How To Think About Whether Misinformation Interventions Work

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September 23, 2022

Abstract

Recent years have seen a proliferation of experiments seeking to combat misinformation. Yet there has been little consistency across studies in how the effectiveness of interventions is evaluated, which undermines the field's ability to identify efficacious strategies. Here we provide a framework for differentiating between common research designs. We recommend an approach that aligns with the normative claim that citizens should maximize the accuracy of the content they believe and share, which requires (i) a design that includes both true and false content, and (ii) an analysis that includes examining discernment between the two. Using data from recent misinformation studies, we show that using the wrong research design can lead to misleading conclusions about who is most likely to spread misinformation and how to stop it.

This working paper has not yet been peer reviewed

Keywords: misinformation, fake news, social media, methodology

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Introduction

Growing concern about misinformation has spurred an influx of research on who believes and shares false and misleading content (Grinberg et al., 2019; Guess et al., 2019; Osmundsen et al., 2021) and what can be done about it (e.g., Pennycook et al., 2021; Guess et al., 2020; Nyhan et al., 2020). This work aims to answer lingering questions about the origins and consequences of misinformation: What causes people to believe and share false content? Are people merely confused about what is real or do they intentionally spread falsehoods? How effective are interventions aimed at increasing digital literacy, nudging people to consider the accuracy of content before sharing it, and flagging specific articles as misleading?

However, surprisingly little attention has been paid to the most fundamental prerequisite to answering any of these questions: how to measure belief in and sharing of false claims. The resulting lack of cohesion in research design among studies purporting to answer the same question diminishes our understanding of how to address the growing problem of misinformation.

One common research design entails survey respondents rating a series of false (e.g. as rated by professional fact-checkers) content on the likelihood that they believe it to be true and/or whether they would share it (e.g., Zimmermann and Kohring, 2020; Pereira et al., 2021; Halpern et al., 2019; Tsang, 2021; Pretus et al., 2022; Andı and Akesson, 2020). Other studies ask respondents to rate a mix of false and true (i.e., accurate) content (e.g., Guess et al., 2020; Lyons et al., 2021; Pennycook et al., 2020, 2021). Even among studies that include both false and true content, there is further variation which outcomes scholars use to capture susceptibility to misinformation, with some focused primarily on belief or sharing of the false content (e.g., Lawson and Kakkar, 2022; Clayton et al., 2020) and others focused instead on discernment—belief or sharing of true content relative to false content (e.g., Guay et al., 2022; Guess et al., 2020; Pennycook et al., 2020, 2021). Using different outcomes can lead to conflicting conclusions about who is most likely to share false claims and which interventions are effective in combating it, impairing our understanding of—and ability to

effectively combat—the problem of misinformation.

This paper provides a unified framework for measuring and operationalizing susceptibility to misinformation. We consider the full range of research designs and the normative claims that each design implicitly makes about how citizens should engage with the information environment. We argue that the appropriate normative claim—that citizens should maximize the accuracy of their beliefs and of the content that they share—requires (i) a design in which respondents rate a mix of both true and false content, and (ii) an analysis that includes examining discernment between the two. While a treatment that reduces belief or sharing of false content while having no effect (or a positive effect) on true content is unambiguously effective, the efficacy of treatments that simultaneously decrease (or increase) both true and false is unclear. In these situations, efficacy is dependent on the relative magnitude of the treatment effect on each type of content, as well as normative prescriptions of the cost of believing/sharing false content relative to the benefit of believing/sharing true content. Determining the efficacy of these interventions requires data on both true and false content, and researchers to compare their effect on true versus false content (i.e., discernment).

Furthermore, we specify different types of discernment: additive discernment and multiplicative discernment. Additive discernment captures absolute differences in how much more likely one is to believe or share true versus false news false news) , while multiplicative discernment captures relative differences between true and false news. As an example, the distinction between the two types of discernment becomes clear when in the following case: imagine one group is more likely to share news in general (i.e., regardless of veracity), but both groups are twice as likely to share true content than false content. There is no difference in multiplicative discernment because both have equal ability to discern between true and false content (relatively speaking), but there is a greater baseline rate of sharing in one group resulting in a difference in additive discernment. Though tests for additive discernment are ubiquitous in the misinformation literature, below we argue that multiplicative discernment is typically more closely aligned with the stated aim of misinformation studies.

Finally, we re-analyze data from recent misinformation studies to illustrate the importance of measuring discernment, and the difference between the two types of discernment. We demonstrate how using the wrong research design can lead to misleading conclusions about who believes and shares false claims and the efficacy of misinformation interventions.

Issues With Measuring Ratings of Only False Content

Misinformation studies often focus exclusively on how people interact with false content. Despite the intuitive appeal of this approach, it is poorly suited to the task of studying how individuals interact with false claims. Most importantly, its use implies a normative claim that is at odds with the reality of the information environment on social media—namely that users should not believe or share false content, but that whether they believe or share true content is inconsequential.

This normative claim is problematic for two reasons. First, after years of politicians decrying unfavorable news coverage as fake and with trust in the news media in recent years at an all-time low (Brenan, 2021), disbelieving true news is an increasingly salient problem. Just as believing false content touting the benefits of Ivermectin for treating Covid-19 are clearly problematic, so too is not believing in true content about the benefits of masks and MRNA vaccines. Indeed, not believing true content is often synonymous with holding a false belief—in the case of Covid, not believing information about the effectiveness of vaccines is equivalent to believing they are ineffective. Not sharing true content on social media is also consequential, as what users see on social media is largely determined by what their friends share. While users do not have a responsibility to share all true content upon encountering it, sharing true content crowds out false content and is therefore not inconsequential.

Second, true news is far more prevalent than false news. Indeed, explicitly false content is rare on social media relative to true content and often originates from a small number of individuals (Grinberg et al., 2019; Guess et al., 2020; Nikolov et al., 2020). Thus, studies examining how people interact with only false content not only set up a highly unrealistic

information environment, but also overlook how people interact with the vast majority of content they encounter.

In addition to these normative issues, there is also an important inferential issue with studies using only false content: conflating the propensity to believe and share false content with the propensity to believe and share all content. A person may appear less likely to believe false content simply because they are less likely to believe all content, perhaps because they are distrusting of news in general (Maertens et al., 2021; Lawson and Kakkar, 2022). Without measuring belief in true and false content, these two scenarios are observationally equivalent. Inversely, some individuals may believe a lot of true and false content, indicating that they are generally gullible and therefore not specifically susceptible to false content per se.

This issue is particularly salient for studies that evaluate the efficacy of misinformation interventions, as interventions determined to be effective using only ratings of false content (but that have similar effects on true content) can actually do more harm than good. Given the greater prevalence of true content on social media, interventions that reduce belief/sharing of false content by reducing belief/sharing of all content (Maertens et al., 2021) will more frequently affect perceptions of true content. An individual will occasionally encounter and, as a result of the intervention, be skeptical of false content, but they will much more frequently encounter and be skeptical of true content. In fact, the goal of some disinformation campaigns is to spread widespread disbelief, rather than promoting a particular set of false beliefs (Yablokov, 2022).

Accuracy and Sharing Discernment

An alternative research design that addresses these limitations exposes participants to a mix of true and false content, and incorporates ratings of both into a measure of discernment. Discernment represents the extent to which a person believes or shares false content relative to true content. By capturing how individuals interact with true and false content,

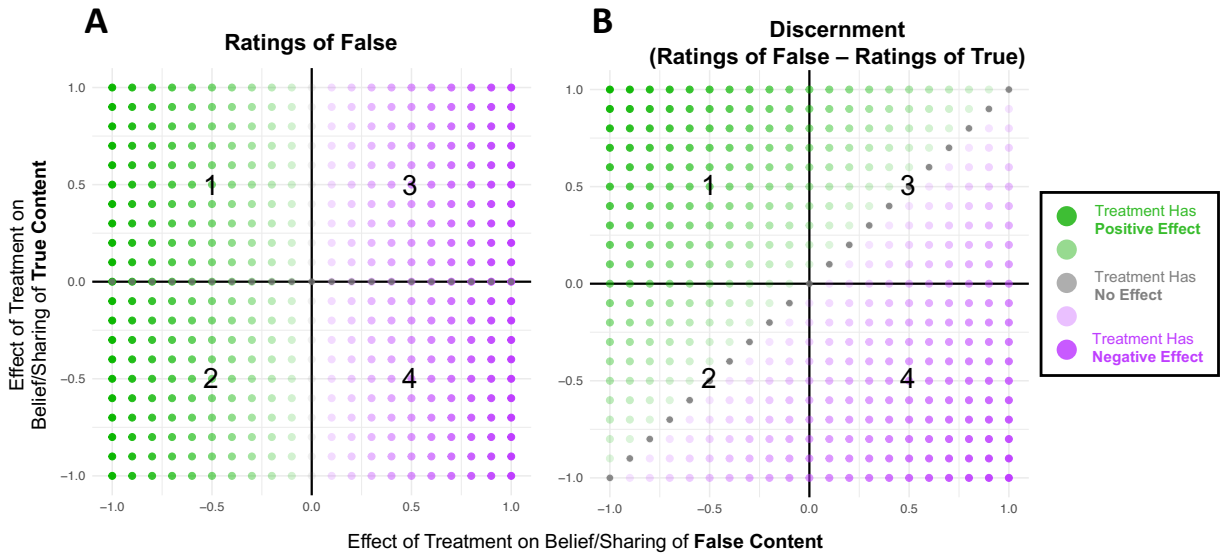
discernment (which is akin to overall accuracy) is more closely aligned with (typical) normative concerns over misinformation—that benefits are derived not only from abstaining from believing and sharing false content, but also from believing and sharing true content.

As such, results of studies that use only false ratings and those that use discernment diverge in meaningful ways. To illustrate how, we use the hypothetical example of a study that examines the efficacy of a misinformation intervention, though the same logic applies to studies that aim to compare belief/sharing of false claims among non-experimental groups (e.g., Democrats/Republicans, young vs. old, etc.). Figure 1 plots the effect of hypothetical treatments, each with different effects on belief in true (y-axis) and false (x-axis) content. Panel A determines the efficacy of an intervention using only ratings of false content, where a treatment is considered effective when it decreases belief in false content, regardless of its effect on true content. Notably, interventions in quadrants 1 and 2 are all determined to be effective because they have a negative effect on belief in false content, despite having opposite effects on belief in true content.

Panel B shows the exact same simulated data, but judges efficacy using discernment - and therefore is jointly determined by the intervention's effect on belief in true and false content. Interventions in Quadrant 1 are still classified as effective as they both decrease belief in false content and increase belief in true content. However, now only half of interventions in Quadrant 2 are classified as effective—only those that decrease belief in false content more than they decrease belief in true content. Likewise, half of interventions in Quadrant 3 are classified as effective, despite increasing belief in false content, because they increase belief in true content by a relatively greater amount. Note that this assumes that belief in (or sharing of) one piece of false content is as negative as believing or sharing one piece of true content is positive; an assumption that we will return to subsequently.

Given that discernment is jointly determined by judgments of true and false content, it is critical to also examine its constituent parts to determine what is driving the observed effect of discernment. Thus, a two-step approach is needed: first, use a measure of discernment as

Figure 1: Using Discernment vs. Ratings of Only False Content to Determine the Efficacy of Misinformation Interventions



Efficacy of hypothetical misinformation interventions, as determined by ratings of only false content (Panel A) and discernment between true and false content (Panel B). In Panel A, interventions are judged as effective if they have a negative effect on belief/sharing of false content, regardless of their effect on ratings of true content. In Panel B, however, interventions are judged as effective if they decrease belief/sharing of false news more than they decrease belief/sharing of true news. While in Panel A an intervention that decreases belief in all news (true and false) equally is judged as effective, it is judged as having no effect on Panel B because it does not increase a person's ability to distinguish between true and false content.

the primary outcome of interest. Second, if there is a significant effect on discernment, then decompose the constituent components of discernment (separately examine effects on true versus false content); and if there is no significant effect on discernment, then examine the treatment's overall effect (i.e. pooling across true and false content).

Operationalizing Discernment

Past work typically operationalizes discernment as the difference between average ratings of true versus false content (discernment = meanTrue - meanFalse). This is often done by modeling ratings of individual headlines with an interaction between dummy variables for veracity (true vs. false) and group (e.g., treatment vs. control), often using OLS with two-

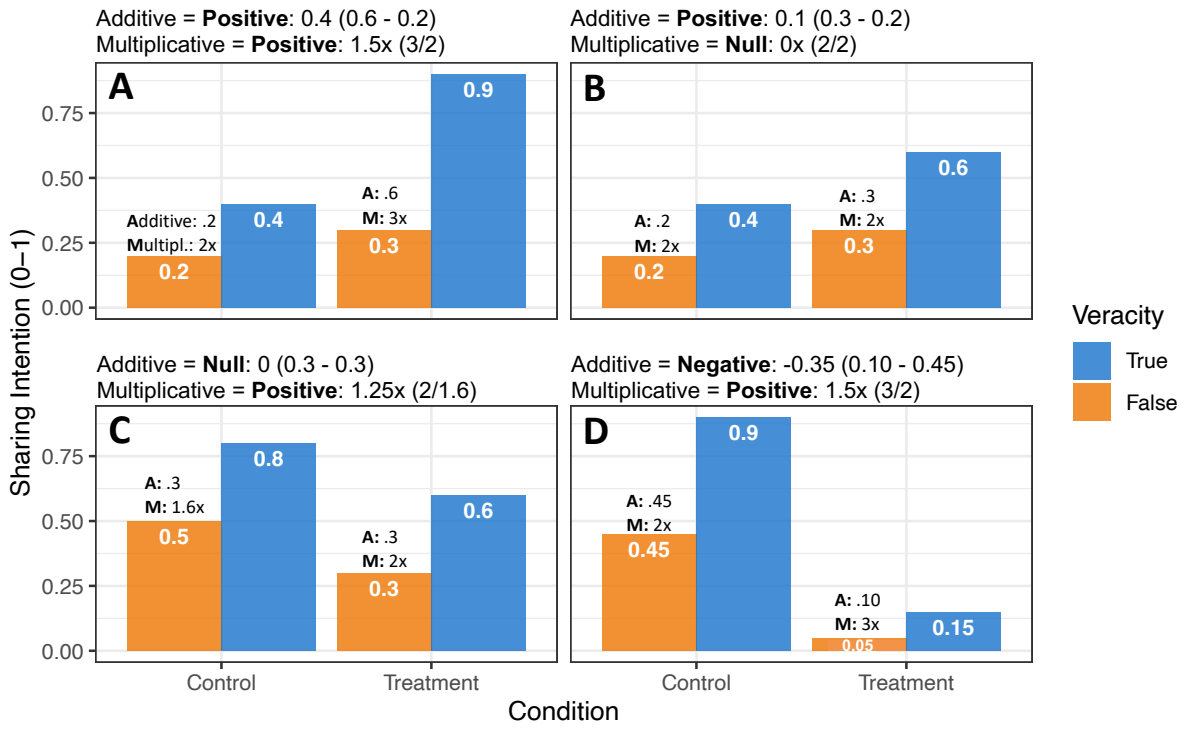
way standard errors clustered on subject and headline. There is a difference in discernment between groups when the coefficient representing this difference-in-differences is statistically significant. Importantly, the interaction used in this modeling approach provides the additive difference between true and false news across conditions, and is therefore sometimes referred to as the additive interaction (VanderWeele and Knol, 2014).

$$\text{Additive Discernment} = (True_A - False_A) - (True_B - False_B) \tag{1}$$

Panel A of Figure 2 illustrates an example of a hypothetical fake news intervention that increases additive sharing discernment. In Panel A, additive discernment in the treatment group (0.9 - 0.3 = 0.6) is higher than in the control group (0.4 - 0.2 = 0.2), and the OLS coefficient representing the interaction between condition and headline veracity represents the difference between them (0.6 - 0.2 = 0.4), indicating that the treatment increases additive discernment.

Illustrative examples of the difference between additive and multiplicative discernment. In Panel A, the treatment increases both types of discernment. Additive discernment is calculated by subtracting the difference between ratings of true news and false news in the control condition (.4-.2 = .2) from the difference between ratings of true and false news in the treatment condition (.9-.3 = .6). This difference in differences (.6-.2 = .4) indicates that the treatment has a positive effect on additive discernment. Multiplicative discernment is calculated with ratios instead of differences: the ratio of true ratings to false ratings in the treatment group (.9/.3 = 3) divided by the ratio of true ratings to false ratings in the control groups (.4/.2=2). The quotient is the treatment effect on multiplicative discernment (3/2 = 1.5) and is greater than one, indicating that multiplicative discernment is 1.5 times higher in the treatment group relative to the control group. Additive and multiplicative discernment are calculated the same way in Panels B and C. In Panel B, the treatment has no effect on additive discernment, (.8-.5)-(.6-.3) = 0, but has a negative effect on multiplicative discernment: the level of multiplicative discernment in the treatment groups is 0.8 times the

Figure 2: Additive vs. Multiplicative Discernment



Illustrative examples of the difference between additive and multiplicative discernment. In Panel A, the treatment increases both types of discernment. Additive discernment is calculated by subtracting the difference between ratings of true news and false news in the control condition (.4-.2 = .2) from the difference between ratings of true and false news in the treatment condition (.9-.3 = .6). This difference in differences (.6-.2 = .4) indicates that the treatment has a positive effect on additive discernment. Multiplicative discernment is calculated with ratios instead of differences: the ratio of true ratings to false ratings in the treatment group (.9/.3 = 3) divided by the ratio of true ratings to false ratings in the control groups (.4/.2=2). The quotient is the treatment effect on multiplicative discernment (3/2 = 1.5) and is greater than one, indicating that multiplicative discernment is 1.5 times higher in the treatment group relative to the control group. Additive and multiplicative discernment are calculated the same way in Panels B and C. In Panel B, the treatment has no effect on additive discernment, (.8-.5)-(.6-.3) = 0, but has a negative effect on multiplicative discernment: the level of multiplicative discernment in the treatment groups is 0.8 times the level of multiplicative discernment in the control group ((.8/.5)/(.6/.3) = 0.8). Finally, in Panel C the treatment decreases additive discernment, (.9-.45)-(.15-.05) = -.35, but has a positive effect on multiplicative discernment ((.15/.05)/(.9/.45) = 1.5).

level of multiplicative discernment in the control group ((.8/.5)/(.6/.3) = 0.8). Finally, in Panel C the treatment decreases additive discernment, (.9-.45)-(.15-.05) = -.35, but has a positive effect on multiplicative discernment ((.15/.05)/(.9/.45) = 1.5).

Additive differences are so commonplace in the social sciences that researchers rarely consider whether multiplicative differences are more appropriate. Multiplicative differences capture multiplicative, or relative, differences between groups (VanderWeele and Knol, 2014; Walter and Holford, 1978) and are calculated by computing a ratio of ratios—the ratio of true ratings to false ratings in one group (e.g., treatment group) to the same ratio in another group (e.g., control group).

$$\text{Multiplicative Discernment} = \frac{True_A/False_A}{True_B/False_B} \tag{2}$$

The intervention in Panel A that increases additive discernment also increases multiplicative discernment, given that the treatment group shares 3 times more true news than false news (0.9 / 0.3 = 3x) while the control group shares only 2 times more true news than false news (0.4 / 0.2 = 2x). The effect of treatment on multiplicative discernment is represented as the ratio of these two quantities (3 / 2 = 1.5).

Additive and multiplicative differences are not always in the same direction. For instance, Panel B illustrates a case in which the treatment has no effect on additive discernment but has a negative effect on multiplicative discernment, while Panel C illustrates a case in which the treatment decreases additive discernment but increases multiplicative discernment.

These discrepancies between additive and multiplicative differences are the result of differences in overall sharing propensity. In Panel B, for instance, respondents in the treatment condition are less likely to share any content (true or false). The difference between additive and multiplicative interaction is particularly important for evaluating the effect of misinformation interventions on discernment because it is not uncommon to see treatments decrease people's tendency to believe and share all news (e.g., Maertens et al., 2021). This results in baseline differences in sharing and believing all news across conditions, but not necessarily improved ability to discern between true and false content. Similarly, baseline differences are common when assessing differences in discernment across subgroups in the population, such as political party (e.g., Guay et al., 2022) and age (Guess et al., 2019).

One likely reason that additive differences are so commonplace in the social sciences is that they can be calculated simply by including an interaction in a linear model estimated with Ordinary Least Squares (OLS). In the case of additive discernment, the coefficient for an interaction between headline veracity and experimental condition gives the difference-in-differences for ratings of true and false content across conditions (Equation 1). Fortunately, multiplicative differences can be calculated easily using an identical modeling approach with a quasi-poisson model rather than OLS. Whereas linear models with identity-link functions (e.g., Gaussian) provide an estimate of additive differences, the Quasi-poisson model provides an estimate of multiplicative differences due to their use of the log-link function. In this case, the exponentiated interaction coefficient reflects how much more discerning one group is compared to another, expressed in multiplicative terms (Equation 2). For instance, a value of 1 indicates that the treatment group is as discerning as the control group, a value of 1.5 indicates that the treatment group is 1.5 times as discerning as the control group, and a value of .5 indicates that the treatment group is half as discerning as the control group. R code to model additive and multiplicative discernment with and without clustered standard errors is available on Open Science Framework[1]

Is additive or multiplicative discernment more appropriate for judging the efficacy of misinformation interventions and assessing differences in discernment across subgroups? The answer depends on the researcher's normative claim about what the intervention should do, which has implications for how differences in baseline rates of belief or sharing are handled. By taking these baseline differences into account, multiplicative discernment reflects differences in the ability of individuals to discern between true and false news—the stated goal of many misinformation studies. As additive discernment does not take these baseline differences into account, it reflects differences in the total amount of true news shared related to false news. A researcher may, for instance, be concerned only with whether an intervention affects the total amount of false news that is shared online, regardless of whether baseline

[1] https://osf.io/ph5yv/?view$_o nly = 1294 ddb906b24620 aed8ec63cf85311e$

differences between the treatment and control group are driving this difference (e.g., as in Figure 2, Panel B).

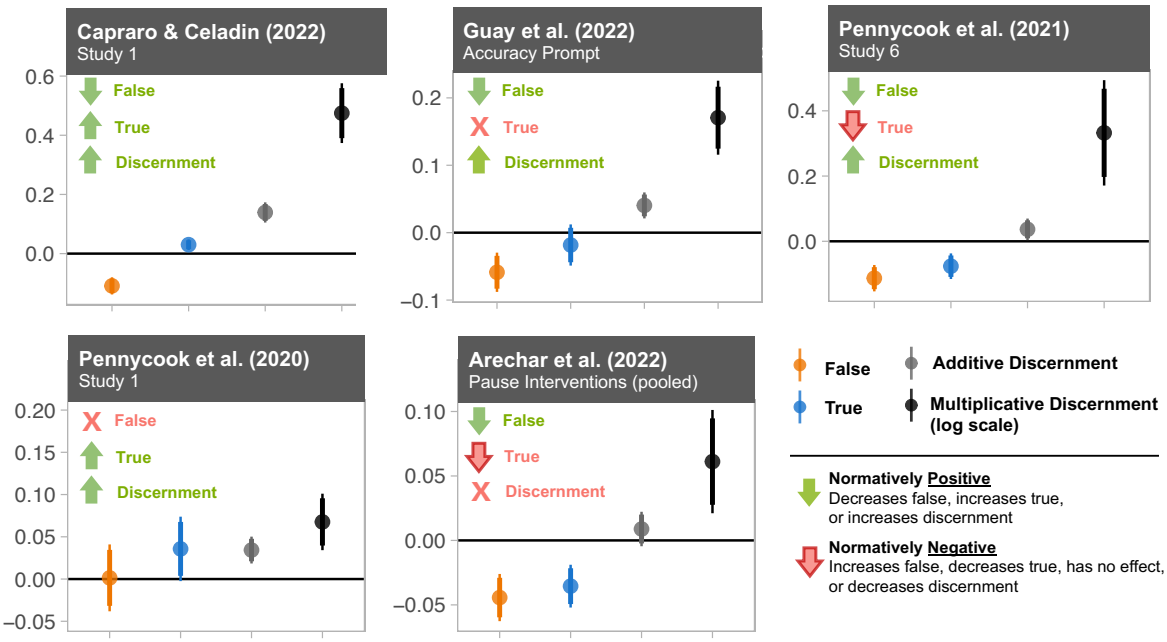
To claim that an intervention is unambiguously effective, researchers should show evidence that it decreases both additive and multiplicative discernment. When researchers have a strong *a priori* reason to judge an intervention as effective if it increases only one type of discernment, however, that reason should be justified and the decision to model only one type of discernment should be pre-registered. Doing so favors analytical decisions that are grounded in theory rather than made post-hoc and improves our understanding of which interventions succeed in slowing the spread of misinformation. We discuss relevant considerations for choosing between additive and multiplicative interaction further in the discussion.

Re-analysis of Fake News Studies Using Belief and Sharing Discernment

To illustrate the importance of belief and sharing discernment, we re-analyze data from seven recent studies that asked respondents to rate true and false news content. Across these studies there is heterogeneity in the construct of interest (belief vs. sharing), the outcome originally used (ratings of only false content vs. discernment), and the research question being evaluated (efficacy of misinformation interventions vs. subgroup differences in susceptibility to false claims).

Figure 3 illustrates the importance of measuring ratings of both true and false content. Interventions that decrease ratings of false headlines (i.e., decrease belief/sharing) can have a positive effect on discernment by increasing ratings of true headlines (capraro2022think , , Panel A) having no effect on ratings of true headlines (guay2022examining , , Panel B) or also having a (smaller) negative effect on ratings of true headlines (Pennycook et al., 2021, , Panel C). In all cases the treatment has a negative effect on false headlines and a positive effect on discernment, despite having very different effects on true headlines.

Figure 3: Different Operationalizations Lead to Different Conclusions



Reanalysis of misinformation studies that measure belief in and sharing of both true and false content. Treatment effects on false content, true content, additive discernment, and multiplicative discernment are plotted separately for each study, where positive coefficients indicate that the treatment increased the outcome. Coefficients representing multiplicative discernment are parameter estimates for the interaction between group (treatment vs. control) and veracity (true vs. false) from the Quasi-poisson models and are on the log scale. Exponentiating these coefficients provides an estimate of how much more likely one group is to share true (vs. false) news than another group. For instance, the parameter estimate for multiplicative discernment in Capraro and Celadin (2022) is 0.78 (log scale). Exponentiated, this number ($e^{0.78} = 2.18$) indicates that the treatment group has 2.18 times higher discernment than the control group. Standard errors are clustered at the respondent and headline level, and vertical lines represent 90% and 95% confidence intervals.

The importance of true headlines is also illustrated in Panel D (Pennycook et al., 2020), where the positive effect of the treatment on true headlines drives increased discernment, despite having no effect on false headlines. Finally, Panel E features a study (Arechar et al. 2022) in which an intervention has no effect on additive discernment because it significantly decreases ratings of true and false content. Without measuring true headlines, interventions that decrease sharing of all content are observationally equivalent to those that target false content specifically. Studies like these are not uncommon. Indeed, Maertens et al. (2021) show that playing a fake news game decreases belief in true and false content equally, and

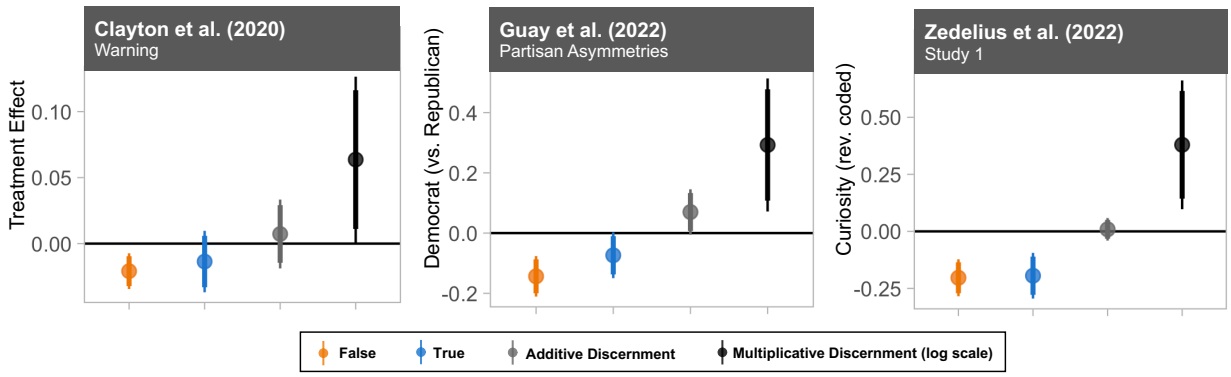
therefore has no effect on discernment. Similarly, Lawson and Kakkar (2022) argue that the liberal-conservative gap in sharing false content is moderated by conscientiousness, with low conscientious conservatives sharing more false content than low conscientiousness liberals. However, an identical pattern emerges for sharing of true content, and there is therefore no moderating effect of conscientiousness on discernment (Lin and Pennycook, 2022).

Panel E also illustrates how additive and multiplicative discernment can differ: while the treatment has no effect on additive discernment, it has a positive effect on multiplicative discernment. Figure 4 illustrates more of these cases. Clayton et al.'s (2020) misinformation warning has no significant effect on additive discernment ($p = .58$), but has a significant effect on multiplicative discernment ($p = .047$). Similarly, Guay et al. (2022) find that Democrats have higher levels of multiplicative discernment ($p < .05$) but not additive discernment ($p = .18$). Similar patterns are evidenced in data from Zedelius et al. (2022), which indicate that deprivation curiosity is associated with multiplicative ($p < .01$) but not additive discernment ($p = .72$). As discussed previously, discrepancies between additive and multiplicative discernment occur when there are differences in overall sharing rates across groups (e.g., treatment and control), and these differences are evident here. For instance, Republicans in Guay et al. (2022) share more of all types of news (true and false) on average than Democrats (Republicans = 0.41, Democrat: 0.30, $p < .01$), people with higher levels of deprivation curiosity in Zedelius et al. (2022) believe news of any kind than those with lower levels (high curiosity = .50, low curiosity = 0.44, $p < .01$), and people in the treatment condition believe more than people in the control condition (treatment = .46, control = .49, $p < .01$).

Discussion

Despite the growing number of interventions aimed at reducing online misinformation, there is widespread incoherence in how the efficacy of these interventions is established. We provide a detailed discussion of common research designs and a clear set of recommendations

Figure 4: Additive and Multiplicative Discernment Can Lead to Different Conclusions



Examples of recent studies with different findings for additive and multiplicative discernment. Standard errors are clustered at the respondent and headline level, and vertical lines represent 90% and 95% confidence intervals. Once again, coefficients representing multiplicative discernment are on the log scale, and once exponentiated indicate the degree to which one group is more discerning than the other. For instance, in Guay et al. (2022), Democrats have 1.34 higher discernment than Republicans ($e^{0.29} = 1.34$); in Zedelius et al. (2022), people with low deprivation curiosity have 1.46 timer higher discernment than those with high deprivation curiosity ($e^{0.38} = 1.46$); in Clayton et al. (2020), people who received a misinformation warning had 1.06 times higher discernment than those who did not ($e^{0.06} = 1.06$).

for how to measure who believes and shares misinformation, and when interventions work. Specifically, we recommend that researchers have participants rate a combination of true and false content, and use discernment between the two as the primary outcome used to determine the efficacy of interventions. This approach avoids conflating the propensity to believe false content with the propensity to believe all content, recognizes the problematic nature of not believing true content, and aligns with the normative claim that people should maximize the accuracy of what they believe and share. We also introduce a multiplicative operationalization of discernment, which captures the ability to distinguish between true and false content better than additive discernment because it accounts for baseline differences in how likely people are to believe or share news of any kind.

Importantly, while our primary focus is on selecting the appropriate research design for testing the efficacy of misinformation interventions, the same considerations and recommendations apply anytime researchers measure how much people believe or share misleading

content. Most research on misinformation compares rates of believing or sharing misleading content across groups, whether those groups are randomly assigned—as in an experiment testing the efficacy of an intervention—or not. For instance, studies often compare rates of believing and sharing misleading content across political ideology

Our primary objective is to guide researchers in choosing a research design that aligns with the intended goal of their study, rather than to prescribe a singular research design for all research on misinformation. While we believe that for most studies on misinformation interventions the intended goal is to maximize the accuracy of the content people believe and share, this may not always be the case. For instance, additive discernment may be appropriate to test the efficacy of an intervention that is intended to reduce the overall amount of false content in the information environment rather than to improve an individual's ability to discern between true and false content. Likewise, an intervention may be intended to decrease belief in false news regardless of whether it decreases belief in true news as well. In all cases, researchers should declare the intent of their intervention and pre-register the research design and approach to analyzing the results that most closely aligns with it.

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