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Judging My-side versus Thy-side: Meta-Forecasting Accuracy Predicts Forecasting Accuracy in the Political Domain

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Abstract

Forecasting research has capitalized on performance-related individual difference measures to improve forecasting accuracy by indicating who is likely a better forecaster, but few studies have examined how socially-relevant factors influence forecasting accuracy. In two experiments (*N* = 2,921), we examined how accurately participants estimated the average forecasts of political ingroups and outgroups (meta-forecasts). We tested whether these meta-forecasts predicted participants' forecasts of the actual outcomes. We found that participants were better at predicting the forecasts of ingroups than of outgroups on group-relevant topics (politics in our study), but not on group-adjacent (i.e, non-political) topics. While meta-forecasting accuracy was predictive of forecasting accuracy, in general, ingroup meta-forecasts on group-relevant topics were particularly good at predicting forecasting accuracy on the topics themselves. Moreover, this did not depend on participants' political affiliation. Meta-forecasts added indicative value regarding forecasting accuracy above and beyond numeracy and an actively open-minded thinking style.

Keywords: Intergroup perception; Forecasting; Outgroup bias; Meta-forecasts; Prediction

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The ability to accurately forecast future events is critical for effective planning and decision-making. Such predictions range from relatively innocuous judgments (e.g., predicting the outcome of a sporting event; Herzog & Hertwig, 2011) to those with substantial real-world consequences (e.g., providing intelligence forecasts to policymakers responsible for national security; Mandel & Barnes, 2018). Forecasting accuracy, along with the factors that systematically influence it, remains a central concern for decision-makers, especially since efforts to accurately forecast complex, social phenomena often fail (The Forecasting Collaborative, 2024). Prior work shows that forecasting accuracy (or probabilistic judgment accuracy) varies across domains and is shaped by individual characteristics (e.g., numeracy; Himmelstein et al., 2021, and logical coherence; Collins et al., 2024; Mellers et al., 2017), behavioral variables (e.g., deliberation time; Mellers et al., 2015), and situational features (e.g., incentives; Chen et al., 2015, accountability; Chang et al., 2017, and training; Chang et al., 2023; Mandel, 2015).

One factor that has received comparatively little attention, however, is the social context in which many forecasting judgments are embedded. Forecasting does not occur in a vacuum: individuals are often aware that others, particularly members of different social groups, hold different expectations about the future, and these perceived group beliefs can serve as informational inputs that inform their own predictions. A key question, then, is whether forecasters can accurately represent these group-level beliefs and how the accuracy of such representations shapes their own forecasts. We refer to estimates of others' probabilistic beliefs as *meta-forecasts* (i.e., forecasts about what others would forecast on a given topic), and propose that their accuracy constitutes a meaningful and measurable dimension of forecasting competence, one that predicts first-order forecasting accuracy (i.e., the accuracy of one's own forecast about a given topic) above and beyond established individual-difference predictors.

Efforts to increase forecasting accuracy range from interventions targeting the individual (e.g., probability training; Chang et al., 2023; Mandel, 2015) to those leveraging the potential benefits of working in teams (Mellers et al., 2014). Concerning the latter, Mellers et al. (2014) found that individuals working in teams to forecast geopolitical outcomes produced more accurate predictions than those working independently. This performance advantage can be attributed to at least two mechanisms. First, some improvement may be due to the increased precision offered by aggregating predictions from multiple individuals—the aptly named wisdom of the crowds effect (Surowiecki, 2004). Second, working in groups may enhance accuracy by introducing forecasters to outside perspectives that they might not otherwise consider (Herzog & Hertwig, 2009). If incorporating diverse perspectives within teams improves forecasting accuracy, can similar improvements be achieved within *individuals* by encouraging them to consider alternative perspectives?

Decades of research reveal that adopting alternate perspectives can improve judgement and decision-making (eg., Epstude & Roese, 2008; Galinsky et al., 2008; Gleicher et al., 1990). For example, the "consider-the-opposite" technique (Lord et al., 1984), in which individuals are prompted to consider alternative event outcomes, has been shown to reduce bias in social judgment. Similarly, making alternative hypotheses explicit improves the accuracy and coherence of probabilistic judgments (Williams & Mandel, 2007). An important question raised by this work, however, is whether all alternative perspectives are equally useful. The beliefs of others are not passively received but must be actively constructed. As such, peoples' perceptions of others' beliefs may vary in accuracy, with some containing systematic errors and others being quite accurate. This raises a further question: does the accuracy of such perceptions determine the degree of wisdom they afford? When alternative perspectives are misrepresented, the potential benefits of considering multiple viewpoints may be substantially diminished.

People often hold systematically distorted mental models of outgroup members, exaggerating their extremity, misattributing their motives, and underestimating the degree to which they share common ground (Boldry et al., 2007; Judd et al., 2005). These misperceptions have been documented across social, political, and organizational contexts, and have downstream consequences for intergroup conflict, cooperation, and collective decision-making (Fiske, 2002; Iyengar et al., 2019; McInnis & Page-Gould, 2015). In the domain of politics, reasoning is often shaped by partisan affiliations, biased information environments (Brady et al., 2023; Iyengar & Hahn, 2009; Stroud, 2008, 2010), motivated cognition (Kunda, 1990), and meta-perceptual biases (Bogart & Lees, 2023). These dynamics facilitate partisan misperceptions. For example, Democrats and Republicans tend to overestimate the homogeneity and hostility of rival partisans (Rothschild et al., 2021), and attribute more bias to political out-group compared to in-group members (Walker et al., 2026).

The current paper investigates the utility of prompting individuals to consider group-level beliefs as a means of introducing perspective diversity into individual forecasts. In contrast to prior work on group-based forecasting—which allows individuals to incorporate the views of multiple forecasters—we examine whether asking individuals to estimate, and thus explicitly consider, the forecasts of others, particularly out-group others, improves forecasting performance. We posit that considering alternative perspectives in this way is not a universal boon for forecasting accuracy. Individuals often misperceive others' beliefs, especially those of out-group members, and such misperceptions may lead the consideration of others' beliefs to reduce rather than improve forecasting accuracy. We therefore test whether the accuracy of forecasters' meta-forecasts of other's beliefs (specifically, their estimates of others' predictions regarding a given event) is itself predictive of forecasting accuracy. That is, we examine whether the ability to accurately infer the forecasts of others, particularly dissimilar others, serves as a useful indicator of forecasting performance.

Meta-forecasts as Social Perception

Forecasting is not simply a matter of reasoning about events; it is, in many cases, an act of social inference. When people form probabilistic judgments about future outcomes, they often do so with awareness that different social groups hold different expectations, and these perceived expectations can shape their own beliefs (Gigerenzer & Gaissmaier, 2011). Thus, in addition to estimating the probability of an event, forecasters might also represent how others will respond to that same question (i.e., generate *meta-forecasts*) and use these representations as inputs that guide their own predictions. Meta-forecasting is a form of meta-representation, requiring individuals to decouple their own beliefs from higher-order representations of group-level beliefs (Leslie & Happe, 1989). As such, it depends on processes of social perception (Battich et al., 2025), meta-perception (Vorauer et al., 2025), and theory of mind (Eyal et al., 2018), processes that are only partially shared with those underlying event prediction. Importantly, this means that meta-forecasting accuracy is not merely a byproduct of general forecasting skill. Instead, because it draws on partially distinct social-cognitive processes, it may capture variance in forecasting competence that cognitive measures such as numeracy and actively open-minded thinking do not.

People process information about ingroups and outgroups differently. For example, individuals are generally more motivated to form accurate impressions of ingroup members, with whom they anticipate future interaction, than of outgroup members, toward whom accuracy motivation is lower and reliance on heuristic, stereotype-based inference is greater (Fiske & Neuberg, 1990). Moreover, people tend to have limited contact with outgroup members, often self-selecting into socially and ideologically homogenous networks (Cinelli et al., 2021; Mosleh et al., 2021; Motyl et al., 2014). Likewise, individuals tend to consume information that reflects the perspectives of their ingroup (Iyengar & Hahn, 2009; Peterson et al., 2021; Stroud, 2008, 2010), while failing to adequately correct for biased sampling (van der Valk et al., 2025). The consequence is that outgroup mental models tend to be caricatures rather than accurate representations, and it is these caricatures that forecasters draw on when asked to represent outgroup beliefs. Accordingly, we hypothesize that meta-forecasts will be more accurate when individuals estimate the average forecast of ingroup members rather than outgroup members (Hypothesis 1).

Forecasting Domain

Forecasting performance depends in part on information structure: some domains offer stable, information-rich environments that support relatively high accuracy (e.g., short-term meteorological predictions; Grossmann-Matheson et al., 2024), whereas others involve long causal chains or unresolvable uncertainty, thereby reducing accuracy (e.g., clinical trial outcomes; Benjamin et al., 2022; Kimmelman et al., 2023, predicting societal change; Grossmann et al., 2023). Even within a single domain, accuracy can diverge substantially depending on incentives, accountability pressures, and audience expectations. For instance, geopolitical forecasts of political experts polled in a research context (i.e., low accountability pressure) barely surpass chance-level accuracy (Tetlock, 2005). Yet, under high-accountability conditions, strategic intelligence analysts' on-the-job forecasts exhibit high accuracy and under-confidence (Mandel & Barnes, 2014, 2018).

The relevance of group membership to forecasting also varies across domains. Political forecasting warrants specific attention because it involves judgments embedded in group identities, ideological commitments, and partisan animosity. Political contexts often contain strong informational streams (i.e., news, polling, campaign messaging, and widespread discourse) that, in principle, can support more accurate predictions than many non-political analogs. However, political reasoning is also shaped by partisan affiliations, motivated cognition (Kunda, 1990), and meta-perceptual biases (Bogart & Lees, 2023), giving rise to partisan misperceptions (Flynn et al., 2017). This creates a distinctive forecasting environment in which misrepresentation may override the informational advantages that political context otherwise provide.

When individuals consider ingroup beliefs, they can draw on direct familiarity across both political and non-political domains. Conversely, when considering outgroup beliefs, they are more likely to rely on indirect or stereotyped representations (Rothschild et al., 2019). In the United States, for example, political identity often structures disagreement, and public discourse frequently highlights differences between Democrats and Republicans (Collins et al, 2021; Gentzkow et al., 2019; Irwin et al., 2023; Iyengar et al., 2019; Sterling et al., 2020; Walker et al., 2025). Thus, when group boundaries are defined along ideological lines, they are directly relevant to political questions and less relevant to non-political ones. Consequently, perspective-taking should have clearer implications for meta-forecasting accuracy in political contexts, where partisan group distinctions are tightly coupled to the content of the judgment, than in non-political contexts, where this coupling is weaker. When reasoning from an outgroup perspective in political contexts, individuals must estimate the beliefs of partisan opponents—judgments that are often shaped by stereotyping and exaggeration of group differences (Denning & Hodges, 2022; Rubin & Badea, 2007). As such, we expect that the forecasting domain (political versus non-political) will moderate the relationship between perspective and meta-forecasting accuracy, such that the reduced accuracy of outgroup meta-forecasts (relative to ingroup meta-forecasts) will be greater in the political domain (Hypothesis 2).

Linking Meta-forecasts to Forecasts

There are several reasons to expect meta-forecasting accuracy to serve as a reliable indicator of forecasting performance. First, both tasks require probabilistic reasoning, calibration, and the integration of information under uncertainty. Research on forecasting performance suggests that accuracy reflects stable individual differences (e.g., Mellers et al., 2017; Poore et al., 2014). For example, individuals who perform well on one set of forecasting tasks tend to perform well on others, with characteristics such as numeracy and analytic cognitive style associated with greater accuracy (Ghazal et al., 2014). Compared to lower-performing forecasters, high-performing forecasters also discriminate among verbal probabilities used to convey uncertainty in forecasts more effectively (Mellers et al., 2017) and exhibit more coherent probabilistic judgments (Collins et al., 2024). Together, this evidence is consistent with the existence of a general component of forecasting ability that contributes to performance across tasks. Accordingly, meta-forecasting accuracy should be positively associated with forecasting performance. Individuals who are more skilled at probabilistic reasoning should perform better both when estimating event probabilities and when inferring others' judgments. Moreover, meta-forecasts may guide how individuals structure their own probabilistic judgments. People routinely rely on perceived norms and expectations when making such judgments (Gigerenzer & Gaissmaier, 2011), with more accurate meta-perceptions being associated with better social reasoning (Ames & Wakslak, 2014). In short, if meta-forecasting accuracy varies as a function of forecasting perspective (as proposed in Hypothesis 2), and if it predicts forecasting accuracy, then it should mediate the effect of forecasting perspective on forecasting accuracy (Hypothesis 3).

Since we expect meta-forecasting accuracy to vary more strongly when inferring outgroup perspectives and across political versus non-political domains, the indirect effect of perspective on forecasting accuracy should be conditional on domain. Ingroup-outgroup distortions should be amplified in political settings, where polarization can highlight salient group differences and provide abundant (often biased) cues about how groups respond (Denning & Hodges, 2022). Accordingly, the extent to which meta-forecasting accuracy mediates the relationship between forecasting perspective and forecasting accuracy should be greater in political rather than non-political domains (Hypothesis 4).

Finally, we assess whether meta-forecasting accuracy serves as a unique predictor of forecasting performance by accounting for a broad set of individual differences associated with forecasting accuracy. A well-established literature identifies statistical numeracy, analytic cognitive style, and actively open-minded thinking as consistent predictors of forecasting accuracy (Himmelstein et al., 2021; Mellers et al., 2015; Cokely et al., 2012). These traits index capacities such as probabilistic calibration, reflective reasoning, and resistance to motivated judgment, all of which can contribute to forecasting performance. At the same time, forecasting accuracy may be shaped by individual differences in intergroup perception and motivated political judgment. For example, stronger negative affect toward outgroups may undermine accuracy by directing attention toward stereotype-consistent information and away from disconfirming evidence (Kunda, 1990). Similarly, strong partisan identity and perceptions of outgroup bias may encourage identity-consistent interpretations of political events and more dismissive or distorted judgments of opposing partisans. Conversely, dispositional empathy may support more accurate judgments by promoting greater consideration of others' perspectives (Hodges & Wegner, 1997). As such, we include age, sex, education, empathy, actively open-minded thinking, affective polarization, relative bias, political identity strength, numeracy, and polling knowledge as covariates. This approach allows us to test whether meta-forecasting accuracy explains unique variance in forecasting performance above and beyond established correlates. If so, it would suggest that the ability to accurately represent others' beliefs—particularly those of political outgroup members—constitutes a distinct forecasting skill, one that is especially valuable in polarized environments where misperceptions are both common and consequential for judgment accuracy.

Overview of Experiments

We conducted two experiments that were approved by Defence Research and Development Canada's Human Research Ethics Committee (protocol #2023-032) to test our hypotheses. In both Experiments 1 and 2, we used a 2 (Political Party: Democrat, Republican) x 2 (Forecasting Perspective: Ingroup, Outgroup)[1] x 2 (Forecasting Domain: Political, Non-Political) mixed effects design. . Rather than having an intrinsic interest in our subsamples, we selected Democrat and Republican subsamples so that we could define ingroups and outgroups

[1] We included an additional condition in which participants were asked to forecast the perspective of the average survey respondent. However, we did not include this condition in analyses reported here as it was not relevant to current investigation.

where unambiguous group polarization is met and where we could be adequately sample for well-powered studies. To be clear, we are not investigating particular insights into the United States of America political system or studying United States of America political affiliations for their own sake, and the choice is purely methodological. In addition, Experiment 2 included an exploratory Partisan Depolarization Task (Intervention Condition vs. Control Writing Task) but was identical to Experiment 1 in all other respects. Experiment 1 was run simultaneously with Experiment 2 to control for differences in forecasting information. Specifically, many of the events forecasted were tied to specific timelines and resolved at a certain point in time. Collecting both datasets simultaneously allowed us to control the amount of domain information participants had about particular events. For example, asking participants to forecast the likelihood of the Sacramento Kings advancing to the second round of the NBA playoffs in 2024 would be confounded if some participants responded midway through the first round of the playoffs while others responded prior to the first game.

Experiment 1

Methods

Both studies in this paper were not preregistered. Data, analyses, and supporting files are available from the Open Science Foundation (OSF) project page (https://osf.io/4hp7j/overview?view_only=ec298588d6fc46e8a0fffc85f4b42917).

Participants

Participants were recruited on the Prolific [2] crowdsourcing platform such that only those who met our eligibility criteria (i.e., 18 or older, completed high school, English as a first

[2] See https://www.prolific.com/ for information on the crowdsource provider.

language, U.S. resident, self-identifying Republican or Democrat, 100-10,000 work submissions completed on Prolific, Prolific submission approval ≥ 95%) were invited to complete Experiment 1. After consenting to participate, participants confirmed their eligibility by completing the same questions used to prescreen their eligibility. Participants whose responses did not match their Prolific profile were asked to return the survey on Prolific. Eligible participants who completed Experiment 1 received $5 USD.

Given that our primary hypothesis concerned the interaction between perspective and domain on meta-forecasting accuracy, sensitivity power analyses conducted in G*Power (Faul et al., 2007) we estimated a sample size to provide at least 80% power to detect effects as small as ηp2 = .113. We recruited 1,665 participants and excluded data from participants who provided duplicate or fraudulent responses (as per Qualtrics identifiers), did not complete the full survey, reported an age different than in their Prolific profile, or chose “Independent” on the Political Ideology survey question. Our final sample comprised 922 participants (52.52% female, M_{age} = 43.98, SD_{age} = 13.83, 60% Democrats; 76% post-secondary educated).

Procedure

After validating their eligibility, participants answered several questions assessing the strength of their political party. Participants were then randomly assigned to adopt the perspective of the average Democrat or Republican while forecasting the probability of 28 future events. Half of these events were political in nature (e.g., “What is the probability that Republicans will control the Senate after the 2024 elections?”) and the other half non-political (e.g., “What is the probability that Bronny James will be drafted to the NBA this year?”), with the order of these two forecasting domains and the events within each domain randomized between participants.

Forecasting task

Participants completed a series of forecasting questions, making predictions for 14 political and 14 non-political events (order counterbalanced between and within forecasting event type; see Appendix A in the Supplementary Materials for a complete list of forecasting items)[3]. These events were sampled from Polymarket.com, Good Judgement Open (gjopen.com), and Metaculus.com. To balance the wording of items so that they were not biased in a partisan direction, we used Democrat-congruent wording for half of political items (e.g., "What is the probability that Democrats will win control of the U.S. House of Representatives in 2024?") and Republican-congruent wording for the other half of political items (e.g., "What is the probability that Donald Trump will win the 2024 U.S. Presidential election?"). In other words, if the events were to occur, Democrats would be expected to be pleased with the Democrat-congruent outcomes and, likewise, Republicans would be expected to be pleased with the Republican-congruent outcomes.

Participants made two sets of predictions for each event: a set of meta-forecasts followed by a set of forecasts, for 56 judgments in total. For meta-forecasting items, participants made forecasts from the perspective of either the average Democrat or Republican, depending on random assignment. Thus, as we exclusively recruited Democrats and Republicans in Experiment 1, participants were randomly assigned to provide meta-forecasts of the average political ingroup or outgroup member. Each event was prefaced with the prompt: "How do you think the average [Democrat/Republican] would respond to the following question?" For

[3] One item was removed from our analysis due to unclear event resolution, where the research team could not conclusively determine the outcome of the event.

forecasts, each event was prefaced with the following: "How would you personally respond to the following question?"

After the end of the experiment, forecast accuracy was assessed using Brier scores, which are calculated by taking the mean square error of the difference between participants' forecasted probability and the resolved outcome of the forecasted event (1 = *occurred* or 0 = *did not occur*). Lower Brier scores indicate better accuracy, with 0 being the best possible score.

Brier Scores are calculated as:

$$Brier\ Score = \frac{1}{\mathrm{N}}\sum_{t=1}^{N}(f_t - O_t)^2$$

where: N is the number of forecasts made, t is the individual forecast (t, N), f_t is the probability of the forecast (0 - 1), and O_t is the outcome of the event (0, 1).

Meta-forecasting accuracy was calculated as the squared deviation between a participants' forecast for that group and that group's mean forecast. For example, if on average, Democrats assigned a 35% probability to Donald Trump winning the 2024 U.S. Presidential election, then the meta-forecasting accuracy for participants asked to estimate the forecasts of the average Democrat for this item was calculated as the squared deviation between 0.35 and their estimate. Lower scores indicate more accurate perception of group responses.

Meta-forecasting accuracy scores were calculated as:

$$\text{Accuracy}_{i,j} = (\text{MF}_{i,j} - \overline{\text{S}}F_{Group,j})^2$$

where: i = Participant, j = Item, MF = Meta-forecasts, and $\overline{SF}$ = Mean forecast for that group on item j.

After completing all forecasting trials, participants reported their affective feelings and bias attributions toward the average Democrat and Republican. Additional measures were presented in a randomized order and assessed thinking style, empathy, numeracy, and familiarity with online forecasting and prediction markets. Finally, participants were debriefed, thanked for their participation, and remunerated. All measures used can be found in the Supplementary Materials, and we describe each measure in brief below.

Political Identity Strength

We measured the strength of participants' identification with their preferred political party using five items adapted from Leach et al. (2008). Participants judged how much they agreed with statements assessing the strength of their partisan identification (e.g., "I have a lot in common with the average [Democrat/Republican]") using a 7-point scale that ranged from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). These items showed excellent internal consistency (α = .93) supporting their aggregation into a composite measure of political identity strength.

Active Open-mindedness (AOT)

Participants completed a recent adaptation of the Actively Open-Minded Thinking Questionnaire (AOT; Stanovich & Toplak, 2023), featuring 13-items designed to assess their consideration of alternative opinions and propensity toward reflective thought (e.g., "People should always take into consideration evidence that goes against their opinions"). Responses were made using a 6-point scale with no midpoint (-2.5 = *Disagree strongly*, +2.5 = *Agree strongly*) and then averaged into a composite measure of open-mindedness (α = .87).

Empathy (IRI)

Participants completed the Interpersonal Reactivity Index (IRI: Davis, 1980), a 14-item questionnaire indexing empathy. Participants responded to a series of statements describing various thoughts and feelings in various situations (e.g., "I try to look at everybody's side of a disagreement before I make a decision") and indicated how well they described themselves (0 = *Does not describe me at all,* 4 = *Describes me very well*). Items were averaged to form an empathy composite score ($\alpha = .91$) where higher values indicate greater empathy.

Numeracy

An adapted version of the Berlin Numeracy Test (Cokely et al., 2012) assessed participants' statistical numeracy. Participants completed four mathematical thought problems (e.g., "Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws, how many times would this five-sided die show an even number (2 or 4)?") and were scored based on the number of correct answers.

Familiarity with polling/betting websites

Using a 7-point scale, participants rated how familiar they were with polling/betting websites where individuals can predict/bet on real-world events (1 = *Not familiar at all*, 7 = *Extremely familiar*).

Affective polarization

To control for differences in how participants felt about each forecasting group, they were asked to rate their feelings toward the average Democrat and Republican. Responses were made using a sliding scale ranging from 0 (*Extremely negative*) to 100 (*Extremely positive*). In line with previous studies measuring affective polarization (e.g., Druckman & Levendusky, 2019; Renström et al., 2023), we calculated an affective polarization score by subtracting participants' political outgroup affect rating from their political ingroup affect rating (i.e., ingroup affect – outgroup affect). Higher scores indicate higher levels of affective polarization.

Relative bias

Participants also rated how biased they perceived the average Democrat and Republican to be (adapted from Walker et al., 2026). Participants responded on a sliding scale ranging from 0 (*Not at all biased*) to 100 (*Extremely biased*). We calculated relative bias by subtracting participants' political outgroup bias rating from their ingroup bias rating (i.e., ingroup bias - outgroup bias).

Results

All analyses were performed using R Statistical Software (v4.5.2; R Core Team 2025). Table 1 contains descriptive statistics and zero-order correlations among all variables of interest. Political meta-forecasting accuracy was significantly correlated with political forecasting accuracy ($r = .29$, $p < .001$), indicating that participants who more accurately estimated the beliefs of political group members also tended to make more accurate political forecasts. By contrast, non-political meta-forecasting accuracy was not reliably associated with forecasting performance for either political ($r = .03$, $p = .505$) or non-political items ($r = .05$, $p = .313$). The specificity of this relationship to political meta-forecasting suggests that the link between social belief accuracy and forecasting performance is not a general artifact of shared task demands, but rather reflects something particular to the political domain where partisan biases are most likely to distort group representations.

To test the proposed mechanism, we estimated a moderated mediation model with the R package *lavaan* (Version 0.6-20; Roseel et al., 2025) in which forecasting perspective (ingroup vs. outgroup) predicted meta-forecasting accuracy (Stage 1), which in turn predicted forecasting accuracy (Stage 2). Forecasting domain (political vs. non-political) moderated the effect of perspective on meta-forecasting accuracy (the *a* path) and the direct effect of perspective on forecasting accuracy (the c' path). All predictors were centered prior to analysis. Political party was included as a covariate in both stages of the model, while age, sex, education, empathy, actively open-minded thinking, affective polarization, relative bias, political identity strength, numeracy, and polling knowledge were included as covariates in the second stage of the model only.[4] Political party was included in both stages to account for its potential association with both meta-forecasting and forecasting, whereas the remaining covariates were included only at the outcome stage to reduce model complexity and because they were not central predictors of meta-forecasting accuracy. This model is treated as the primary model and demonstrated good fit (CFI = 0.95, TLI = 0.86, RMSEA = .04, SRMR = .02). Results from the model are summarized below in Table 2, with all relevant model paths visually presented in Figure 2.

Forecasting perspective had a significant effect on meta-forecasting accuracy (Table 2). Supporting Hypothesis 1, participants were more accurate when estimating the beliefs of their political ingroup compared to outgroup. The interaction between domain and perspective was significant (see Figure 1, Panel A). In the political domain, meta-forecasting accuracy differed

[4] As we had no a priori hypotheses regarding how political party (i.e., party identification) would influence the relationships among our primary variables, we included political party only as a covariate rather than as a focal predictor. However, because party identification could plausibly shape how participants adopt ingroup versus outgroup perspectives, we conducted an exploratory model testing the three-way interaction among item domain, perspective, and political party on meta-forecasting accuracy. This interaction was not significant, and the full results of this exploratory analysis are reported in the Supplementary Materials (Table S2).

significantly by forecasting perspective, $b = -.009$, SE = .001, 95% CI [-.011, -.006], $p < .001$. In contrast, for non-political events, there was no difference in meta-forecasting accuracy between perspectives, $b = -.001$, SE = .001, 95% CI [-.002, .001], $p = .505$. The difference between these slopes was significant, revealing that decreases in accuracy when estimating the forecasts of outgroup relative to ingroup members were more pronounced in the political domain, providing support for Hypothesis 2. These effects held after adjusting for participants' political party.

Next, we examined the indirect effect of perspective on forecast accuracy via meta-forecasting accuracy. This conditional indirect effect of perspective was significant for political items but not for non-political items. The index of moderated mediation was also significant, indicating that the magnitude of the indirect effect differed between domains. These results support Hypotheses 3 and 4.

To better ascertain whether the predictive effect of meta-forecasting accuracy on forecasting accuracy depends on whether the target of meta-forecasting is the ingroup or the outgroup, we compared the correlation between forecasting accuracy and meta-forecasting accuracy across ingroup and outgroup perspectives separately for political and non-political items using Fisher's r-to-z test for independent correlations. For participants who judged ingroup members, the correlation was significantly stronger among ingroup participants, ($r = .54$), than among outgroup participants, ($r = .37$), $z = 3.04$, $p = .002$. In contrast, for participants who judged outgroup members, the difference in correlations among ingroup participants, ($r = .27$) and outgroup participants, ($r = .32$) was not significantly different, z = -0.68, $p = .50$. It is also noteworthy that the correlation in the outgroup-political subset ($r = .33$) was not significantly different from the correlation in the outgroup-nonpolitical subset ($r = .37$), $z = 0.11$, $p = .78$.

In addition to the main hypothesized paths, several covariates showed unique associations with forecasting accuracy in the outcome stage of the model. Greater political identity strength and empathy were associated with lower forecasting accuracy, whereas more actively open-minded thinking and higher numeracy, as well as lower affective polarization, were associated with improved forecasting performance. Identifying as Democrat (effects coded as Republican = -1, Democrat = 1) was associated with lower forecasting accuracy. No other covariates were associated with forecasting accuracy in our model.

We also estimated a more parsimonious version of this model including only basic demographic covariates. The focal parameters (paths a and b, the perspective and domain interaction, and the conditional indirect effects) were substantively unchanged. A robust likelihood-ratio test indicated that this model fit the data significantly worse than the model above, $\Delta\chi^2(10) = 43.56$, $p < .001$. The previous model was also favored by information criteria (ΔAIC ≈ -51; ΔBIC ≈ -4), indicating that the added covariates improved model fit beyond what would be expected from increased complexity. Results from this reduced model are reported in the Supplementary Materials (Table S1).

Discussion

Experiment 1 examined whether meta-forecasting accuracy affects forecasting performance across political and non-political domains. Three key findings emerged. First, participants were more accurate when estimating the forecasts of the average political ingroup compared to outgroup member. Second, this heightened accuracy was restricted to the political domain. Third, meta-forecasting accuracy predicted forecasting accuracy, and this association was conditional on domain. The conditional indirect effect of perspective on forecasting accuracy via meta-forecasting accuracy was significant for political, but not non-political judgments. The predictive effect of meta-forecasting accuracy on forecasting accuracy was strongest in the ingroup condition and when judging group-relevant (i.e., political) forecasting topics. Overall, the results from Experiment 1 suggest that, when adopting alternative perspectives, people hold more accurate perceptions of political in-group than out-group members and that meta-forecasting accuracy determines the impact that perspective taking has on forecasting performance.

Experiment 2

Experiments 1 and 2 were run concurrently. The primary aim of Experiment 2 was to assess the replicability of Experiment 1 results. In addition, we introduced an exploratory depolarization task to examine whether it could improve the accuracy of participants' meta-forecasts of outgroup members and, in turn, enhance forecasting accuracy among those assigned to estimate, and thus explicitly consider, outgroup perspectives.

Methods

Participants

Participants were screened on Prolific (Prolific, 2024) using the same eligibility criteria as Experiment 1. Eligible participants who completed the study received $6 USD as compensation for their participation. We excluded data from participants who provided duplicate or fraudulent responses (as per Qualtrics identifiers), did not meet inclusion criteria, did not complete Experiment 2, reported demographic characteristics that did not match their Prolific profile, identified politically as an Independent, or who did not adhere to instructions provided to them during a writing task. Our final sample comprised 1,530 participants (56.93% female, M_{age} = 41.60, SD_{age} = 14.00; 70% Democrats; 78% College educated).

Procedure

Similar to Experiment 1, Experiment 2 used a 2 (Political Affiliation: Democrat, Republican) x 2 (Forecasting Perspective: Partisan Ingroup, Partisan Outgroup) x 2 (Forecasting Domain: Political, Non-Political) x 2 (Partisan Depolarization Task: Intervention Condition, Control Writing Task) mixed effects design. Regarding the final addition, Experiment 2 included a partisan depolarization task (adapted from Levandusky, 2018; Voelkel et al., 2024). Participants were randomly assigned to a depolarization intervention condition or a control writing task. Those assigned to the depolarization intervention were instructed to think about a partisan outgroup member they liked or respected. If none existed, they were instructed to think of the partisan outgroup member they viewed the most positively (or least negatively). Participants were then instructed to write a minimum of 150 characters about why they liked and respected this person. They then identified whether the person they wrote about was a friend, family member, co-worker, neighbor, or someone else, and rated how close they were to this person on a 5-point scale (0 = *Not at all close*, 4 = *Extremely close*). Participants assigned to the control writing task re-wrote a short paragraph presented to them (displayed as a photo and scrambled with JavaScript to prevent them from copying and pasting the text). Verbatim instructions for the depolarization task can be found in Part C of the Supplementary Materials. Following this writing task, participants concluded Experiment 2 by completing the same series of forecasting items and individual difference measures as Experiment 1.

Results

Table 3 contains descriptive statistics and zero-order correlations among all variables of interest. We estimated the same moderated mediation model as in Experiment 1, again including the full set of demographic, political, and psychological covariates in both stages. For preliminary analyses, we allowed all focal paths to vary by intervention condition, but the intervention showed no main effects and did not moderate any of the relationships among perspective, domain, meta-forecasting accuracy, and forecasting accuracy (all *p*s > .70). As the intervention was exploratory and ancillary to our main hypotheses, and because it showed no main effects nor moderated any of the focal relationships, we treated intervention condition as a covariate rather than a moderator in all subsequent analyses. Full results from the model including intervention interactions are reported in the Supplementary Materials (Table S3).

Replicating Experiment 1, forecasting perspective predicted meta-forecasting accuracy (b = -.006, SE = .001, 95% CI [-.007, -.004], $p < .001$. That is, participants were more accurate when estimating ingroup beliefs than outgroup beliefs. As in Experiment 1, there was a significant interaction between perspective and domain, b = -.005, SE = .001, $p < .001$. Probing this interaction by domain showed that the effect of perspective on meta-forecasting accuracy was negligible for non-political items, but significant for political items, indicating that the impact of perspective on meta-forecasting accuracy was specific to the political domain, in line with Hypothesis 2 (see Figure 1B). The conditional indirect effect of perspective on forecasting accuracy via meta-forecasting accuracy was moderated by domain. This indirect effect was significant for political items, but not for non-political items, as in Experiment 1. The index of moderated mediation was significant (b = .009, SE = .001, 95% CI [.007, .012], $p < .001$, indicating that the conditional indirect effect of perspective on forecasting accuracy via meta-forecasting accuracy was stronger in the political compared to non-political domain.

Similar to Experiment 1, we compared the correlation between forecasting accuracy and meta-forecasting accuracy within ingroup and outgroup conditions separately for political and nonpolitical items. As we found in Experiment 1, for participants judging political items, the correlation was significantly stronger among participants judging the ingroup, (r = .57), than among those judging the outgroup, (r = .35), z = 4.38, p < .001. In contrast, and once again replicating the findings of Experiment 1, for participants judging nonpolitical items, the difference in correlations among participants judging the ingroup (r = .40) and those judging the outgroup (r = .30) was not significant, z = 0.70, p = .08. Moreover, once again, the correlation in the outgroup-political subset (r = .35) was not significantly different from the correlation in the outgroup-nonpolitical subset (r = .30), z = 0.84, p = .40.

The pattern of covariate effects in Experiment 2 partially mirrored those observed in Experiment 1. In Experiment 2, more actively open-minded thinking was again associated with greater forecasting accuracy, whereas stronger political identity and Democratic party identification were again associated with lower forecasting accuracy. In contrast with Experiment 1, numeracy and empathy were no longer significant predictors in Experiment 2, whereas age emerged as a significant predictor of decreased forecasting accuracy. Education, relative bias, and polling familiarity were not reliably associated with forecasting accuracy in either experiment. These effects are summarized in Table 4 and Figure 3.

Discussion

Experiment 2 replicated the main findings from Experiment 1 and supported Hypotheses 1-4. Participants were more accurate at estimating the forecasts of political ingroup compared to outgroup members in the political domain, with no such advantage being observed for non-political judgments. Meta-forecasting accuracy, in turn, predicted the accuracy of individuals' forecasts, with more accurate meta-forecasts being associated with more accurate forecasting judgments. The depolarization intervention did not influence meta-forecasting accuracy, forecasting accuracy, or any other theoretically relevant variables. Thus, political forecasts may not be sensitive to brief manipulations of outgroup affect, in part, because such interventions do not improve the accuracy with which individuals represent outgroup beliefs. Experiment 2 also partially replicated the pattern of individual differences observed in Experiment 1. Across both experiments, forecasting accuracy was most consistently associated with actively open-minded thinking and weaker political party identification.

General Discussion

A substantial body of research has identified cognitive and motivational predictors of forecasting accuracy, with numeracy, actively open-minded thinking, and analytic cognitive style emerging as reliable predictors of performance (e.g., Mellers et al., 2014; 2025; Moore et al., 2017; Poore et al., 2014). The present findings add a social-perceptual dimension to this picture, demonstrating that the fidelity with which individuals represent the forecasts of others—particularly outgroup members—shapes how accurately they predict future outcomes. Across two experiments, we examined how forecasting perspective (ingroup vs. outgroup) and domain (political vs non-political) jointly influence accuracy. We find that individuals are less accurate when representing the beliefs of political outgroup members than ingroup members, and that this heightened inaccuracy cascades into reduced forecasting performance, but only for political, not non-political, events. This pattern emerged consistently across both studies and held after accounting for partisan affiliation, demographic variables, and established predictors of forecasting performance. The pattern of correlations further suggests that meta-forecasting accuracy was especially informative when participants estimated the political forecasts of their ingroup. Thus, the diagnostic value of meta-forecasting may depend not only on whether people can accurately represent others' beliefs, but also on whether those beliefs are drawn from a socially relevant ingroup. However, the lower accuracy observed for political outgroup meta-forecasts did not translate into lower predictive value relative to non-political outgroup meta-forecasts. In other words, although accuracy in forecasting outgroup members' political forecasts was low—and lower than for forecasting their nonpolitical forecasts—it appears that as a predictive indicator, forecasting the outgroup on ingroup-outgroup-relevant topics is no worse than forecasting the outgroup on topics unrelated to ingroup-outgroup selection.

These findings suggest that adopting others' perspectives alters forecasts by changing which beliefs enter the judgment process, and that outgroup misperceptions may anchor forecasters' predictions to less accurate probability estimates. That these effects emerge specifically in the political domain is consistent with prior work on group stereotypes and political meta-perceptions (van Boven et al., 2012; Rothschild et al., 2019). Political contexts provide an abundance of public information (e.g., polls, media coverage, elite discourse) that can support accurate forecasting. At the same time, they are characterized by polarization, stereotyping, and motivated reasoning, which distort beliefs about political opponents (Turner-Zwinkels et al., 2025).

Across both studies, forecasting accuracy was consistently associated with actively open-minded thinking and lower political identity strength. The former replicates prior work linking actively open-minded thinking to better calibrated probabilistic judgment (Martin & Mandel, 2025; Mellers et al., 2015; Stanovich & Toplak, 2023) and extends it to a political forecasting context, where the willingness to consider disconfirming evidence may be particularly important for mitigating motivated reasoning (Kunda, 1990; Tetlock, 2005). The latter is consistent with research showing that strong partisan identifications are associated with probability estimates that reflect desired rather than likely outcomes (Gerber & Huber, 2009).

Critically, participants' meta-forecasting accuracy predicted the accuracy of their own forecasts above and beyond these individual traits (i.e., numeracy, actively open-minded thinking, empathy, political identity strength, and affective polarization). Thus, the cognitive and motivational tendencies that produce inaccurate meta-forecasts undermine forecasting accuracy in ways that are distinct from these traits, such that meta-forecasting accuracy captures a distinct dimension of cognition that existing measures of forecasting ability do not fully index. For instance, a forecaster susceptible to motivated reasoning may allow partisan goals to colour both their representation of outgroup beliefs and their own probability estimates. More broadly, meta-forecasting accuracy may reflect the extent to which a forecaster can set aside social biases and reason in a calibrated way about how others engage with uncertainty. As such it may function less as a direct cause of forecasting accuracy and more as a diagnostic indicator of forecasting ability, including in contexts where outcomes are not yet observable, providing a reliable and efficient means of identifying high-performing forecasters without relying on prior performance data.

Limitations and Future Directions

Our study is not without limitations, which also suggest important avenues for future research. First, the sample was drawn from American partisans (i.e., Democrats and Republicans), limiting generalizability to other group boundaries (e.g., racial, religious, national identity). Thus, it is an open question whether the ingroup advantage in meta-forecasting accuracy extends beyond political contexts. Future research should examine whether this ingroup advantage persists when ingroup and outgroup differ in their actual forecasting calibration (e.g., groups that systematically over- or underestimate probabilities, such as the extreme case of doomsday cults that overestimate the likelihood of disasters). In such cases, accuracy-as-a-social-cue logic (Gigerenzer & Gaissmaier, 2011) may break down, as an ingroup whose base rates are biased would not confer an advantage. At the same time, our focus on the divisive context of American politics provides insights into how polarized environments may influence forecasting accuracy. That is, the same cognitive and contextual processes that lead individuals to misperceive outgroup members may also reduce the informational value of considering alternative perspectives, thereby impairing personal judgments. Future research should examine whether meta-forecasting accuracy generalizes as a predictor of forecasting ability across domains and whether targeted interventions that improve meta-forecasting accuracy (i.e., makes individuals' representations of others more accurate) also enhance forecasting performance.

Second, neither experiment included a control condition without perspective-taking, in which participants forecasted events without considering others' beliefs. As a result, although we show that outgroup perspective-taking impairs forecasting accuracy relative to ingroup perspective-taking, we cannot determine whether this reflects a cost of considering outgroup forecasts, a benefit of considering ingroup forecasts, or a combination of both. However, our results comparing the political and non-political domain areas suggest that the effect is likely to be an outgroup disadvantage rather than an ingroup advantage (see Figure 1). Future research employing a three-condition design, comparing ingroup perspective-taking, outgroup perspective-taking, and a no-perspective baseline, would also help disentangle these possibilities. If outgroup perspective-taking yields lower accuracy than a no-perspective baseline, this would suggest that distorted meta-representations actively mislead forecasters. Conversely, if outgroup and no-perspective conditions produce comparable performance, then the advantage of ingroup perspective-taking would be better characterized as a benefit of accurate social belief representation (e.g., Eyal et al., 2018) rather than a cost of inaccuracy.

Conclusion

The present investigation highlights the importance of meta-forecasting ability as a meaningful construct in forecasting research. We showed that forecasters are better able to predict the average forecast of their ingroup than of their outgroup on topics that are group-relevant (namely, in this study, th forecasting of political outcomes). We also showed that individual differences in this meta-forecasting ability are useful for identifying which individuals will later prove to be more accurate in forecasting the topics themselves. Such work contributes to ongoing efforts to improve forecasting accuracy through performance-based methods (for a review, see Collins et al., 2023), but importantly shed light on a social dimension of such an approach. Our research suggests that in cases where predicting others' forecasts may be used as an indicator of accuracy, it may be best to require individuals to predict the forecasts of their ingroup members. As we showed in both studies, the strength of the relationship between meta-forecasting accuracy and forecasting accuracy was especially strong for those focused on their ingroup and on group-relevant topics (again, politics in our study). Given that social information plays such an important role in our lives, it is a ripe avenue for research on methods to improve the forecasting accuracy of experts and novices alike.

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Table 1

Means, standard deviations and correlations for all variables in Experiment 1

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Perspective	-0.02	1															
2. Political party	0.2	0.98	0.01														
3. Intervention	0.2	0.09	-0.03	.12**													
4. F. Pol.	0.27	0.06	0.04	0	.15**												
5. F. Non pol.	0.06	0.04	-.21**	-0.02	.44**	.13**											
6. Meta Pol.	0.05	0.03	-0.02	-.09**	0.03	.29**	.30**										
7. Meta Non pol.	43.63	13.63	-0.01	-.18**	.08*	0.03	0.05	0.06									
8. Sex	0.05	1	0.02	.10**	.13**	0.03	0.03	0	.09**								
9. Education	4.59	1.14	-0.01	0.06	-0.04	0.01	-.08*	-0.03	.07*	.07*							
10. IRI	2.83	0.67	0.03	.08*	0.05	.07*	0	0.05	0.03	.23**	-0.06						
11. AOT	1.17	0.64	0	.31**	-.15**	0.01	-.09**	0.06	-0.03	0.02	0	.32**					
12. Affect. Pol.	41.1	28.94	-0.03	.23**	.13**	-0.06	.11**	.10**	.07*	0.04	0.04	.08*	0.03				

13. Rel bias	-17.07	25.47	-0.01	-.25**	-.11**	0.01	-.09**	-.07*	-0.03	-0.05	0.04	-.10**	-.18**	-.45**			
14. PIS	4.67	1.3	-0.01	0.01	.18**	-0.01	.10**	0.04	.17**	0.06	0.06	.16**	-.11**	.57**	-.24**		
15. Numeracy	1.53	1.34	-0.01	0.05	-.19**	-0.05	-.16**	-.09**	-.14**	-.17**	.16**	-.07*	.13**	-0.06	.09**	-0.05	
16. Polling	2.62	1.72	-0.02	-0.06	0.01	-0.03	0	-0.02	-.22**	-.26**	.07*	-0.05	-.09**	-0.01	.07*	0.06	.09**

Note. Code for political party: Republican = -1, Democrat = 1. Code for perspective: Outgroup = -1, Ingroup = 1. Code for domain: Political = 1, Non-political -1. Code for sex: Male = -1, Female = 1. F. Pol. = Political forecasts; F. Non pol. = Non-political forecasts; Meta Pol. = Political meta-forecasts; Meta Non pool. = Non-political meta-forecasts; Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking

Table 2

Results of the Moderated-Mediation Model for Experiment 1

Model Paths	Predictor / Effect	*b*	95% *CI* Lower	95% *CI* Upper	*SE*	*p*	β
Stage 1 (Meta-forecast)	Perspective	-.005	-.006	-.003	.001	**<.001**	-.132
	Domain	.005	.003	.006	.001	**<.001**	.137
	Domain × Perspective	-.004	-.005	-.003	.001	**<.001**	-.114
	Political Party	-.002	-.003	.000	.001	.077	-.045
	R^2	.052					
Stage 2 (1st-order)	Perspective	.003	.000	.007	.002	.050	.040
	Domain	-.038	-.041	-.035	.002	**<.001**	-.446
	Domain × Perspective	.001	-.003	.004	.002	.729	.006
	Meta-forecast	.906	.776	1.037	.067	**<.001**	.365
	Political Party	.011	.007	.015	.002	**<.001**	.127
	Age	.000	.000	.001	.000	.052	.045
	Sex	.004	.000	.008	.002	**.036**	.047
	Education	.000	-.003	.003	.002	.996	.000
	IRI	.006	.000	.011	.003	**.046**	.045
	AOT	-.014	-.020	-.008	.003	**<.001**	-.104
	Affect. Pol.	.000	.000	.000	.000	**.004**	-.081
	Rel. Bias	.000	.000	.000	.000	.379	-.024
	PIS	.005	.001	.009	.002	**.007**	.075
	Berlin	-.003	-.006	-.001	.001	**.012**	-.052
	Polling	.001	-.001	.004	.001	.255	.026
	R^2	.315					
Indirect Effects	Indirect (Political)	-.008	-.010	-.005	.001	**<.001**	-.090
	Indirect (Non-political)	-.001	-.002	.001	.001	.505	-.006

	Index of Moderated-Mediation	.007	.005	.010	.001	**<.001**	.083

Note. Code for political party: Republican = -1, Democrat = 1. Code for perspective: Outgroup = -1, Ingroup = 1. Code for domain: Political = 1, Non-political -1. Code for sex: Male = -1, Female = 1

Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking.

Table 3

Means, standard deviations and correlations for all variables in Experiment 2

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Perspective	-0.33	0.94																
2. Political party	0.39	0.92	-.01															
3. Intervention	0.03	1.00	.04	-.01														
4. F. Pol.	0.21	0.10	-.05	.04	.02													
5. F. Non pol.	0.27	0.06	.01	.01	.06*	.22**												
6. Meta Pol.	0.06	0.04	-.12**	-.03	-.01	.51**	.20**											
7. Meta Non pol.	0.05	0.03	.00	-.03	.00	.13**	.33**	.37**										
8. Age	41.61	14.00	.01	-.11**	-.03	.18**	.07**	.11**	.06*									
9. Sex	0.14	0.99	-.01	.01	-.01	.05*	-.05	.03	-.05*	.01								
10. Education	4.61	1.14	-.01	.13**	-.01	.02	.02	-.06*	-.05	.10**	.00							
11. IRI	2.91	0.59	.02	.09**	.02	.07**	.04	.04	.03	.08**	.17**	-.03						
12. AOT	1.24	0.62	.03	.29**	-.03	-.13**	-.03	-.10**	-.02	.02	.04	.01	.39**					

13. Affect. Pol.	38.99	27.36	-.07**	.25**	-.01	.13**	.03	.13**	.03	.15**	.00	.02	.03	.07**				
14. Rel bias	-15.63	24.27	.02	-.19**	-.01	-.05	.00	-.05	.00	-.06*	.00	-.01	-.05	-.13**	-.40**			
15. PIS	4.63	1.30	.00	.01	.00	.19**	.04	.12**	.04	.24**	-.01	.09**	.14**	-.09**	.50**	-.14**		
16. Numeracy	1.44	1.29	.02	.15**	-.01	-.09**	-.08**	-.14**	-.05	-.16**	-.15**	.17**	-.07**	.12**	-.04	-.01	-.07**	
17. Polling	2.53	1.62	-.02	-.02	-.03	.04	-.01	-.02	-.04	-.11**	-.23**	.06*	-.07**	-.15**	-.05	.10**	.08**	.05*

Note. Code for political party: Republican = -1, Democrat = 1. Code for perspective: Outgroup = -1, Ingroup = 1. Code for domain: Political = 1, Non-political -1 Code for sex: Male = -1, Female = 1. F. Pol. = Political forecasts; F. Non pol. = Non-political forecasts; Meta Pol. = Political meta-forecasts; Meta Non pool. = Non-political meta-forecasts; Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking.

Table 4

Results of the Moderated-Mediation Model for Experiment 2

Model Paths	Predictor / Effect	*b*	95% *CI* Lower	95% *CI* Upper	*SE*	*p*	β
Stage 1 (Meta-forecast)	Perspective	-.006	-.007	-.004	.001	**<.001**	-.153
	Domain	.006	.004	.007	.001	**<.001**	.149
	Domain × Perspective	-.005	-.006	-.004	.001	**<.001**	-.135
	Intervention	-.001	-.003	.001	.001	.319	-.025
	Political Party	-.001	-.003	.000	.001	.145	-.035
	R^2	.065					
Stage 2 (Forecast)	Perspective	.001	-.003	.004	.002	.742	.007
	Domain	-.038	-.041	-.034	.002	**<.001**	-.413
	Domain × Perspective	-.001	-.004	.003	.002	.739	-.006
	Meta-forecast	.936	.788	1.083	.075	**<.001**	.381
	Intervention	-.004	-.007	.000	.002	.050	-.039
	Political Party	.006	.002	.011	.002	**.008**	.062
	Age	.001	.000	.001	.000	**<.001**	.092
	Sex	.002	-.001	.006	.002	.223	.026
	Education	.002	-.001	.005	.002	.213	.026
	IRI	.005	-.002	.012	.004	.159	.033
	AOT	-.012	-.020	-.005	.004	**.001**	-.083
	Affect pol.	.000	.000	.000	.000	.685	-.011
	Relative Bias	.000	.000	.000	.000	.807	.007

	PIS	.004	.000	.008	.002	**.039**	.056
	Numeracy	-.002	-.005	.001	.001	.167	-.029
	Polling	.002	-.001	.004	.001	.132	.034
	*R*²	.297					
Indirect Effects	Indirect (Political)	-.010	-.012	-.008	.001	**<.001**	-.109
	Indirect (Non-political)	-.001	-.002	.001	.001	.490	-.007
	Index of Moderated Mediation	.009	.007	.012	.001	**<.001**	.103

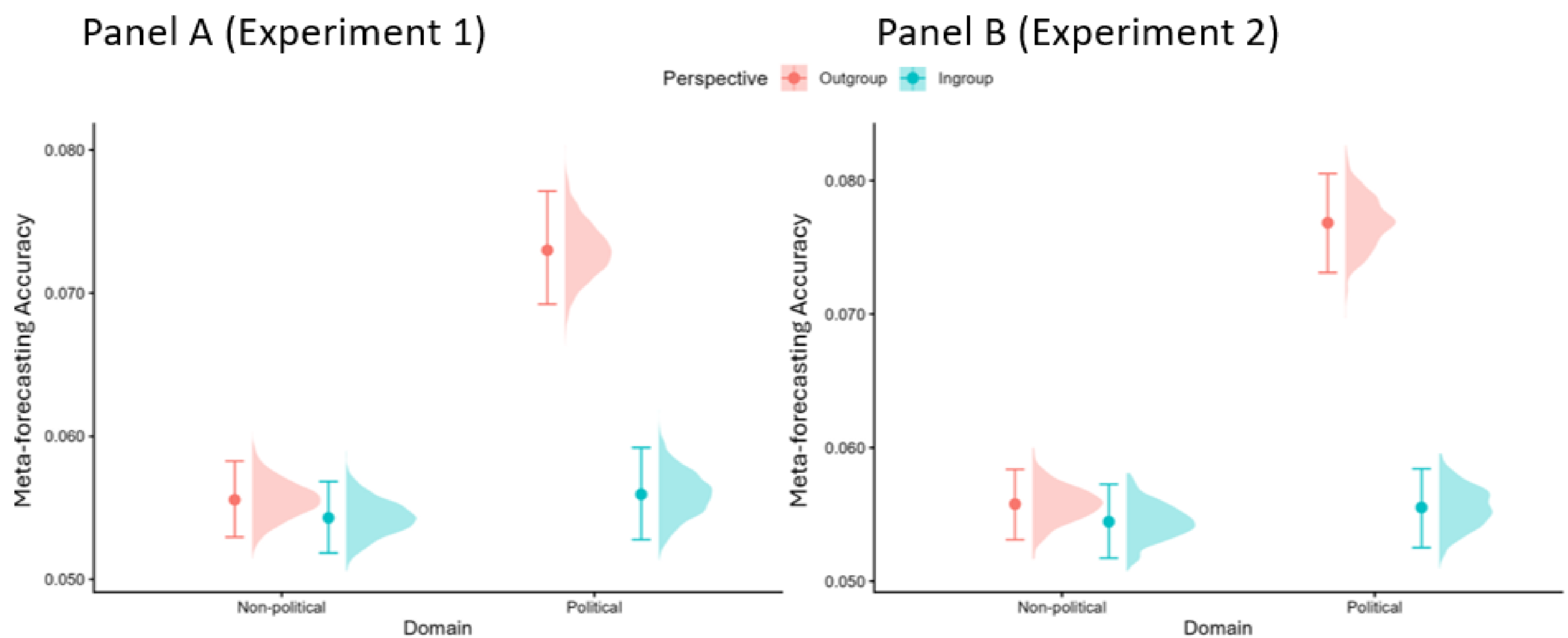
Note. Dummy code for political party: Republican = -1, Democrat = 1. Dummy code for perspective: Outgroup = -1, Ingroup = 1.

Dummy code for domain: Political = 1, Non-political -1. Dummy code for sex: Male = -1, Female = 1

Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking.

Figure 1

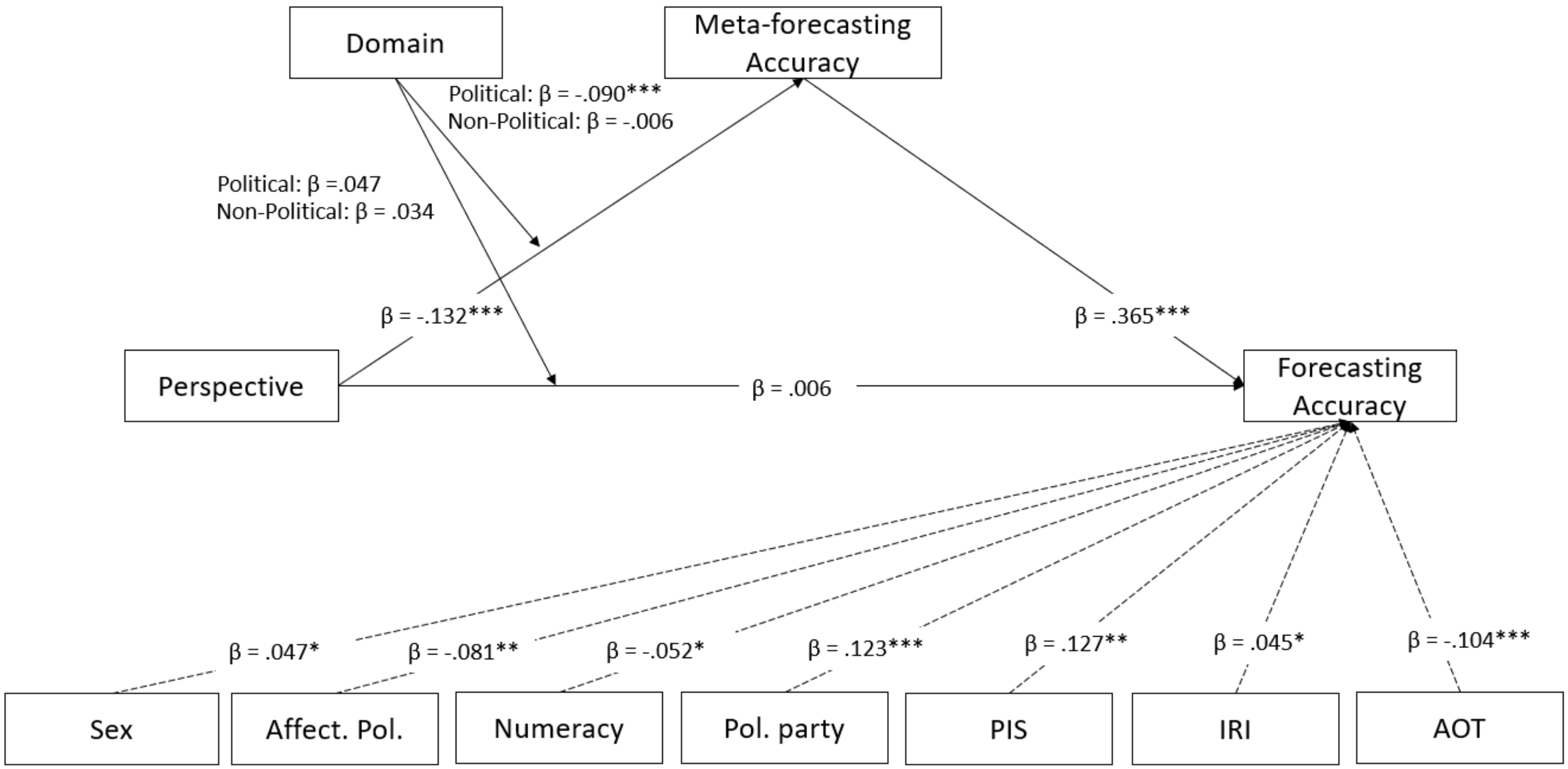
Experiment 1 and Experiment 2 Domain and Perspective on Meta-forecasting Accuracy



Note. Error bars represent the 95% confidence interval and the distribution of data is shown to the right of each condition.

Figure 2

Path Diagram Summarizing the Moderated Mediation Model in Experiment 1.

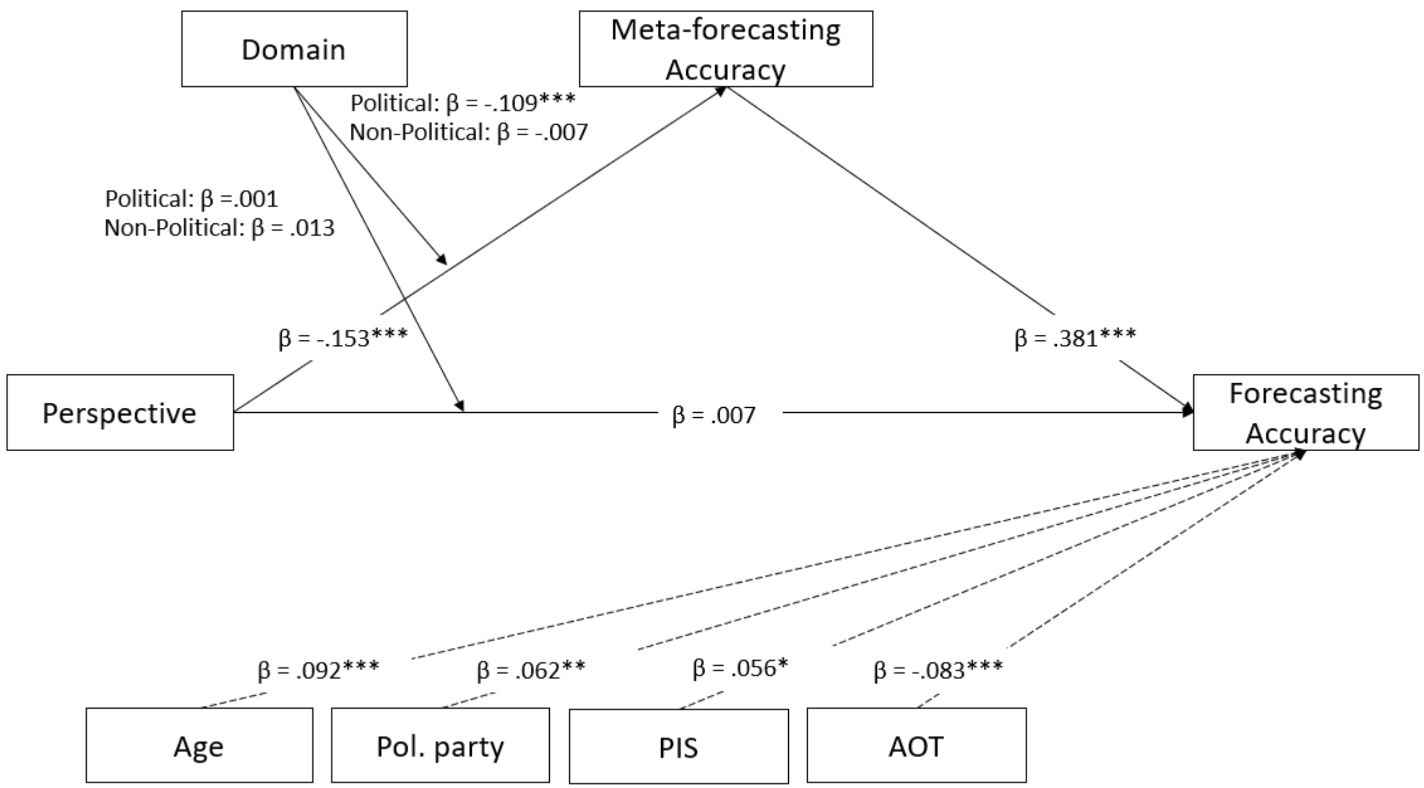


Note. Solid lines indicate focal structural paths; dashed lines indicate covariate effects. Values are standardized regression coefficients (β). Coefficients on the path from perspective to meta-forecasting accuracy are shown separately for political and non-political domains to reflect the perspective and domain interaction. All reported paths are from the fully adjusted model including covariates in both stages. For clarity, non-significant paths among covariates are omitted; full model results are reported in Table 2. Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking. Code for political party: Republican = -1, Democrat = 1. Code for perspective: Outgroup = -1, Ingroup = 1.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Figure 3

Path Diagram Summarizing the Moderated Mediation Model in Experiment 2.



Note. Solid lines indicate focal structural paths; dashed lines indicate covariate effects. Values are standardized regression coefficients (β). Coefficients on the path from perspective to meta-forecasting accuracy are shown separately for political and non-political domains to reflect the perspective and domain interaction. All reported paths are from the fully adjusted model including covariates in both stages. For clarity, non-significant paths among covariates are omitted; full model results are reported in Table 4. Affect. Pol. = Affective polarization; PIS = Political identity strength; IRI = Empathy; AOT = Active open-minded thinking. Code for political party: Republican = -1, Democrat = 1. Code for perspective: Outgroup = -1, Ingroup = 1.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.