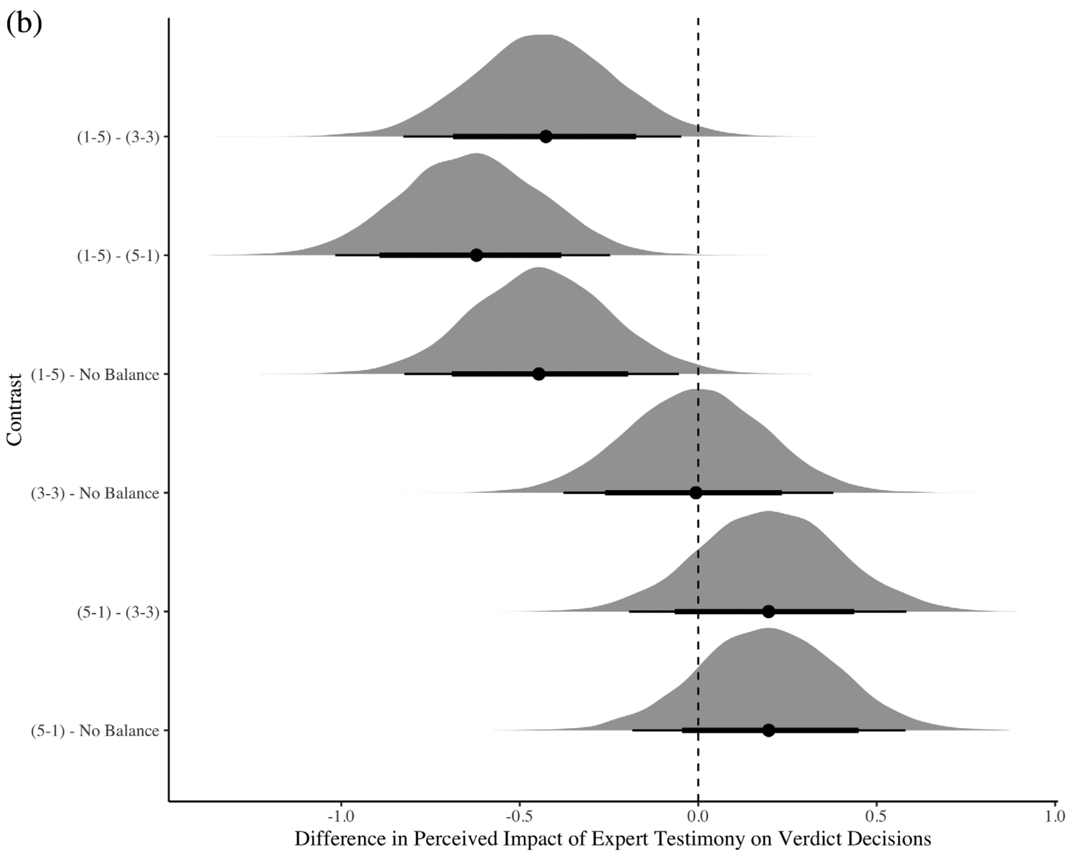


FIGURE 3 | Panel (a) The posterior probability distribution of the mean differences among the conditions for support for expert testimony on false evidence ploys based on expert consensus; Panel (b) the posterior probability distribution of the mean differences among the conditions for the perceived impact of expert testimony about false evidence ploys on verdict decisions.

One might easily assume that people would estimate the exact level of expert consensus when presented with data on the actual level of expert consensus (e.g., 94% agree vs. 6% disagree). However, we did not find that to be the case.

Our results seemingly contradict findings in the persuasion literature about the effect of two-sided messages on source credibility. Research has suggested that presenting a two-sided message that raises and refutes an advocated view can increase the source's credibility (e.g., Cornelis, Cauberghe, and De Pelsmacker 2015; Kamins and Assael 1987; O'Keefe 1999). However, the current study revealed that presenting conflicting messages from sources on opposing sides interfered with perceptions of expert consensus. While message-sidedness may inoculate message receivers against possible counterarguments (e.g., Eisend 2007; McGuire 1961), our findings suggest that "both-siding" arguments from sources holding opposing positions may create the illusion of a debate through its information representation. In addition, empirical evidence has demonstrated that presenting data (WOE information) alongside a balanced message can mitigate the distorting impact of the balanced message (vs. presenting only the balanced message; Clarke et al. 2015; Dixon et al. 2015). Nevertheless, our findings suggest that balanced comments from experts on both sides can outweigh statistical evidence, thus leading people to believe there is less consensus among experts than what exists. These findings align with the persuasion literature on how testimonials are more influential than objective statistics when making risk perceptions (e.g., Borgida and Nisbett 1977; De Wit, Das, and Vet 2008; Zebregs et al. 2015).

Our findings are particularly troubling when considering that the adversarial legal system often has two opposing sides (the defense vs. the prosecution) presenting arguments before triers of fact, who are assumed to be devoid of any pre-existing beliefs (i.e., impartial; Roesch et al. 2013). In this system, judges and jurors must determine the truth of a case, but they often do not have the scientific knowledge needed to evaluate the relevant evidence (e.g., Fallon and Snook 2021; Wallace and Kassin 2012). Therefore, triers of facts must rely on experts' opinions to understand an issue. However, the courts sometimes reject expert testimony on matters they think laypersons can understand. Exposure to false balance might exacerbate the situation by negatively influencing a judge's decision to admit expert testimony or reducing its perceived credibility among jurors. While it is a requisite for experts to be neutral witnesses (they are to assist triers of fact in understanding an issue), an expert might be rebutted by a lawyer or an expert for the opposing side. In legal persuasion, a lawyer may raise a two-sided argument before an opposing lawyer to increase their credibility and derogate the opponent's credibility (a legal strategy known as "stealing thunder"; e.g., Reilly 2012). However, when both lawyers engage in open debate and expose the audience to arguments from opposing perspectives, it could leave an impression that there is much disagreement among experts about the general acceptance of the target issue (e.g., Daubert v. Merrell-Dow Pharmaceuticals 1993; Frye v. US 1923).

When it comes to why falsely balanced messages have the observed effect on the perception of expert consensus, the proposed partition account remains plausible. According to the partition dependence theory, exposure to equally balanced messages creates a dual partition about expert opinions that prompts individuals to assign 50% to the two conflicting viewpoints and hence moves perceptions of expert consensus toward the middle (Fox and Clemen 2005; Koehler 2016; Tversky and Koehler 1994). By varying the number of expert comments to reflect their relevant prevalence (majority vs. minority), we found that it was possible to sway perceptions of expert consensus either closer to or further from the actual level of expert consensus. Specifically, our findings showed that evidentiary balanced comments (five agree vs. one disagree; a sixfold partition with the consensus view in the majority) evoked a stronger perception of expert consensus than evenly balanced comments (three agree vs. three disagree; twofold partition) or two-sided messages with more contrarian comments (one agree vs. five disagree; sixfold partition with the contrarian view in the majority). Since participants read data about 94% of experts agreeing that false evidence ploys can cause false confessions, it makes sense that perceived expert consensus was more accurate when the partition matched the data more closely (i.e., evidentiary balanced > evenly balanced > two-sided with more contrarian comments).

As for the policy support variables, we found that people believed that interrogators should not use false evidence ploys, that its use constituted misconduct, and that confessions collected via false evidence ploys should be ruled inadmissible in court. Consistent with Han, Snook, and Day (2024), exposure to an evenly balanced or evidentiary balanced message led to more disapproval of the interrogation tactic. However, participants did not appear to dismiss false evidence ploys completely, as they gave, on average, a rating of approximately 5 on a 7-point scale across all variables. The above findings seemingly contradict past findings that showed false balance reduces the accuracy of personal beliefs and their policy support for climate change and vaccines (e.g., Cook, Lewandowsky, and Ecker 2017; Dixon and Clarke 2013). Nevertheless, our findings align with the notion that balanced messages might induce ambiguity, thus leading people to pay attention to the expert consensus information and resulting in more expert-aligned beliefs that false evidence ploys should not be used by police (Chaiken and Maheswaran 1994).

While our findings supported the partition account, at least three possible explanations help explain the false balance effect. First, our findings may result from people paying attention to the number of contrarian comments in a two-sided message, not just the partition. In other words, the perception of expert consensus may reduce as denials increase. Second, our findings might be due to selection neglect—where participants are unable to recognize that the sample of expert comments (e.g., 3:3) is unrepresentative of the minority of experts (e.g., 94:6); thus, they fail to discount the contrarian comments (Koehler 2016). Third, people may have updated their belief of base rates (i.e., the data) based on the frequency of comments on each side, committing an error in their probability reasoning rather than depending on only two partitions (Gigerenzer 1993).

Partition dependence may not fully explain the false balance effect. Researchers could conduct at least three experiments to disconfirm this explanation. First, researchers could test whether the sheer number of denials matters by comparing different one-sided messages with a different number of denials to two-sided messages with different levels of balance. If the effect of a balanced message (e.g., 1:1) on estimating WOE is equivalent to that of a one-sided denial when estimating WOE, then the partition account would be disconfirmed. Second, researchers could manipulate the number of comments on each side rather than indicating the number of sources making comments. If our findings are due to the mere frequency of consensus-view comments (e.g., 1/2, 5/6, 1/6), we should still find a distortion of perceived expert consensus even when all of the comments come from a single source on each side; the test of a single source would also challenge the partition dependence account for the false balance effect. Third, future research should use natural frequencies (e.g., 94 out of 100) to replace the base percentages (e.g., 94%) to see if people turn to balanced messages rather than the data because some people may have difficulty understanding percentages. If partition dependence is a plausible explanation, the same effect should be observed when using natural frequencies.

In terms of future research that tests the bounds of the false balance effect, researchers could explore several directions. Firstly, our experimental materials lack ecological validity: participants read percentages of experts agreeing or disagreeing with a statement, followed by opposing expert comments in separate lines [cf., Fox and Clemen 2005]. Although replies and comments on social media platforms may resemble a list of separate lines, falsely balanced messages often include news articles or interviews. Future research should replicate the study using newspapers, magazine articles or interview scripts, and in-person. Additionally, the current study focused solely on a high-consensus issue, partially replicating Han, Snook, and Day (2024) and Koehler (2016). Future research could manipulate levels of expert consensus to explore how the presence of balanced expert comments and the level of balance interact with the data of expert consensus. Furthermore, the current study also used levels of balance (i.e., $5{:}1 \approx 83{:}17$, $3{:}3 = 50{:}50$, $1{:}5 \approx 17{:}83$) lower than the WOE of the issue (i.e., 94:6). While we replicated the false balance effect and found support for partition dependence account (i.e., perceived expert consensus: no balance $\geq 5{:}1 > 3{:}3 > 1{:}5$), future research should examine levels of balance that are equal to or greater than the actual WOE (e.g., 16:1; 20:1). More interestingly, what is the simplest utterance by a denier that could raise doubt about an issue? Could simply having an expert say "I doubt it" be enough to distort perceptions of expert consensus? In line with the partition account, a two-sided message heavily weighted with supporting comments (e.g., 16 agree vs. 1 disagree) might even advocate for the target scientific consensus.

5 | Conclusions

In summary, the current study reinforced past findings that falsely balanced messages can distort perceived expert consensus, even when they know the actual data (numerical WOE information) showing the level of expert consensus. We also provided empirical evidence that such an effect might be due to partition dependence (Koehler 2016; Fox and Clemen 2005). It is worth noting that scientific knowledge is tentative, and the norm of balance can be used as a validity check when there is no clear resolution on which claim is correct (Popper 1959). However, impartiality does not guarantee the veracity of the claims (Dunwoody and Peters 1992), and more importantly, the need to "cover all aspects" should not overshadow the existence of numerous indisputable scientific and historical facts (Ecker et al. 2024). Casting doubt on truth under the appearance of balance is indoctrination, which is no better than the doublethink raised in George Orwell's dystopian classic 1984. Democracy depends on legitimate deliberation and open discussion; thus, it is necessary to identify and understand acts that cause fake debates to defend the truth.

Author Contributions

Tianshuang Han: conceptualization, methodology, investigation, validation, visualization, writing – original draft, writing – review and editing, software, formal analysis, project administration, data curation. **Brent Snook:** conceptualization, methodology, validation, writing – review and editing, writing – original draft, supervision, resources. **Martin V. Day:** conceptualization, methodology, supervision.

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This research has been approved by the Interdisciplinary Committee on Ethics in Human Research (ICEHR) and found to be in compliance with Memorial University's ethics policy. The ICEHR approval number given is 20240801-SC.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available at https://osf.io/bxf74.

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