Perceptions versus Reality: Personal Narrative Persuasion in Anonymous Cross-Partisan Interactions on a Mobile Chat Platform

PAPER PREPARED FOR THE 2024 MEETING OF THE AMERICAN POLITICAL SCIENCE ASSOCIATION

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Abstract

Narrative persuasion techniques have effectively altered attitudes within the contexts of canvassing, video presentations, and survey experiments. This study examines the efficacy of personal narratives, in comparison to evidence-based persuasive techniques, in online conversations among ordinary citizens. It investigates surveys and text from 1,169 United States citizens engaged in cross-partisan conversations about divisive political issues on DiscussIt, an innovative mobile chat platform. Results reveal that receiving personal narratives in online cross-partisan interactions significantly predicts participants' perceptions that their chat partner had a persuasive influence on their opinions. In contrast, evidence-based messaging significantly predicts the opposite. However, neither technique predicted observable attitude change in participants' political attitudes. This perception-reality disconnect highlights the need to better understand the avenues through which narrative-driven messages wield influence in political persuasion and prompts us to examine whether persuasion primarily manifests through perceptions rather than tangible attitude change, especially in dialogue across party lines.

Key Words: persuasion, narration, evidence, cross-partisan dialogue, online

https://doi.org/10.33774/apsa-2024-09m5k **ORCID:** https://orcid.org/0000-0001-5599-1890 Content not peer-reviewed by APSA.

A growing literature suggests that narrative-based persuasive techniques tend to outperform evidence-based messages (e.g., Barton and Pan 2022; Kuklinski 2000; Hopkins, Sides, and Citrin 2019). Across diverse settings–canvassing (e.g., Broockman and Kalla 2016; Kalla and Broockman 2020, 2023), video presentations (Kubin et al. 2021), television shows (Kim 2023), and survey experiments (e.g., Gooch 2018; Kawata, McElwain, and Nakabayashi 2024; Naunov, Rueda-Cañòn, and Ryan 2024)–research consistently highlights the compelling persuasiveness of narratives. Thus, in contrast to evidence-based messaging, narratives should be particularly effective in cross-partisan political discussions that are increasingly viewed as an antidote to today's polarization (e.g., Levendusky and Stecula 2021; Santoro and Broockman 2022).

During cross-partisan interactions, where heightened partisan allegiances and directional goals may impede persuasion (Druckman 2022), narratives may encourage individuals to set aside ego-protecting motivations. Narratives in cross-partisan interactions may allow individuals to engage with a story, shifting attention away from scrutinizing the speaker to immersing themselves in the expressed message (Carpenter 2019). Personal narratives, in particular, may foster deeper emotional resonance with others and be perceived as less coercive than evidence-based messaging (Green and Brock 2000). As a result, messages that convey personal experiences are thought to be less likely to be questioned or challenged (Aarøe 2001, Gross 2008, Slater and Rouner 2002).

This study explores the comparative effectiveness of personal narratives and evidence-based messaging in a novel communication setting. On a mobile chat platform developed for research, similar in style to Facebook Messenger or WhatsApp, 1,169 American citizens engaged in anonymous cross-partisan interactions about divisive political issues (Combs et al. 2023). Examination of survey responses and conversation texts reveals that individuals who receive personal narratives significantly attribute greater persuasive influence to their chat partners in shaping their opinions than those who did not receive such narratives, whereas evidence-based messages showed the opposite association. However, there were no significant findings of actual shifts in attitudes by either mode of persuasive messaging.

The present findings offer some challenge to previous research which has observed significant attitude persuasion from narrative messages. That is, while recent research emphasizes the persuasiveness of personal narratives in asynchronous settings or when presented by skilled canvassers, my findings show some limits to their effectiveness in this setting. This research further suggests that evidence-based messaging, which has been found to be effective in some contexts (e.g., Gilens 2001; Kuklinski et al. 2000) , can be counterproductive in influencing perceptions of persuasion. By examining the effects of personal narration and evidence-based approaches on political opinions and perceptions, my research highlights the need to better understand the nuances of communication effects (e.g., McDonald and Hanmer 2023; Rossiter 2022; Wlezien 2024).

Efficacy of cross-partisan political dialogue

Political conversation is pivotal in democratic governance (Barber 2003; Davis and Finlayson 2022), serving as a key indicator of an informed and active electorate (Conover and Searing 2005; Eveland 2004). Individuals engage in political conversations for a variety of reasons, ranging from passing time, learning from friends and family, and impressing others (Carlson, Abrajano, and García Bedolla 2020; Eveland, Morey, and Hutchens 2011), to deeper pursuits such as gaining knowledge and understanding (Conover, Searing, and Crewe 2002; Smith 2016). Such discourse enables individuals to articulate arguments, refine opinions, and engage in reasoning–essential for shaping collective identities and community values (Moy and Gastil

2006). The rise of social media platforms, forums, and online discussion sites has significantly enhanced the accessibility of political information and opportunities for discussion. These platforms are now seamlessly integrated into daily life, offering citizens numerous avenues to engage in political conversations face-to-face and online.

However, in today's polarized climate, political discussions, particularly those crossing party lines, are increasingly rare (Carlson and Settle 2022). When Americans engage in political conversations, they tend to do so with like-minded individuals (Huber and Malhotra 2017; Huckfeldt, Johnson, and Sprague 2004). The growing homogeneity of social groups, often attributed to increasing polarization, decreases interactions between Democrats and Republicans. Reduced cross-party contact is thought to contribute to exaggerated perceptions of the opposing side (Ahler and Sood 2018; Levendusky and Malhotra 2016). As such, partisans may amplify even minor differences between their party and the opposition (Druckman et al. 2023; Tajfel and Wilkes 1963), viewing the other party as distant and extreme, further fueling partisan animosity.

To reduce the adverse effects of polarization, researchers use cross-partisan interactions, applying contact theory (Rossiter and Carlson 2024). Contact theory suggests that interactions between individuals from different social groups can reduce prejudice (Paluck, Green, and Green 2019), providing a framework for studies using various forms of cross-partisan interaction. While some studies emphasize meeting specific conditions (Levendusky and Stecula 2021), such as equal status, cooperation, and shared goals (Allport et al. 1954). Some conclude that sustained engagement over prolonged periods may be necessary (MacInnis and Page-Gould 2015; Pettigrew and Tropp 2006) to reduce animosity. However, some argue that mere contact could be enough to diminish stereotyping and extremism on issues, even in brief (de Jong 2024) or unintentional encounters (Minozzi et al. 2020).

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Given the multitude of approaches researchers employ in studying cross-partisan conversations, it is unsurprising that there are mixed results for *when* and *why* attitude moderation or backfire occurs. Contact studies typically assume that (1) individuals will moderate their issue positions or achieve affective depolarization, and (2) some form of cross-partisan interaction is sufficient. However, many studies often rely solely on pre-post survey assessments to measure attitude change or its absence, without examining how different types of messages or communication channels influence persuasion. This gap in research leaves us with an incomplete understanding of the conditions and messages needed for cross-partisan contact to effectively persuade. I propose that the varying receptiveness to different modes of persuasive information and the choice of communication channel are pivotal factors in determining the effectiveness of cross-partisan discussions on political attitude change.

Types of persuasive messaging

When individuals engage with others who hold different political identities or attitudes, they often attempt to persuade them to change their views. Persuasion entails a purposeful and successful effort to influence another person's mental state through communication, within a context where the recipient retains some autonomy (O'Keefe 2016). Often, this involves individuals who are presented with messages advocating for specific issues, and the effectiveness of these messages in altering people's opinions is evaluated using the Lasswell Model of Communication (Druckman 2022). This evaluative framework examines how variations in the speaker, message, channel, and receiver (i.e., "who says what to whom," Lasswell 1948; McGuire 1969) impact comprehension and persuasion processes. Research has predominantly focused on the interaction between speakers and receivers, with a particular emphasis on elite-to-citizen communication (e.g., Fowler, Franz, and Ridout 2021; Hersh and Schaffner

2013). This emphasis on top-down communication leaves a significant gap in comprehending persuasion efforts among citizens (with exceptions like Naunov, Rueda-Cañòn, and Ryan 2024), which includes both the choice of messages and the channels individuals select.

To understand the persuasive messages citizens might prefer, I explore a substantial body of literature on two prominent forms of persuasive messaging: narrative- and evidence-based approaches. Personalized stories are often pitted against statistical messages (Baumeister and Newman 1994; Small, Loewenstein, and Slovic 2007), with mixed findings on their comparative persuasiveness. Evidence-based methods are frequently praised as effective and consistent (Reynolds and Reynolds 2002), presenting individual behaviors as aggregate statistics and facts. This approach enhances perceived objectivity and credibility, leading to greater acceptance by recipients. However, the effectiveness of evidence depends on its perceived legitimacy (Parrott et al. 2005) or novelty (Morley and Walker 1987), though some disagree (Green, Chatham, and Sestir 2012; Green and Donahue 2011).

Narrative persuasion contrasts with evidence-based messaging by using individual cases to illustrate broader social patterns. Unlike evidence-based approaches, narratives unfold with a beginning, middle, and end, featuring characters with unique perspectives (Polletta and Lee 2006). Narrative messaging influences information processing, aiding in the storage and interpretation of events (Howard 1991). Some even argue that individuals do not assess others (or themselves) based on propositions and statements (i.e., formal arguments); instead, they recount specific experiences to justify their attitudes (De Raad 1984). Realistic narratives, using concrete language and imagery, can evoke stronger emotional reactions than abstract facts or statistics, even when the story is fictional (Cho, Shen, and Wilson 2014). The ongoing debate over the effectiveness of statistical versus narrative information largely hinges on timing and delivery methods. Therefore, it's crucial to discuss which approach might be more effective in cross-partisan interactions.

Personal narratives in cross-partisan interactions

While much literature acknowledges evidence and narrative as effective persuasive tools, in cross-partisan exchanges often marked by entrenched allegiance to in-group beliefs, narratives may have the upper hand. In cross-partisan political conversations, directional motives can sway individuals, leading to biased seeking and evaluation of political information (Lodge and Taber 2013). Consequently, individuals tend to interpret information in a manner that aligns with their existing attitudes, prioritizing directional motivations over accuracy (Redlawsk, Civettini, and Emmerson 2010), potentially perceiving evidence-based messages as disputable or deceitful in cross-partisan discussions (Huff 1954). To circumvent individuals' rejection of facts and statistics as irrelevant or inconsistent with their existing beliefs, researchers can alter the recipient's motivation to bolster persuasion (Mullinix 2016).

One effective way to change directional motives is through storytelling. Stories are less likely to trigger psychological defenses and can therefore exert greater influence (Slater and Rouner 2002). Narrative appeals divert attention from scrutinizing the speaker by deeply engaging individuals in the message itself (Perloff 1993). Narration's appeal lies in its captivating and emotionally resonant nature, which aligns with humans' natural inclination towards storytelling rather than dry facts or numerical data. Indeed, anecdotes are perceived as less coercive than factual information (Green and Brock 2000), providing a more immersive approach for individuals to connect with issues (Gerrig 2018). Consequently, people are less inclined to doubt or counter-argue when messages convey personal experiences rather than concrete facts (Slater and Rouner 2002). Narrative influence can persist even when stories contain factual inaccuracies, whether accidental or intentional (Green and Donahue 2011).

Recent research exploring the effectiveness of narrative persuasion has shown promising results. Narratives facilitate depolarization on elite-to-citizen (Gooch 2018) and citizen-to-citizen (Naunov, Rueda-Cañòn, and Ryan 2024) persuasion in surveys. They also increase support for poverty relief programs (Kawata, McElwain, and Nakabayashi 2024) and prove effective on platforms like YouTube and news coverage by appealing to harm and morality rather than relying solely on facts (Kubin et al. 2021). Empirical research also highlights that exposure to rag-to-riches stories on television increases viewers' beliefs in the American Dream and internal attributions of wealth (Kim 2023). Moreover, narrative appeals in canvassing efforts contribute to lasting attitude changes on issues such as immigration and transgender rights (Broockman and Kalla 2016; Kalla and Broockman 2020, 2023). These findings point to the potential of narrative techniques in shaping attitudes and promoting persuasion across diverse societal contexts.

While narratives effectively promote issue-based moderation and show theoretical promise in cross-partisan interactions, recent studies are often constrained by controlled environments, limiting their generalizability. Survey-based research lacks real-time interaction, affording individuals time to craft or fully absorb arguments. Video-based experiments, though informative, are asynchronous and may reveal speaker characteristics absent in anonymous online interactions. Synchronous studies with trained canvassers introduce dynamics diverging from naturalistic settings, where perspective-taking is induced by professionals potentially operating unequally with receivers. Thus, while narrative messages hold promise as a persuasive strategy in free-flowing cross-partisan conversations, further investigation into their efficacy in unmoderated online settings is crucial to fully grasp their impact.

My research explores the role of storytelling within cross-partisan exchanges and its potential to predict both perceived persuasive influence and actual shifts in attitudes. Unlike evidence-based communication, I anticipate that individuals receiving narratives in such interactions will be more likely to have attitude moderation. Building upon existing literature comparing these two persuasion strategies and acknowledging literature pointing to narrative power in altering issue-based attitudes, I aim to shed light on citizens' persuasive-delivery techniques and their efficacy within dyadic cross-partisan dialogues. Specifically, I contrast personal narratives (stories about the sender) with evidence (e.g., statistics, case studies, facts), rather than a broader spectrum of narratives. Gooch 2018 suggests that personalized stories are more impactful than narratives featuring unknown others or historical events, and personal narratives may be particularly resistant to refutation. Furthermore, storytelling is a common feature of everyday conversations and is relatively straightforward to convey, especially when centered around one's experiences.

Data and Methods

The data utilized in this study was sourced from Combs et al. (2023), who collected text and survey data from January 2020 and March 2020 using DiscussIt, a mobile chat platform designed to resemble Facebook Messenger and WhatsApp. DiscussIt was developed to facilitate political discussions on contentious issues among users and anonymous conversation partners. The original study randomly assigned participants to converse with an anonymous opposing partisan on a new social media platform or with a control group that wrote essays.[1] They also randomly assigned treated participants to be aware of their partner's partisan identity, to be informed incorrectly about their partner's partisan identity, or to receive no identifiable information about

[1] Details on recruitment, sample inclusion criterion, and descriptives are in the Appendix A.

their partner (referred to as labeling conditions). I use observational data from 1,169 participants who engaged in anonymous cross-partisan interactions. My sample was 55% female, 49% Democrat, and had an average age of 52 years old.

Figure 1. Onboarding images from DiscussIt

Note. After downloading the app, participants logged in and were guided through several onboarding screens. They were then shown their randomly assigned conversation prompt about either immigration or gun control and matched with a partner from the opposing political party. After matching, the participants entered the chat interface and could begin their conversation.

I analyze how persuasive techniques, measured through text analysis, relate to attitudes assessed via survey responses. Participants' attitudes were evaluated at various points during the study. First, they completed a survey on demographics and political attitudes several days before downloading the app. After downloading the app, participants were randomly assigned to discuss gun control or immigration and immediately surveyed within the app regarding their attitudes on the assigned topic. Participants were told to engage in at least fourteen exchanges with their conversation partner to qualify for payment (though payment was given for a minimum of ten exchanges). Post-conversation, participants were surveyed within the app about their attitudes toward the topic, perceptions of their conversation partner, and overall experience. Several days later, participants received a follow-up survey to assess their attitudes again.

The app recorded and stored the text of all conversations, hand-coded by a team of research assistants overseen by the author. Hand coders were tasked with reading messages exchanged by participants on the app and were responsible for evaluating a specific number of conversations, focusing on several criteria. Hand coders assigned each message a code of 0 or 1 for the presence of each criterion.[2] My analysis concentrates on two hand-coded elements, the presence of personal narrative and evidence in text.[3] In summation, my study investigates the association of persuasive message reception on perceptions of one's chat partner's persuasive influence, as well as, shifts in attitudes towards (movement closer to) the chat partner's attitudes.

Persuasive messages

Participants on the DiscussIt mobile chat platform were onboarded with a message: *"Chat anonymously with other users and try to convince them of your views on different issues."* Participants demonstrated a commitment to this task. Among all treated individuals, a total of 22,971 messages were exchanged. Within these messages, 19% utilized persuasive techniques, with evidence comprising 45% and narration comprising 54% of these persuasive messages. Among the narrative messages, the majority (69%) were personal. Among conversations on the platform, 54% included at least one message featuring a persuasive technique, and the median cross-partisan conversation consisted of approximately 34 exchanges (μ = 31.93), with participants typically receiving around 19 messages (μ = 19.65) from their chat partner.

[2] Handcoders also had the option to code the messages as "XX" meaning the message was hard to code. Such messages were resolved by the author such that it was given a 0 or 1.

[3] Personal narrative and evidence usage is similar across conversation topics, labeling conditions, and by party identity (see Table C1 of Appendix C).

I used persuasive message reception–personal narratives and evidence-based–to predict perceptions of one's chat partner's persuasive ability and post-treatment attitudes (see Table 1 for an example of messages using each technique). For personal narrative reception, the hand coder's instructions were as follows: "Personal narratives make an explicit connection between the issue at hand and the sender's own experiences. They are autobiographical in character. For example, 'I am an illegal immigrant from Mexico and I have faced...'. For Personal Narrative, record: 0 = comment does not include personal narrative, 1 = comment does include personal narrative, XX = comment is hard to code." The intercoder reliability score for the use of personal narration is 92.6%. Over 53.3% of participants received at least one personal narrative from their chat partner, with a median of 1 message containing a personal narrative per participant ($\mu = 1.4$).

For evidence reception, the hand coder's instructions were as follows: "Does the comment offer a statement of fact? The factual claim does not need to be correct. Specific facts often include numbers, dates, a specific case, and so on, but do not always do so. For example, 'In 2011, states passed a law and we have seen zero cases of gun violence' or 'Studies have shown time and time again, immigrants are beneficial for our economy.' For Evidence, record: 0 = comment does not use evidence, 1 = comment does use evidence, XX = the comment is hard to code."[4] It is important to note that evidence-based messages in this study were not authenticated for accuracy. Instead, all attempts to present evidence to their partners, whether through numbers, links, or other means, were categorized as evidence, reflecting an effort to persuade. This approach aligns with how other researchers measure persuasion in text (Naunov, Rueda-Cañòn, and Ryan 2024). The majority of participants (61.8%) received at least one form

[4] I use only non-narrative evidence (Evidence = 1, Narrative = 0) to ensure evidence-based messaging. Intercoder reliability is 87.64% for evidence and 88.64% for narratives.

of evidence from their chat partner, with a median of 2 messages containing evidence per participant (μ = 1).[5]

Table 1. Examples of messages containing persuasive techniques

Type	Topic	Message
Personal narration	Gun control	“We had a babysitter who, unbeknownst to me, kept a loaded gun by her bed. She justified it by saying the kids knew her room was off-limits. Needless to say, she didn’t keep my child anymore. Any adult who keeps any loaded weapon accessible to children should not have the right to own a firearm.”
	Immigration	“I grew up in a very non-diverse rural community but lived most of my life in a very diverse metropolitan area. I recently moved back to my rural roots, and I sorely miss the diversity of the city, including its vibrant immigrant population.”
Evidence	Gun control	“Also recall the recent Texas synagogue shooting. Because the synagogue changed its stance on its parishioners carrying guns, only 2 people were killed before he was stopped.”
	Immigration	“Almost $190 million, or about 25 percent, of the uncompensated costs Southwestern hospitals incurred resulted from emergency medical treatment provided to illegal immigrants.”

Note. Unaltered examples extracted from the dataset, showcasing handcrafted messages by participants featuring persuasive strategies through personal narrative and evidence.

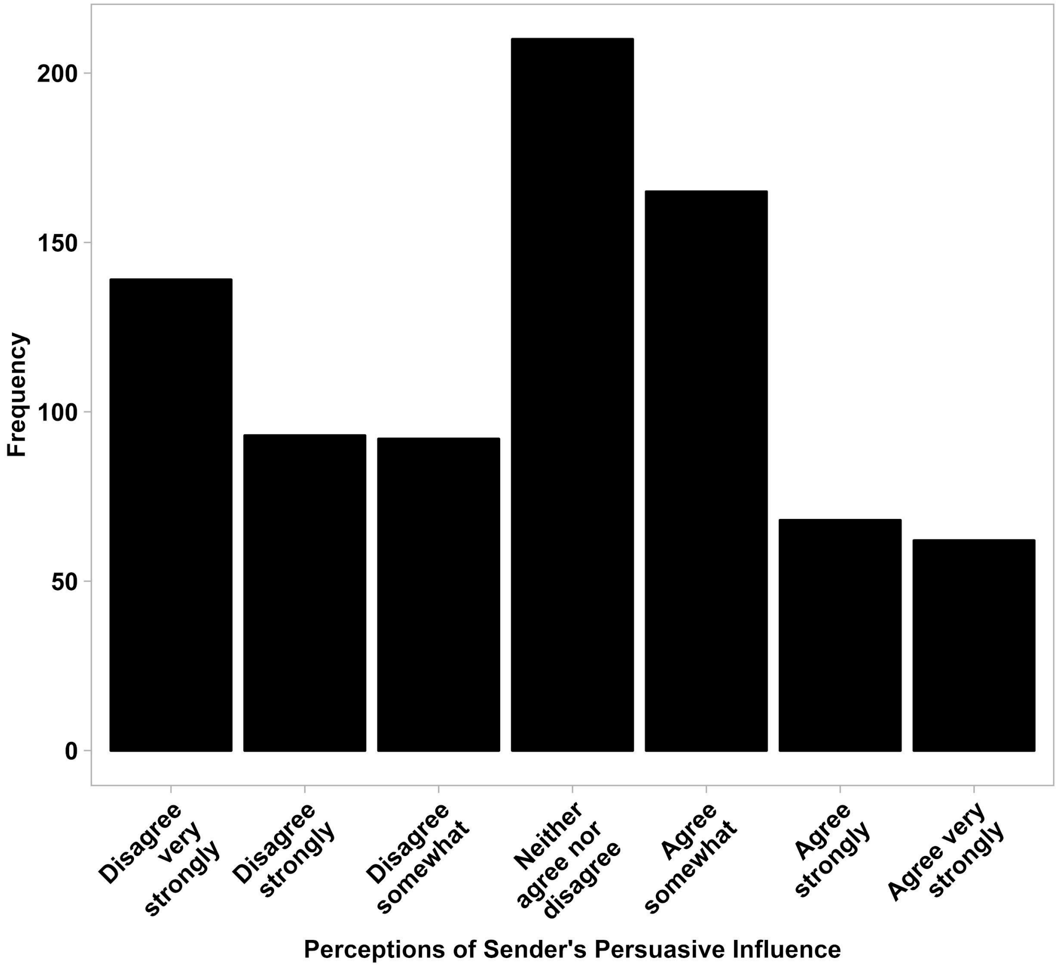
Attitudes

The first dependent variable of interest is the perception of one’s chat partner’s persuasive influence. This is measured by asking participants whether their conversation partner (the sender) influenced their views on their assigned discussion topic (see Table 2 for details). The question wording was as follows: “Do you agree or disagree with the following statement? [Partner name] influenced my views on [topic].” For the distribution see Figure 2.[6]

[5] Table C2 of Appendix C details the demographic characteristics of individuals who used personal narratives only, evidence only, both personal narratives and evidence, or neither. No significant differences were observed among these groups in their use of each persuasion technique or combinations thereof.

[6] For distributions by conversation topic, labeling condition, and partisan identity see Figures C1 of Appendix C.

Figure 2. Distribution of perceptions of the sender's persuasive influence



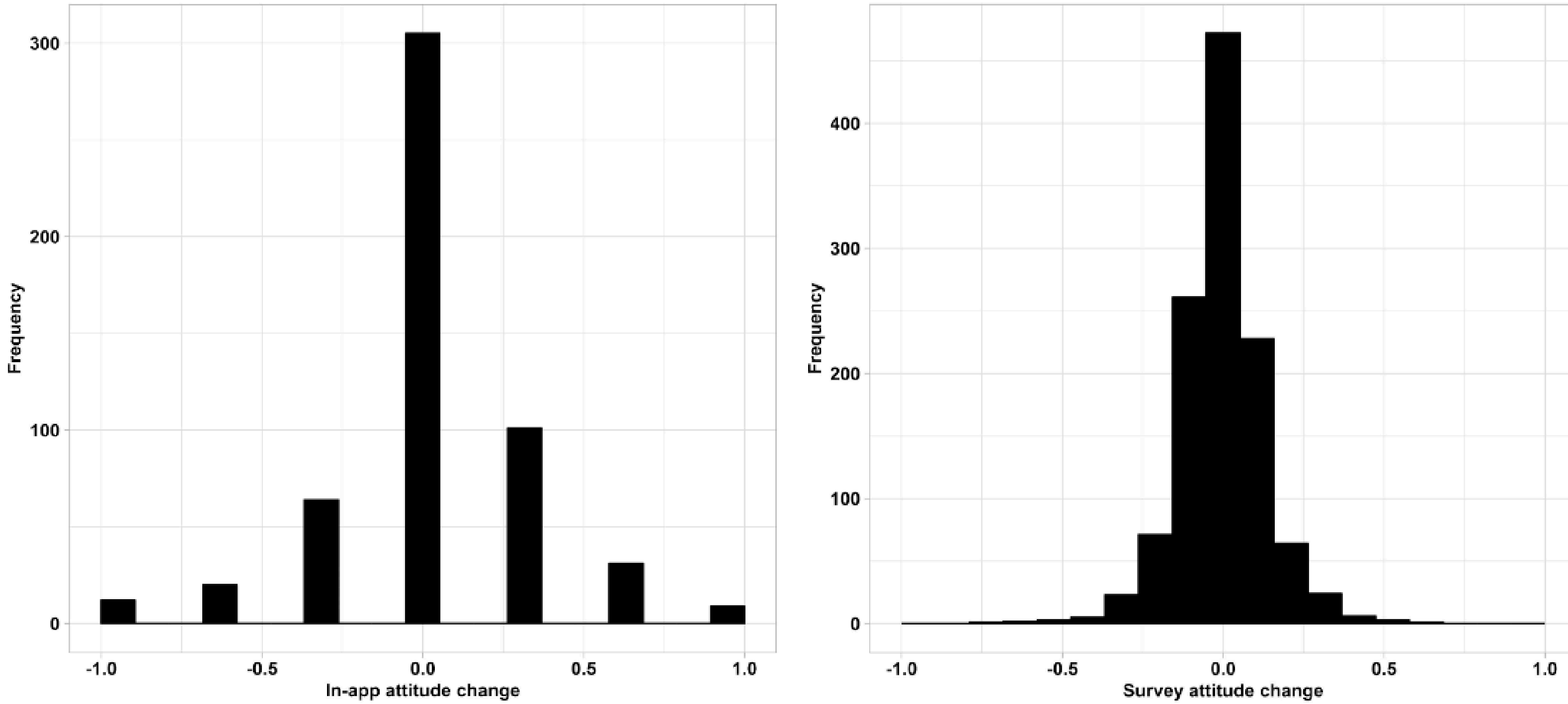
The other dependent variables utilize post-treatment attitudes on political issue positions. This entails assessing post-treatment attitudes and whether they moved closer to the sender's attitudes, measured within a follow-up survey and a survey conducted on the DiscussIt app (see Table 2 for details). Attitudes within the app were evaluated both immediately before and after the conversation, while the follow-up survey occurred several days later. These follow-up survey findings were compared to pre-survey measures collected several days before the conversation. Post-treatment attitudes are coded such that positive values (from 0 to 1) represent more extreme views (i.e., the receiver moves away from the sender's attitudes on the issue), while negative values denote a "backfire" effect (i.e., the receiver moves away from the sender's attitudes on the issue).[7]

The distribution of attitude change between pre-treatment and post-treatment surveys (measured in-app or in follow-ups) is shown in Figure 3. The figure points to some attitude change across all treated participants, not controlling for the use of personal narration. For in-app change, 21.7% of users moved closer to their partners, 25.3% moved away from them, and 53% experienced no change. Within the survey change, 46.7% moved toward their partners, 43.4% moved away from them, and 10% saw no change. In the follow-up survey, 46.7% of users moved closer to their partners, 43.4% moved away from them, and 10% experienced no change.[8]

[7] The full question wording of attitudes is in Appendix B.

[8] Changes by topic, labeling condition, and party affiliation are shown in Figures C2 and C3 of Appendix C for in-app and follow-up attitudes.

Figure 3. Comparison of attitude change distributions



Note. In-app attitude change represents the pre-post difference in responses to a single question about the assigned topic for each participant. This question was posed immediately before and immediately after the conversation. Survey attitude change represents the pre-post difference in the average index of questions related to the assigned topic. These questions were posed several days before and several days after the conversation.

Table 2. Key variables

Variable	Source	Operationalization	*N*
Personal narration	DiscussIt conversations	Binary variable indicating whether a participant received at least one personal narrative.	1169
Evidence	DiscussIt conversations	Binary variable indicating whether a participant received at least one form of evidence.	1169
Perceptions of sender's persuasive influence	DiscussIt survey	Participants' agreement with the statement: "[Partner name] influenced my views on [topic]." Scale ranges from 0 to 1, with higher values indicating higher agreement.	829
In-app post-treatment attitudes	DiscussIt survey	Participants' attitudes towards gun control or immigration (dependent on random assignment) were assessed immediately after the conversation on the assigned topic. Scale ranges from 0 to 1, with higher values representing more extreme liberal or conservative views, controlled for political identity.	542
Follow-up attitudes	Survey	Attitudes towards gun control or immigration (dependent on random assignment) were assessed through an index derived from the average of ten items several days after the conversation. Scale ranges from 0 to 1, with higher values representing more extreme liberal or conservative views, controlled for political identity.	1169

Note. N is the number of observations available for analysis.

Table 3. Correlation matrix of key variables

Variable	1	2	3	4
Personal narrative				
Evidence	.19** [.14, .25]			
Perceptions of sender's persuasive influence	.05 [–.02, .11]	–.11** [–.17, –.14]		
In-app post-treatment attitudes	.01 [–.06, .08]	–.01 [–.08, .06]	–.14** [–.21, -.08]	
Follow-up attitudes	.03 [–.03, .08]	.05 [.00, .11]	–.15** [–.21, –.08]	.50** [.45, .55]

Note. Values in the square brackets indicate the 95% confidence interval representing a plausible range of population correlations that could have caused the sample correlation. *p < .05; **p < .01

https://doi.org/10.33774/apsa-2024-09m5k **ORCID:** https://orcid.org/0000-0001-5599-1890

Controls

All analyses rely on controlling for demographic factors. I control for gender, age, race/ethnicity, and college attendance in the analysis. Further, I control for political variables, such as political identity.[9] Including such controls helps to account for potential confounding factors or differences in the characteristics of individuals that may affect the outcome variable. I also control treatment labeling conditions and the topic of conversation. I incorporate controls for the quality of the conversation. This entails considering factors such as the conversation's duration or the reception of at least one irrelevant message by one's partner (i.e., messages that show the participant was not faithfully participating in the discussion).[10] By including controls for both the reception of junk messages and the number of messages exchanged between the respondent and their partner, my goal is to highlight the overall quality of the conversations and their potential influence on the effectiveness of persuasive techniques.

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[9] Gender is represented by 1 for female and 0 for male. Age is measured in years. Race/ethnicity is represented by 1 for white and 0 for non-white. College education is indicated by 1 for individuals with a college degree and 0 for those without. Political identity is coded 1 for Democrat and 0 for Republican. Partisan strength is coded 1 for strong partisan and 0 for not strong partisan (as self-identified by participants).

[10] Handcoders coded whether a message was considered junk. That is, hand coders had the following instructions: "For some comments that are coded as off-topic, comments may show the participant was not faithfully participating in the study. An example would be discussing compensation, smashing the keyboard, and making an irrelevant comment that looks like they were just trying to get to 14 exchanges rather than having a real conversation. Questions that are asked out of curiosity about the other's opinion do not count as junk responses (i.e., 'Do you think guns should be banned everywhere' or 'Why do you think that'). For Junk response, record: 0 = comment is not a junk response, 1 = comment is a junk response, XX = comment is hard to code." This had an 82.98% intercoder reliability score.

Moreover, in predicting post-treatment attitudes, I incorporate controls for pre-treatment attitudes and the degree of distance between partners' attitudes. This approach accounts for potential floor and ceiling effects on observed attitude changes. Conversational pairs with greater initial differences in attitudes have more room for change compared to those with more similar opinions. Thus, I include a control for the disparity between partners' pre-treatment attitudes to address this consideration.[11]

Results

Does receiving persuasive messages predict perceptions of the sender's persuasive influence?

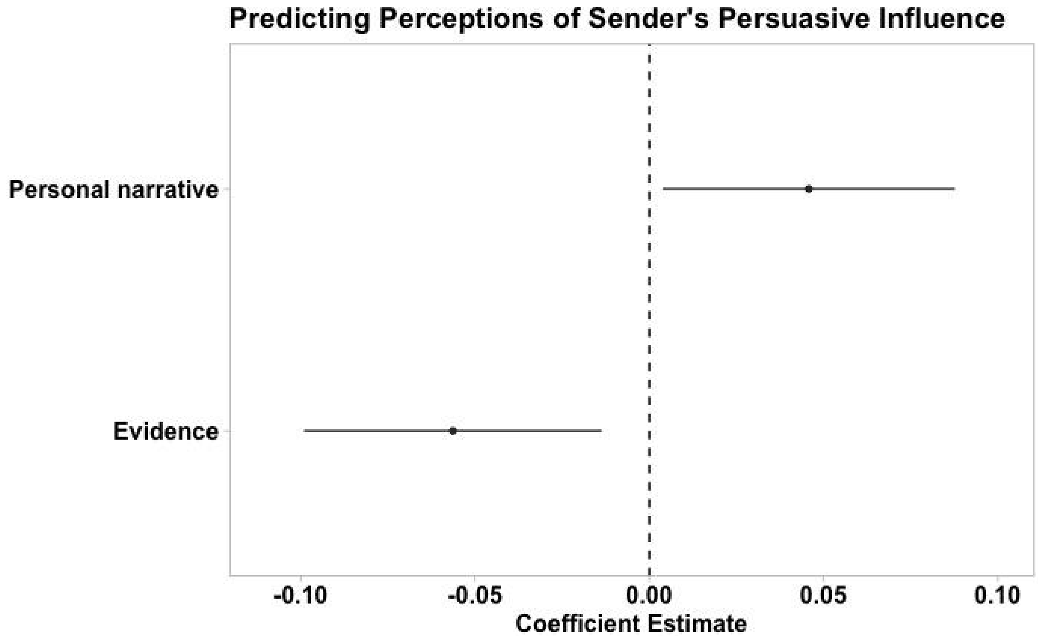
I conducted multiple regression analyses to predict how respondents rated their chat partner's (the sender's) ability to influence their attitudes on the conversation topic based on the reception of persuasive messages (see Figure 4). Perceptions of the sender's persuasive influence are coded such that higher values between 0 and 1 indicate greater agreement that one's chat partner influenced their opinions on the topic of discussion.

The results show a significant difference in perceptions of the sender's persuasive influence between those who received a personal narrative and those who did not. Specifically, the reception of at least one personal narrative is correlated to a heightened perception that the sender had a persuasive influence on the receiver's attitudes by .046 (SE = .023, p < .05). As a result, the reception of a personal narrative predicts a notable increase in perceiving one's conversation partner as persuasive in altering the participant's attitudes on the assigned topic. On the other hand, the reception of evidence-based messages is correlated with a .056 (SE = .023, p < .05) decrease in the perception that the sender had a persuasive influence on the receiver's

[11] The average in-app pre-treatment attitude distances between partners is μ = .39 with a standard deviation of .30 and a range of 0-1. The average survey pre-treatment attitude distances between partners is μ = .24 with a standard deviation of .18 and a range of 0-.90

opinions. In contrast to personal narratives, receiving evidence is linked to perceiving the sender as having less influence on one's attitudes toward gun control or immigration.[12]

Figure 4. Predicting perceptions of the sender's persuasive influence



Note. Positive values on the x-axis denote higher perceptions that their partner influenced their opinions. Linear regression model controls for labeling conditions, conversation topics, demographic and political variables, and conversation quality indicators. *SE*s are clustered at the dyad conversation level.

Does receiving persuasive messages predict post-treatment attitude change?

I predict post-treatment attitudes (coded such that higher values equals increased extremity) by persuasive message reception (see Figure 5). The findings indicate that the reception of a personal narrative or evidence does not significantly predict in-app post-treatment attitudes. Specifically, receiving a personal narrative is associated with a marginal decrease in in-app post-treatment attitudes by .007 (SE = .026, p = .786). As a result, individuals who

[12] Participants who were older, had a college education, and white were less likely to perceive their partner as influencing their opinions (-.003, SE = .001, p < .001; -.085 SE = .021, p < .001; -.061 SE = .027, p < .05). See Table D1 in Appendix D.

received at least one personal narrative tended to move closer to the attitudinal beliefs of their senders compared to those who did not receive such messages (i.e., they became less extreme). However, this effect did not reach statistical significance. Similarly, individuals who received an evidence-based message exhibited a non-significant decrease in in-app post-treatment attitudes by .022 (*SE* = .026, *p* = .425). Therefore, receiving a personal narrative or evidence was expected to predict moderation of in-app attitudinal beliefs post-conversation, but these findings did not reach statistical significance.[13]

Furthermore, the reception of a personal narrative or evidence does not significantly predict follow-up attitudes measured several days later. That is, receiving a personal narrative is associated with a marginal decrease in follow-up attitudes by .002 (*SE* = .008, *p* = .815). As such, those who received personal narratives were predicted to be more likely to moderate several days after having a conversation than those who did not. On the other hand, individuals who received an evidence-based message exhibited a non-significant increase in follow-up attitudes by .010 (*SE* = .008, *p* = .212). That is, the reception of an evidence-based message predicts non-significant shifts in follow-up attitudes becoming more extreme.[14]

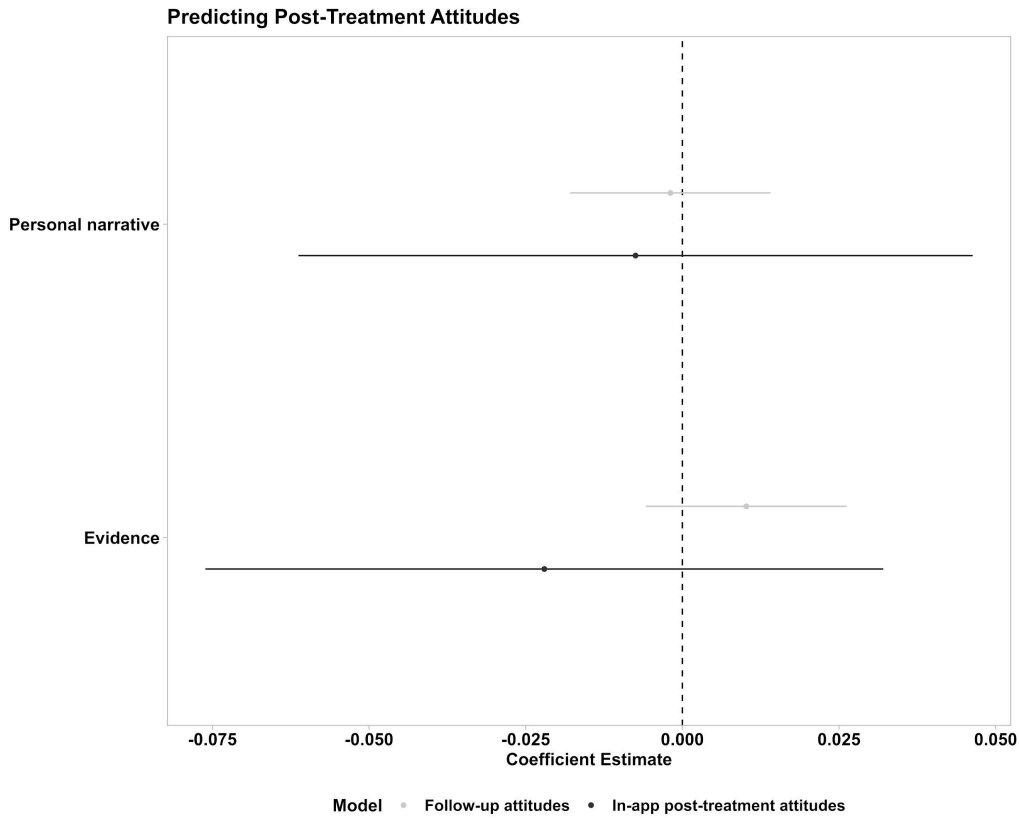
In summary, the findings suggest that receiving personal narratives or evidence-based messages is not associated with any significant changes in in-app or follow-up attitudes after having a cross-partisan conversation. The utilization of personal narratives and evidence-based

[13] Participants who were Democrat and older were less likely to have moved closer in attitudes with their chat partners by .098 (*SE* = .035, *p* < .01) and .003 (*SE* = .001, *p* < .01) (see Table D2 of Appendix D).

[14] Participants discussing immigration were significantly more likely to moderate their attitudes compared to those discussing gun control by .029 (*SE* = .008, *p* < .01). Democrats (.025, *SE* = .009, p < .01) and individuals with strong partisanship (.026, *SE* = .008, *p* < .01) tended to exhibit more extreme attitudes after their conversations compared to before (see Table D3 in Appendix D).

messages does not appear to predict persuasive influence in the form of attitude moderation.

Figure 5. Predicting post-treatment attitudes



Note. Positive values on the x-axis denote attitude changes in the direction of one's conversation partner (i.e., attitude moderation). Linear regression model controls for pre-treatment attitudes, partner's pre-treatment attitude difference, labeling condition, conversation topic, demographic and political variables, and conversation quality indicators. *SE*s are clustered at the dyad conversation level. Large *SE*s for in-app post-treatment attitudes are likely due to the small sample size of those who completed the in-app questions.

Robustness Checks

In addition to the previous findings, I conducted several robustness checks. I replicated my primary analyses using continuous measures for each persuasive technique, utilizing the total count of messages and words received for each type, rather than relying on binary indicators. Results show consistent patterns: an increase in the number of messages employing personal narratives by one predicts an increase in the perception of partner's persuasiveness by .012 (*SE* =

.006, $p < .05$), while for evidence, it decreases by .011 ($SE = .004$, $p < .05$). Similar trends were observed in message length: longer personal narratives predict slight increases in perceptions of partner persuasiveness by .0004 ($SE = .00005$, p =.380), whereas longer evidence-based messages decrease it by .0001 ($SE = .0001$, p < .05). These findings suggest that whether employing binary or continuous measures of persuasive techniques, similar effects emerge. Moreover, using continuous measures to predict post-treatment attitudes suggests no significant moderation of attitudes following conversations with opposing party members.[15]

Next, I investigated whether similar predictive patterns could be observed with other forms of narration, including stories about oneself, stories about others, and general narratives. While I expected personal narratives to exhibit the strongest potential for persuasion due to their ability to forge a personal connection between individuals and the sender, other research employs narratives in a broader sense. I replicated my main results to assess if narratives maintain their persuasive edge over evidence-based messages and to align with existing studies.[16] Using the same procedures and control variables, I found that receiving at least one narrative slightly increased perceptions of the partner's persuasive ability by .044 ($SE = .024$, $p < .10$). Similarly, narratives showed a comparable association with in-app post-treatment attitudes to personal

[15] See Table E1-3 in Appendix E for full model results.

[16] Narration underwent meticulous hand coding by the same team of research assistants under my supervision, adhering to the established methodology. Narratives were hand-coded using the following instructions: Narratives make an explicit connection between an issue at hand and a story. These are not necessarily about the sender themself. Hypothetical scenarios and stereotyping do not count. For example, ‘My mom has gone through so much in her life as an immigrant’ or ‘I am a woman and I feel more comfortable having a gun with me.’ For Narrative, record: 0 = comment does not use narration, 1 = comment does use narration, XX = comment is hard to code.” Hand-coded narration indicated 88.63% intercoder reliability.

https://doi.org/10.33774/apsa-2024-09m5k ORCID: https://orcid.org/0000-0001-5599-1890 Content not peer-reviewed by APSA.

narratives, with a moderation prediction of .025 (*SE* = .028, *p* = .411). Follow-up attitudes indicated a non-significant increase of .008 (*SE* = .009, *p* = .332) in attitude extremity for individuals exposed to narration.[17] These results suggest that both personal narratives and broader forms of narration yield similar effects on attitude changes and perceptions of persuasive influence. Nonetheless, personal narratives may hold a slight advantage in enhancing perceptions of a chat partner's persuasiveness, achieving higher statistical significance.

Finally, my main analyses controlled for labeling conditions, where respondents in the treatment condition received varied information about their conversation partner's partisanship. Previous analyses showed no significant differences in issue-based depolarization across these groups (Combs et al. 2023). However, I tested for interactions between my main independent variable, the reception of personal narratives, and these differing conditions. Results indicate that the reception of personal narratives had non-significant differences across different information conditions on all dependent variables. This suggests that regardless of the information received about their partner's political identity, the impact of personal narratives on in-app post-treatment attitudes, follow-up attitudes, and perceptions of persuasive influence remained consistent.[18]

Conclusion

This study sheds light on citizen persuasion in online cross-partisan interactions using data from 1,169 American participants engaged in discussions on a mobile chat platform. It explores the associative effectiveness of personal narration and evidence-based messages on actual attitude change and perceptions of persuasion regarding one's conversation partner. Descriptive analyses

[17] Refer to Table E4-6 of Appendix E.

[18] OLS regression results and linear predictions in Tables E7-9 and Figures E1-3 of Appendix E.

and linear regressions reveal the persuasive strategies employed, including the effectiveness of personal narratives and evidence, in citizen-to-citizen interactions.

Despite recent conclusions that narratives are persuasive (e.g., Gooch 2018; Kubin et al. 2021)–and perhaps the key to cross-partisan interaction's political opinion moderation–I have identified a case where they are ineffective. Both personal narration and narratives broadly, did not predict issue-based attitude moderation. Additionally, despite evidence's persuasive reputation in other contexts, it did not predict attitude change in cross-partisan interactions and instead decreased the likelihood of perceiving one's partner as persuasive. These findings are consistent with existing literature showing that citizen attitudes are often resistant to change and heavily influenced by signals from political leaders (Lenz 2012; Tesler 2015).

My findings highlight the importance of further investigating the effectiveness of personal narration as a persuasive tool and reevaluating the conditions under which it can truly influence attitude change. For example, personal narratives might be more effective in face-to-face interactions involving trained professionals, non-anonymous settings, or carefully structured survey experiments. In a field experiment where individuals engage in discussions with anonymous chat partners they've never met or seen, achieving attitude change may prove challenging, especially in a one-off cross-partisan conversation. My results challenge the notion that personal narratives inherently possess a robust ability to induce actual attitude change.

However, the goal of cross-partisan interactions should go beyond persuasion alone. Many researchers use such interventions to promote attitude moderation, but they also emphasize additional benefits not strictly tied to moderation. For instance, scholars studying cross-cutting interactions often highlight outcomes like reflective thinking (Levitan and Visser, 2008), increased awareness and recognition of opposing viewpoints' legitimacy (Lord et al., 1984;

Lyons and Sokhey, 2017), and empathy (Santos et al., 2022). These positive outcomes may not directly translate into changes in survey responses but could instead lead individuals to reconsider their perspectives when discussing divisive issues like gun control or immigration (Zaller 1992). If this is the case, these effects might be reflected in how individuals perceive their conversation partners.

Indeed, the findings suggest that individuals perceive their conversation partner as influential in shaping their attitudes when personal narratives are present, and these results remain robust across various checks. There are several reasons why political attitudes may not change significantly despite this perception of influence. Individuals might view the sender as influential due to social desirability bias or a tendency to conform to perceived social norms, regardless of genuine persuasion by the message. Additionally, the emotional appeal of the message or the sender's delivery style can impact perceptions of persuasion. Factors such as the sender's credibility, likability, or perceived expertise can influence perceptions of their persuasive ability, even if the message itself does not lead to attitude change.

To explore such possibilities, I conducted several analyses. I found that perceptions of attitude change, rather than actual attitude changes, were influenced by the reception of personal narratives and evidence-based messages. This perception-reality disconnect may stem from perceptions of influence aligning more closely with affective depolarization rather than issue-based depolarization. In affective depolarization, the receiver tends to feel more positively or warmly towards the sender (or out-party members in general) without necessarily changing their opinions on specific issues. When predicting variables like out-party member social distance, traits, and thermometer ratings, neither the reception of personal narratives nor evidence-based messages predicted affective depolarization.[19] Therefore, factors such as warmth, traits, and social distance do not substitute for perceptions of the sender's persuasive ability. The dependent variable here remains distinct from measures of affective depolarization when predicted by the reception of personal narratives.

Using personal narratives as the main predictor, if persuasion is reflected in perceptions of the conversation partner or driven by social desirability rather than general traits of opposing party members, we would expect individuals exposed to personal narratives to report higher enjoyment of their conversation partner. The results confirm this expectation: those who received personal narratives were more likely to express greater enjoyment in the conversation compared to those who did not (.037, $SE = .019$, $p < .05$). This inclination decreased if they received evidence (–.032, $SE = .019$, $p = .089$).[20] Notably, enjoyment of the conversation was the initial post-treatment question on the app, thereby reducing the possibility of a substitution effect where enjoyment affects perceptions of the partner's persuasiveness. It is plausible that personal narratives are both enjoyable and perceived as more persuasive simultaneously, aligning with literature indicating their immersive quality in connecting individuals with the sender.

Once more, the impact of persuasion through personal narratives or evidence-based messaging might not manifest directly in post-treatment survey attitudes, but rather in how individuals perceive their partner's persuasive influence. If individuals view this perception of influence as merely reflecting social desirability, enjoyment, or something separate from persuasion, it doesn't necessarily indicate failure in cross-partisan interactions or the

[19] See results in Figure E4 of Appendix E.

[20] For full model results see Table E10 of Appendix E.

effectiveness of these persuasive techniques. Instead, it underscores that the objective extends beyond mere issue moderation.

One limitation pertains to our post-treatment measures, which could benefit from further exploration. For example, including open-ended questions about individuals' genuine perceptions of their partner or more detailed inquiries into specific topics they were persuaded on could provide valuable insights. In other words, it's possible that attitude change did occur but went unnoticed because we did not ask about the specific components discussed within the broad topics of gun control or immigration. Moreover, incorporating questions about how individuals perceive their partner's intelligence, honesty, empathy, or openness could offer insights into whether perceptions of the partner shift after a conversation due to these persuasive techniques. This could uncover whether the treatment influences people to see the other side's opinions and attitudes as more aligned with their own than previously thought.

In summary, my findings reveal a disconnect between perceptions of influence, influenced by the reception of personal narratives and evidence-based messaging, and actual attitudes. This departure from prior studies highlighting the effectiveness of narratives in attitude change is notable, particularly in online anonymous cross-partisan interactions where their impact seems diminished. However, there remains potential to positively (or negatively, in the case of evidence-based messaging) influence perceptions of the opposing side through the effective use of personal narration. For those interested in leveraging cross-partisan interactions, understanding conversational dynamics is crucial, recognizing specific elements that can either mitigate or exacerbate polarization. Further exploration into the persuasive strategies used by everyday citizens, their self-perceptions, and their efforts to persuade others, promises valuable insights into the mechanisms driving interpersonal influence and polarization.

References

Aarøe, Lene. 2011. "Investigating Frame Strength: The Case of Episodic and Thematic Frames." *Political Communication* 28 (2): 207–26.

Ahler, Douglas J., and Gaurav Sood. 2018. "The Parties in Our Heads: Misperceptions about Party Composition and their Consequences." *The Journal of Politics* 80 (3): 964–81.

Allport, Floyd H. 1954. "The Structuring of Events: Outline of a General Theory with Applications to Psychology." *Psychological Review* 61 (5): 281.

Barber, Benjamin. 2003. *Strong Democracy: Participatory Politics for a New Age*. Berkeley: University of California Press.

Barton, Jared, and Xiaofei Pan. 2022. "Movin'on up? A Survey Experiment on Mobility Enhancing Policies." *European Journal of Political Economy* 74: 102172.

Baumeister, Roy F., and Leonard S. Newman. 1994. "How Stories Make Sense of Personal Experiences: Motives that Shape Autobiographical Narratives." *Personality and Social Psychology Bulletin* 20 (6): 676–90.

Broockman, David, and Joshua Kalla. 2016. "Durably Reducing Transphobia: A Field Experiment on Door-to-Door Canvassing." *Science* 352 (6282): 220–24.

Broockman, David E., and Daniel M. Butler. 2017. "The Causal Effects of Elite Position‐Taking on Voter Attitudes: Field Experiments with Elite Communication." *American Journal of Political Science* 61 (1): 208–21.

Carlson, Taylor N., and Jaime E. Settle. 2022. *What Goes Without Saying*. New York: Cambridge University Press.

Carlson, Taylor N., Marisa Abrajano, and Lisa García Bedolla. 2020. *Talking Politics: Political Discussion Networks and the New American Electorate*. New York: Oxford University

Press.

Carpenter, Christopher J. 2019. "Cognitive Dissonance, Ego-Involvement, and Motivated Reasoning." *Annals of the International Communication Association* 43 (1): 1–23.

Cho, Hyunyi, Lijiang Shen, and Kari Wilson. 2014. "Perceived Realism: Dimensions and Roles In Narrative Persuasion." *Communication Research* 41 (6): 828–51.

Combs, Aidan, Graham Tierney, Brian Guay, Friedolin Merhout, Christopher A. Bail, D. Sunshine Hillygus, and Alexander Volfovsky. 2023. "Reducing Political Polarization in the United States with a Mobile Chat Platform." *Nature Human Behaviour* 7 (9): 1454–61.

Conover, Pamela Johnston, Donald D. Searing, and Ivor M. Crewe. 2002. "The Deliberative Potential of Political Discussion." *British Journal of Political Science* 32 (1): 21–62.

Conover, Pamela Johnston, and Donald D. Searing. 2005. "Studying 'Everyday Political Talk'in the Deliberative System." *Acta Politica* 40: 269–83.

Davis, Ryan W., and Rachel Finlayson. 2022. "Public Reasoning Together: Gender and Political Deliberation." *The Journal of Politics* 84 (3): 1556–69.

de Jong, Jona F. 2024. "Cross-Partisan Discussions Reduced Political Polarization between UK Voters, but less so When they Disagreed." *Communications Psychology* 2 (1): 5.

De Raad, Boele. 1984. "Person-Talk in Everyday Situations." *Personality Psychology in Europe: Theoretical and Empirical Developments* 1: 31–44.

Druckman, James N. 2022. "A Framework for the Study of Persuasion." *Annual Review of Political Science* 25: 65–88.

Druckman, James N., Samara Klar, Yanna Krupnikov, Matthew Levendusky, and John Barry Ryan. 2022. "(Mis)estimating Affective Polarization." *The Journal of Politics* 84 (2):

1106–17.

Eveland, Jr, William P. 2004. "The Effect of Political Discussion in Producing Informed Citizens: The Roles of Information, Motivation, and Elaboration." *Political Communication* 21 (2): 177–93.

Eveland Jr, William P., Alyssa C. Morey, and Myiah J. Hutchens. 2011. "Beyond Deliberation: New Directions for the Study of Informal Political Conversation from a Communication Perspective." *Journal of Communication* 61 (6): 1082–1103.

Fowler, Erika Franklin, Michael Franz, and Travis Ridout. 2021. *Political Advertising in the United States*. New York: Routledge.

Gerrig, Richard. 2018. *Experiencing Narrative Worlds*. New York: Routledge.

Gilens, Martin. 2001. "Political Ignorance and Collective Policy Preferences." *American Political Science Review* 95 (2): 379–96.

Gooch, Andrew. 2018. "Ripping Yarn: Experiments on Storytelling by Partisan Elites." *Political Communication* 35 (2): 220–38.

Green, Melanie C., and Timothy C. Brock. 2000. "The Role of Transportation in the Persuasiveness of Public Narratives." *Journal of Personality and Social Psychology* 79 (5): 701.

Green, Melanie C., Christopher Chatham, and Marc A. Sestir. 2012. "Emotion and Transportation into Fact and Fiction." *Scientific Study of Literature* 2 (1): 37–59.

Green, Melanie C., and John K. Donahue. 2011. "Persistence of Belief Change in the Face of Deception: The Effect of Factual Stories Revealed to be False." *Media Psychology* 14 (3): 312–31.

Gross, Kimberly. 2008. "Framing Persuasive Appeals: Episodic and Thematic Framing, Emotional Response, and Policy Opinion." *Political Psychology* 29 (2): 169–92.

Hersh, Eitan D., and Brian F. Schaffner. 2013. "Targeted Campaign Appeals and the Value of Ambiguity." *The Journal of Politics* 75 (2): 520–34.

Hopkins, Daniel J., John Sides, and Jack Citrin. 2019. "The Muted Consequences of Correct Information About Immigration." *The Journal of Politics* 81 (1): 315–20.

Howard, George S. 1991. "Culture Tales: A Narrative Approach to Thinking, Cross-Cultural Psychology, and Psychotherapy." *American Psychologist* 46 (3): 187.

Huber, Gregory A., and Neil Malhotra. 2017. "Political Homophily in Social Relationships: Evidence from Online Dating Behavior." *The Journal of Politics* 79 (1): 269–83.

Huff, Darrell. 1954. *How to Lie with Statistics.* New York: W. W. Norton & Company.

Huckfeldt, Robert, Paul E. Johnson, and John Sprague. 2004. *Political Disagreement: The Survival of Diverse Opinions within Communication Networks*. New York: Cambridge University Press.

Kalla, Joshua L., and David E. Broockman. 2020. "Reducing Exclusionary Attitudes through Interpersonal Conversation: Evidence from Three Field Experiments." *American Political Science Review* 114 (2): 410–25.

Kalla, Joshua L., and David E. Broockman. 2023. "Which Narrative Strategies Durably Reduce Prejudice? Evidence from Field and Survey Experiments Supporting the Efficacy of Perspective‐Getting." *American Journal of Political Science* 67 (1): 185–204.

Kawata, Keisuke, Kenneth Mori McElwain, and Masaki Nakabayashi. 2024. "Narrative Premiums in Policy Persuasion." *Political Psychology* 45 (2): 383–405.

Kim, Eunji. 2023. "Entertaining Beliefs in Economic Mobility." *American Journal of Political Science* 67 (1): 39–54.

Kubin, Emily, Curtis Puryear, Chelsea Schein, and Kurt Gray. 2021. "Personal Experiences Bridge Moral and Political Divides Better than Facts." *Proceedings of the National Academy of Sciences* 118 (6): e2008389118.

Kuklinski, James H., Paul J. Quirk, Jennifer Jerit, David Schwieder, and Robert F. Rich. 2000. "Misinformation and the Currency of Democratic Citizenship." *The Journal of Politics* 62 (3): 790–816.

Lasswell, Harold D. 1948. "The Structure and Function of Communication in Society." *The Communication of Ideas* 37 (1): 136–39.

Lenz, Gabriel S. 2012. *Follow the Leader?: How Voters Respond to Politicians' Policies and Performance.* Chicago: University of Chicago Press.

Levendusky, Matthew, and Neil Malhotra. 2016. "Does Media Coverage of Partisan Polarization Affect Political Attitudes?" *Political Communication* 33 (2): 283–301.

Levendusky, Matthew S., and Dominik A. Stecula. 2021. *We Need to Talk: How Cross-Party Dialogue Reduces Affective Polarization*. New York: Cambridge University Press.

Levitan, Lindsey Clark, and Penny S. Visser. 2008. "The Impact of the Social Context on Resistance to Persuasion: Effortful versus Effortless Responses to Counter-Attitudinal Information." *Journal of Experimental Social Psychology* 44 (3): 640–49.

Lodge, Milton, and Charles S. Taber. 2013. *The Rationalizing Voter*. New York: Cambridge University Press.

Lord, Charles G., Mark R. Lepper, and Elizabeth Preston. 1984. "Considering the Opposite: a Corrective Strategy for Social Judgment." *Journal of Personality and Social Psychology* 47 (6): 1231.

Lyons, Jeffrey, and Anand E. Sokhey. 2017. "Discussion Networks, Issues, and Perceptions of

Polarization in the American Electorate." *Political Behavior* 39: 967–88.

MacInnis, Cara C., and Elizabeth Page-Gould. 2015. "How can Intergroup Interaction be Bad if Intergroup contact is Good? Exploring and Reconciling an Apparent Paradox in the Science of Intergroup Relations." *Perspectives on Psychological Science* 10 (3): 307–27.

McDonald, Jared, and Michael J. Hanmer. 2023. "Evaluating Methods for Examining the Relative Persuasiveness of Policy Arguments." *Political Science Research and Methods* 1–8.

McGuire W. 1969. The Nature of Attitudes and Attitude Change. In Elliot Aronson and Gardner Lindzey, eds. *The Handbook of Social Psychology*. Massachusetts: Addison-Wesley, 136–314.

Minozzi, William, Hyunjin Song, David M. J. Lazer, Michael A. Neblo, and Katherine Ognyanova. "The Incidental Pundit: Who Talks Politics with Whom, and Why?" *American Journal of Political Science* 64 (1): 135–51.

Morley, Donald Dean, and Kim B. Walker. 1987. "The Role of Importance, Novelty, and Plausibility in Producing Belief Change." Communications Monographs 54 (4): 436–42.

Moy, Patricia, and John Gastil. 2006. "Predicting Deliberative Conversation: The Impact of Discussion Networks, Media Use, and Political Cognitions." *Political Communication* 23 (4): 443–60.

Mullinix, Kevin J. 2016. "Partisanship and Preference Formation: Competing Motivations, Elite Polarization, and Issue Importance." *Political Behavior* 38: 383–411.

Naunov, Martin, Carlos Rueda-Cañòn, and Tim Ryan. 2024. "Who's Persuasive: Understanding Citizen-to-Citizen Efforts to Change Minds." *University of North Carolina, Chapel Hill.*

O'Keefe, Daniel J. 2016. "Persuasion and Social Influence." *The International Encyclopedia of*

Communication Theory and Philosophy 1–19.

Paluck, Elizabeth Levy, Seth A. Green, and Donald P. Green. 2019. "The Contact Hypothesis Re-Evaluated." *Behavioural Public Policy* 3 (2): 129–58.

Parrott, Roxanne, Kami Silk, Kelly Dorgan, Celeste Condit, and Tina Harris. 2005. "Risk Comprehension and Judgments of Statistical Evidentiary Appeals: When a Picture is Not Worth a Thousand Words." *Human Communication Research* 31 (3): 423–52.

Perloff, Richard M. 1993. *The Dynamics of Persuasion: Communication and Attitudes in the 21st Century*. New York: Routledge.

Pettigrew, Thomas F., and Linda R. Tropp. 2006. "A Meta-Analytic Test of Intergroup Contact Theory." *Journal of Personality and Social Psychology* 90 (5): 751.

Polletta, Francesca, and John Lee. 2006. "Is Telling Stories Good for Democracy? Rhetoric in Public Deliberation after 9/11." *American Sociological Review* 71 (5): 699–721.

Redlawsk, David P., Andrew JW Civettini, and Karen M. Emmerson. 2010. "The Affective Tipping Point: Do Motivated Reasoners Ever 'Get It'?." *Political Psychology* 31 (4): 563–93.

Reynolds, Rodney A., and J. Lynn Reynolds. 2022. What We Know so Far About Evidence. In James P. Dillard and Michael Pfau, eds. *The Persuasion Handbook: Developments in Theory and Practice*. California: Sage Publications, 427–32.

Rossiter, Erin L. 2022. "Measuring Agenda Setting in Interactive Political Communication." *American Journal of Political Science* 66 (2): 337–51.

Rossiter, Erin L., and Taylor N. Carlson. 2024. "Cross-Partisan Conversation Reduced Affective Polarization for Republicans and Democrats Even After the Contentious 2020 Election." *The Journal of Politics* 86 (4): 000-000.

Santoro, Erik, and David E. Broockman. 2022. "The Promise and Pitfalls of Cross-Partisan Conversations for Reducing Affective Polarization: Evidence from Randomized Experiments." *Science Advances* 8 (25): eabn5515.

Santos, Luiza A., Jan G. Voelkel, Robb Willer, and Jamil Zaki. 2022. "Belief in the Utility of Cross-Partisan Empathy Reduces Partisan Animosity and Facilitates Political Persuasion." *Psychological Science* 33 (9): 1557–73.

Slater, Michael D., and Donna Rouner. 2002. "Entertainment–Education and Elaboration Likelihood: Understanding the Processing of Narrative Persuasion." *Communication Theory* 12 (2): 173–91.

Small, Deborah A., George Loewenstein, and Paul Slovic. 2007. "Sympathy and Callousness: The Impact of Deliberative Thought on Donations to Identifiable and Statistical Victims." *Organizational Behavior and Human Decision Processes* 102 (2): 143–53.

Smith, Amy Erica. 2018. "Talking it out: Political Conversation and Knowledge Gaps in Unequal Urban contexts." *British Journal of Political Science* 48 (2): 407–25.

Tajfel, Henri, and Alan L. Wilkes. 1963. "Classification and Quantitative Judgement." *British Journal of Psychology* 54 (2): 101–14.

Tesler, Michael. 2015. Priming Predispositions and Changing Policy Positions: An Account of When Mass Opinion is Primed or Changed. *American Journal of Political Science* 59 (4): 806–24.

Wlezien, Christopher. 2024. "News and Public Opinion: Which Comes First?." *The Journal of Politics* 86 (1): 1–17.

Zaller, John. 1992. *The Nature and Origins of Mass Opinion.* New York: Cambridge University Press.

Appendix A. Information about the sample

Participants

Observational data from 1,169 U.S. citizens examines the association between persuasive techniques, assessed through text analysis, and attitudes gauged through survey responses. The potential pool of respondents was recruited through YouGov. YouGov draws survey respondents from a large national non-probability panel using a combination of quota sampling and weighting to provide a sample that matches the demographic composition of the U.S. population. Participants were at least 18 years of age, self-identified as either Republican or Democrat (including Independents who said they 'leaned' toward one party), used an iOS or Android smartphone or tablet, and self-reported a willingness to install an app on their phone or tablet. By asking them to test a new social media platform, respondents were less aware of the political nature and experimental design to guard against demand effects. Respondents who downloaded the app were randomly assigned to an opposing partisan and were given compensation if completing 10 replies with another user about a specific topic.

The sample completed pre- and post-surveys, passed several survey quality assessments, showed a willingness to download an app, and eventually downloaded the app to engage in a conversation with their designated partner. While the total number of potential treated participants was 1,272, following data quality assessments, the final sample size was reduced to 1,169. Specifically, one individual was excluded for not expressing willingness to download the app, and 102 did not meet the criteria during data quality checks.

Study setting

The observational data utilized in this study were sourced from Combs et al. 2023, who gathered survey and text data from January 2020 to March 2020 on a mobile chat platform designed with the visual and functional resemblance of Facebook Messenger and WhatsApp. The app, DiscussIt, was developed to facilitate political discussions on contentious issues between users and anonymous conversation partners. In the original study, participants were directed to complete a pre-survey via Qualtrics and randomly assigned to either treatment or control groups. Those in the treatment groups received invitations to download and evaluate a mobile app for a novel social media platform, with compensation provided for their participation.

Treated participants were randomly assigned to discuss gun control or immigration and were given gender-neutral pseudonyms to protect their identities. In addition, they were further randomized into one of three sub-conditions. The conversation partner was either correctly identified as an opposing partisan, not labeled with a party, or mislabeled to have the same party identification as the respondent (though participants were always assigned a partner of the opposing political affiliation). These experimental conditions in the original study by Combs et al. 2023 were meant to provide further insight into how information about partisan identity might shape anonymous conversations about politics (Dias and Lelkes 2022; Mason 2018). Combs et al. (2023) discovered that treated individuals who engaged in cross-partisan contact showed reduced polarization compared to control groups, with labeling conditions having no impact on this depolarization.

Those who were not treated were randomly assigned to a control condition. These respondents were asked to write an essay on immigration or gun control in response to the same prompts provided in the app. This ensured individuals in the study (treated and not treated) had given roughly equivalent thought to the specific policy topic (Arceneaux and Vander Wielen 2017). Several days after respondents in the treatment condition completed their chats, all respondents received another invitation to a follow-up survey measuring the key outcomes. This survey included the same measures used in the pre-survey. In addition, questions about the respondents' attitudes were asked on the app immediately before and after the conversation had ended. The app also collected the full text of all conversations that were hand-coded by a team of research assistants.

Table A1. Comparison of the sample to the United States adult citizen population

Variable	United States Population (Mean)	DiscussIt Sample (Mean)
Female	0.51	0.55
Age	52.24	52.30
White	0.67	0.78
Black	0.13	0.08
Hispanic or Latina/o	0.13	0.07
Other race or multiracial	0.07	0.07
No high school	0.10	0.02
High school	0.28	0.20
Some college	0.23	0.27
Two-year degree	0.09	0.15
Four-year degree	0.20	0.24
Postgraduate	0.11	0.12
Less than $50,000	0.31	0.39
$50,000 to $99,999	0.32	0.38
$100,000 to $149,999	0.19	0.15
$150,000 to $199,999	0.08	0.04
$200,000 or more	0.10	0.04
Democrat		0.40
Independent/other party: lean Democrat		0.09
Republican		0.37
Independent/other party: lean Republican		0.12

Note. Population-weighted means are calculated using the 2019 American Community Survey (noncitizens, those under 18, and those residing in Puerto Rico are excluded; $N = 2449277$). Sample means include all respondents used; $N = 1169$.

Appendix B. Variable construction

The analyses reported in the manuscript rely on (1) post-treatment perceptions that one's conversation partner had a persuasive influence in changing their attitudes, (2) follow-up attitude movement in the direction of one's conversation partner as measured by a survey, and (3) in-app post-treatment attitude movement in the direction of one's conversation partner as measured by DiscussIt mobile chat platform. I describe the construction of the attitude measures below.

Follow-up attitudes construction

To derive the follow-up post-treatment attitudes indicating whether an individual changed their attitudes in the direction of the sender's attitudes, a series of steps were taken. Attitudes towards gun control and immigration were assessed through an index derived from the average of ten items several days before and after the interaction. Each item was on a 1-6 or 1-7 scale depending on the number of survey answer options. Higher values on this scale represent more conservative views. These 1-6 or 1-7 ranges were then changed to -1 to 1, with higher values still representing more conservative views. The absolute value was taken to control for political identity, and the average of all ten items for each topic created each index. Thus, higher values from 0-1 represent more extreme liberal or conservative views across the index depending on the participant's political identity. I used the attitude positions for the topic the participants were randomly assigned.

For those randomly assigned to gun control, the index used to create the pre-treatment survey index and follow-up survey index was generated from two sets of questions. The first set of questions was on a 1-6 scale: *1-Strongly support, 2-Moderately support, 3-Slightly support, 4-Slightly oppose, 5-Moderately oppose,* and *6-Strongly oppose.*

How much do you support or oppose the following statements?

Barring gun purchases by people on the federal no-fly or watch lists.

– Requiring background checks for all gun sales.

– Preventing people with mental illnesses from purchasing guns.

– Banning assault-style weapons.

– Allowing people to carry concealed guns in more places.

– Allowing teachers and school officials to carry guns in K-12 schools.

For those randomly assigned to immigration, the index used to create the pre-treatment survey index and follow-up survey index was generated from two sets of questions. The first set of questions was on a 1-7 scale: *1-Agree very strongly, 2-Agree strongly, 3-Agree somewhat, 4-Neither agree nor disagree, 5-Disagree somewhat, 6-Disagree strongly disagree,* and *7-Disagree very strongly.* Some items were reverse coded (*) such that higher values equal more unfavorable attitudes towards immigration (i.e., more conservative).

How much do you agree or disagree with the following statements?

– Recent immigration into the U.S. has done more good than harm.

– Immigrants today strengthen our country because of their hard work and talents.

– Having an increasing number of people of many different races, ethnic groups and nationalities in the United States makes this country a better place to live.

– Immigrants mostly hurt the economy by driving wages down for many Americans.*

– Immigration increases the crime rate in the U.S.*

The second set of questions was on a 1-6 scale: *1-Strongly support, 2-Moderately support, 3- Slightly support, 4- Slightly oppose, 5- Moderately oppose,* and *6- Strongly oppose.* Some items were reverse coded (*) such that higher values equal more favorable attitudes towards immigration (i.e., more conservative).

Please indicate whether you would support or oppose the following proposals about immigration policy:

– Changing the U.S. constitution so that children of unauthorized immigrants do not automatically get citizenship if they are born in this country.*

– Building a wall on the U.S. border with Mexico.*

– Separating the children from those parents who are arrested for crossing the border illegally.*

– Allowing unauthorized immigrants currently living in the United States to remain in the country and eventually qualify for citizenship.

– Requiring that all immigrants to the United States learn to speak English.*

In-app post-treatment attitudes construction

As part of the treatment, participants were randomly assigned to discuss gun control or immigration, responding to a single in-app attitude question for their assigned topic. An in-app pre-treatment and post-treatment variable was then created for both gun control and immigration. Each item was on a 0-6 scale representing the number of survey answer options. Higher values on this scale represent more conservative views. This 0-6 scale was then changed to -1 to 1, with higher values still representing more conservative views. The absolute value of this variable was taken, resulting in values ranging from 0 to 1, with higher values indicating greater extremity in the direction of partisanship.

In the gun control condition, respondents answered the following question:

– Do you agree or disagree with the following statement: 'The laws controlling the sale and ownership of guns in the United States should be made stricter?' (*0-Disagree very strongly*

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to 6-Agree very strongly)

In the immigration condition, respondents answered the following question:

– Do you agree or disagree with the following statement: ‘Recent immigration to this country has done more harm than good?’ (*0-Disagree very strongly to 6-Agree very strongly*)

Depending on the randomly assigned topic of the conversation, either the gun control or immigration change measure was applied to each participant. For those assigned to the gun control condition, their in-app post-treatment measure was considered, while for those in the immigration condition, the corresponding change measure was used. The final dependent variable indicates whether an individual moved in the direction of their partner after the conversation, incorporating the participant’s political identity. For example, a negative in-app post-treatment coefficient for Republicans signifies a shift toward liberal views, whereas for Democrats, it indicates movement toward conservative views.

Appendix C. Additional details and descriptives

Table C1. Frequency of persuasive message reception by conversation topic, labeling conditions, and party

Reception type	Variable	Frequency
Neither	Topic - Gun control	24%
Personal narratives only	Topic - Gun control	21%
Evidence only	Topic - Gun control	21%
Both	Topic - Gun control	34%
		100%
Neither	Topic - Immigration	26%
Personal narratives only	Topic - Immigration	15%
Evidence only	Topic - Immigration	26%
Both	Topic - Immigration	37%
		100%
Neither	Label - Correct	21%
Personal narratives only	Label - Correct	16%
Evidence only	Label - Correct	25%
Both	Label - Correct	38%
		100%
Neither	Label - Incorrect	27%
Personal narratives only	Label - Incorrect	23%
Evidence only	Label - Incorrect	20%
Both	Label - Incorrect	30%
		100%
Neither	Label - None	27%
Personal narratives only	Label - None	14%
Evidence only	Label - None	20%
Both	Label - None	38%
		100%
Neither	Party - Democrat	26%
Personal narratives only	Party - Democrat	17%
Evidence only	Party - Democrat	22%
Both	Party - Democrat	35%
		100%
Neither	Party - Republican	24%
Personal narratives only	Party - Republican	19%
Evidence only	Party - Republican	22%
Both	Party - Republican	36%
		100%

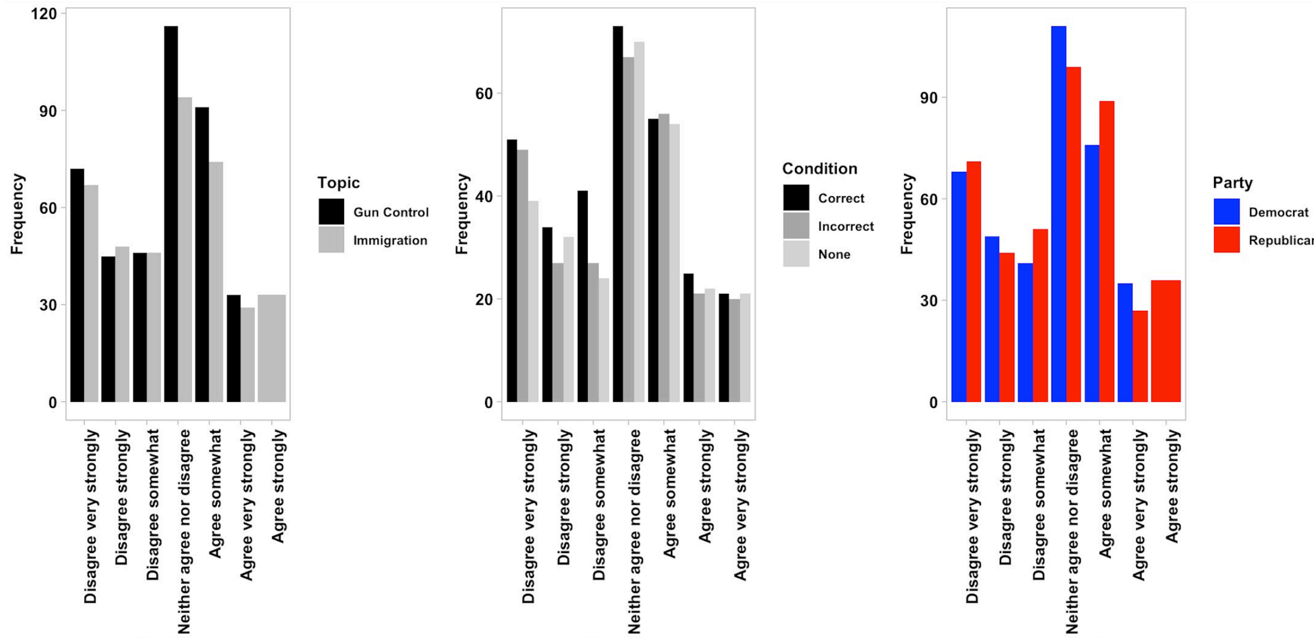
Note. Cross-tabulations show the frequency at which participants from various randomized conditions and different party affiliations encountered at least one personal narrative or evidence, none, or both.

Table C2. Predicting sender's demographics using persuasive messages sent

	Independent variables					
	Democrat	Strong Partisan	Female	College	White	Age (In Years)
Intercept	0.087 *SE* = 0.460 *p* = 0.880	-1.662 *SE* = 1.003 *p* = 0.346	-0.916 *SE* = 1.159 *p* = 0.574	0.873 *SE* = 0.510 *p* = 0.337	1.428 *SE* = 0.115 *p* = 0.511	0.741 *SE* = 0.168 *p* = 0.142
Evidence only	0.669 *SE* = 0.650 *p* = 0.491	2.731 *SE* = 1.418 *p* = 0.305	1.674 *SE* = 1.638 *p* = 0.493	-0.485 *SE* = 0.722 *p* = 0.623	-0.262 *SE* = 0.162 *p* = 0.353	-0.397 *SE* = 0.238 *p* = 0.343
Neither	0.453 *SE* = 0.563 *p* = 0.568	3.012 *SE* = 1.228 *p* = 0.247	1.188 *SE* = 1.419 *p* = 0.556	-0.303 *SE* = 0.625 *p* = 0.713	-1.84 *SE* = 0.141 *p* = 0.048	-0.963 *SE* = 0.206 *p* = 0.135
Personal Narrative Only	0.226 *SE* = 0.650 *p* = 0.787	1.114 *SE* = 1.418 *p* = 0.576	0.784 *SE* = 1.638 *p* = 0.716	-0.317 *SE* = 0.722 *p* = 0.737	-1.45 *SE* = 0.162 *p* = 0.071	-2.05 *SE* = 0.238 *p* = 0.073
Residual Standard Error	0.459	1.003	1.159	0.510	0.115	0.168
Multiple R-squared	0.552	0.879	0.538	0.3207	0.995	0.988
Adjusted R-squared	-0.792	0.519	-0.845	-1.717	0.983	0.953
F-statistic	0.411	2.44	0.389	0.157	79.01	28.29

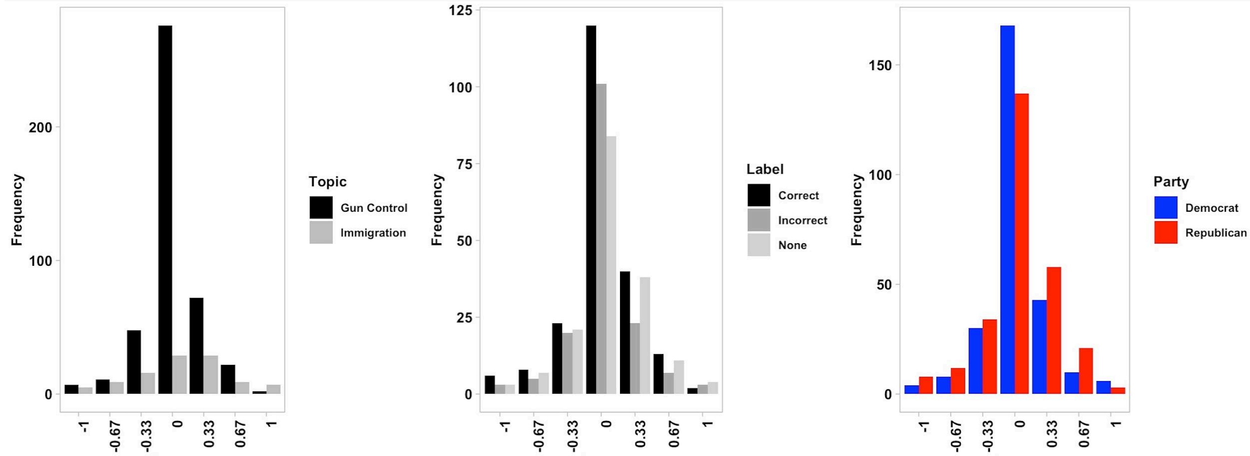
Note. OLS coefficients and significance tests. P-values are for two-tailed tests. Comparison persuasive message scenario is sending both evidence and personal narratives.

Figure C1. Perceptions of the sender’s persuasive influence by conversation topic, labeling condition, and party



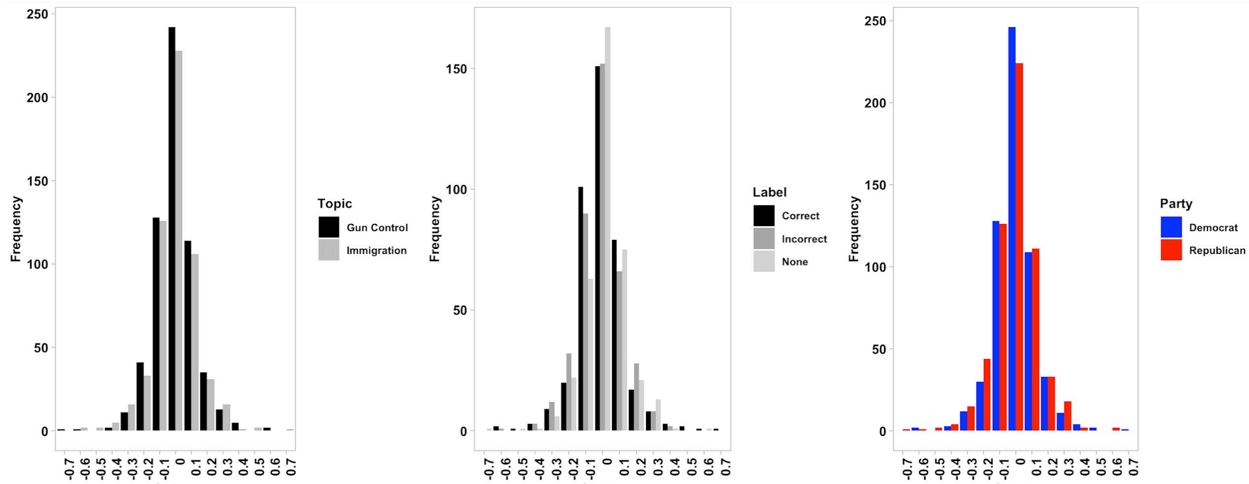
Note. Distribution of whether participants agreed that their chat partner influenced their views split by conversation topic, labeling condition, and party identification.

Figure C2. In-app attitude change by conversation topic, labeling condition, and party identification



Note. Values represent the change in attitudes between a pre-survey attitude question asked on the app immediately before the conversation and the post-survey attitude question asked immediately after the conversation. Attitude change is shown such that it is a change in the attitudes toward the topic the respondent was randomly assigned to discuss. In-app survey change had a lower *N* for those in the immigration topic as individuals filled out both pre- and post-survey.

Figure C3. Distribution of survey-attitude change by conversation topic, labeling condition, and party identification



Note. Values represent the change in attitudes between a pre-survey attitude question asked several days before the conversation and the post-survey attitude question asked several days after. Attitude change is shown such that it is a change in the attitudes toward the topic the respondent was randomly assigned to discuss.

Appendix D. Full model results of main analyses

Table D1. Predicting perceptions of the sender's persuasive influence

	Dependent variable: Perceptions of the sender's persuasive influence		
	(1)	(2)	(3)
Personal Narration (Binary)	0.040*	0.047**	0.046**
	(0.023)	(0.023)	(0.023)
Evidence (Binary)	–0.071**	–0.057**	–0.056**
	(0.022)	(0.022)	(0.023)
Incorrect Label	0.0003	0.004	0.004
	(0.028)	(0.027)	(0.027)
No Label	0.022	0.023	0.023
	(0.027)	(0.027)	(0.027)
Topic: Immigration	–0.008	–0.004	–0.004
	(0.023)	(0.023)	(0.023)
Democrat		–0.006	–0.006
		(0.020)	(0.020)
Strong Partisan		0.007	0.007
		(0.021)	(0.021)
Female		0.019	0.019
		(0.021)	(0.021)
Age (In Years)		–0.003***	–0.003***
		(0.001)	(0.001)
College		–0.085***	–0.085***
		(0.021)	(0.021)
White		–0.061**	–0.061**
		(0.027)	(0.027)
Junk (Binary)			0.006
			(0.024)
Number of messages in conversation			0.0002
			(0.001)
Constant	0.473***	0.656***	0.646***
	(0.027)	(0.054)	(0.058)
Observations	829	829	829
Adjusted R2	0.011	0.041	0.039
Residual Std. Error	0.297 (df=823)	0.292 (df=817)	0.293 (df=815)

F Statistic	2.825** (df=5; 823)	4.195*** (df=11; 817)	3.563*** (df=13, 815)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Perceptions of the sender's persuasive influence are coded such that positive values represent higher ratings that one's partner had influenced their views. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Table D2. Predicting in-app post-treatment attitudes

	Dependent variable: In-app post-treatment attitudes		
	(1)	(2)	(3)
Personal Narration (Binary)	–0.003	–0.008	–0.007
	(0.026)	(0.025)	(0.026)
Evidence (Binary)	0.005	–0.001	–0.022
	(0.026)	(0.025)	(0.026)
Incorrect Label	–0.006	–0.007	–0.006
	(0.030)	(0.029)	(0.031)
No Label	0.010	0.002	–0.030
	(0.030)	(0.029)	(0.031)
Topic: Immigration	–0.042	–0.061	–0.076
	(0.040)	(0.039)	(0.068)
In-app pre-treatment attitudes	0.483***	0.421***	0.503***
	(0.047)	(0.053)	(0.064)
Democrat		0.107***	0.098***
		(0.030)	(0.035)
Strong Partisan		0.032	0.001
		(0.027)	(0.029)
Female		–0.027	–0.027
		(0.025)	(0.027)
Age (In Years)		0.003***	0.003**
		(0.001)	(0.001)
College		0.029	–0.002
		(0.025)	(0.026)
White		–0.055*	–0.045
		(0.029)	(0.031)
Partner’s in-app pre-treatment distance			0.005
			(0.044)
Junk (Binary)			–0.032
			(0.027)
Number of messages in conversation			–0.0004
			(0.001)
Constant	0.389***	0.284***	0.299***
	(0.045)	(0.073)	(0.094)

Observations	542	542	441
Adjusted R2	0.216	0.251	0.306
Residual Std. Error	0.296 (df=535)	0.289 (df=529)	0.275 (df=425)
F Statistic	25.855*** (df=6; 535)	16.092*** (df=12; 529)	13.938*** (df=15; 425)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. In-app post-treatment attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Table D3. Predicting follow-up attitudes

	Dependent variable: Follow-up attitudes		
	(1)	(2)	(3)
Personal Narration (Binary)	0.0004	–0.002	–0.002
	(0.008)	(0.008)	(0.008)
Evidence (Binary)	0.007	0.007	0.010
	(0.008)	(0.007)	(0.008)
Incorrect Label	–0.009	–0.010	–0.008
	(0.009)	(0.009)	(0.009)
No Label	0.011	0.010	0.008
	(0.009)	(0.009)	(0.10)
Topic: Immigration	–0.023***	–0.027***	–0.029***
	(0.008)	(0.008)	(0.008)
Pre-treatment attitudes	0.788***	0.757***	0.768***
	(0.021)	(0.022)	(0.022)
Democrat		0.027***	0.025***
		(0.008)	(0.009)
Strong Partisan		0.026***	0.026***
		(0.008)	(0.008)
Female		0.002	0.002
		(0.007)	(0.008)
Age (In Years)		0.0003	0.0003
		(0.0003)	(0.0003)
College		0.009	0.011
		(0.007)	(0.008)
White		0.004	0.006
		(0.010)	(0.010)
Partner’s pre-treatment distance			0.032
			(0.022)
Junk (Binary)			–0.004
			(0.008)
Number of messages in conversation			0.0001
			(0.0002)
Constant	0.157***	0.130***	0.110***
	(0.019)	(0.024)	(0.026)

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Observations	1,164	1,164	1,066
Adjusted R2	0.614	0.622	0.624
Residual Std. Error	0.126 (df=1157)	0.125 (df=1151)	0.126 (df=1050)
F Statistic	309.722*** (df=6; 1157)	160.403*** (df=12; 1151)	119.081*** (df=15; 1050)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Follow-up attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

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Appendix E. Supplemental analyses

Table E1. Predicting perceptions of the sender's persuasive influence using message count and length

	Dependent variable: Perceptions of the sender's persuasive influence	
	Message count	Word count
Personal Narration	0.012**	0.00004
	(0.006)	(0.00005)
Evidence	–0.011***	–0.0001**
	(0.004)	(0.0001)
Incorrect Label	0.009	0.013
	(0.027)	(0.027)
No Label	0.020	0.023
	(0.027)	(0.027)
Topic: Immigration	–0.004	–0.007
	(0.023)	(0.023)
Democrat	–0.004	–0.007
	(0.020)	(0.019)
Strong Partisan	0.011	0.015
	(0.021)	(0.021)
Female	0.016	0.020
	(0.022)	(0.022)
Age (In Years)	–0.003***	–0.003***
	(0.001)	(0.001)
College	–0.084***	–0.085***
	(0.021)	(0.021)
White	–0.064**	–0.060**
	(0.027)	(0.028)
Junk	–0.002	–0.0001*
	(0.002)	(0.0001)
Number of messages in conversation	0.0004	0.0005
	(0.001)	(0.001)
Constant	0.642***	0.640***
	(0.057)	(0.058)
Observations	829	829
Adjusted R2	0.042	0.037

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Residual Std. Error	0.292 (df=815)	0.293 (df=815)
F Statistic	3.826*** (df=13; 815)	3.432*** (df=13; 815)

Note. *p < 0.1; **p < 0.05; ***p < 0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Perceptions of the sender's persuasive influence are coded such that positive values represent higher ratings that one's partner had influenced their views. Persuasive techniques, as well as the control variable for junk, are coded such that higher values represent receiving more messages or longer messages.

Table E2. Predicting in-app post-treatment attitudes using message count and length

	Dependent variable: In-app post-treatment attitudes	
	Message count	Word count
Personal Narration	0.001	–0.00001
	(0.007)	(0.0001)
Evidence	–0.003	–0.00001
	(0.005)	(0.0001)
Incorrect Label	–0.005	–0.005
	(0.031)	(0.030)
No Label	–0.031	–0.030
	(0.031)	(0.030)
Topic: Immigration	–0.071	–0.072
	(0.068)	(0.069)
In-app pre-treatment attitudes	0.502***	0.503***
	(0.064)	(0.063)
Democrat	0.101***	0.100***
	(0.035)	(0.035)
Strong Partisan	0.0004	–0.001
	(0.030)	(0.029)
Female	–0.027	–0.026
	(0.027)	(0.027)
Age (In Years)	0.003***	0.003***
	(0.001)	(0.001)
College	–0.0005	–0.001
	(0.026)	(0.026)
White	–0.043	–0.042
	(0.031)	(0.032)
Partner's in-app pre-treatment distance	0.001	0.002
	(0.045)	(0.045)
Junk	0.001	0.00005
	(0.003)	(0.0001)
Number of messages in conversation	–0.001	–0.001
	(0.001)	(0.001)
Constant	0.284***	0.112***

	(0.091)	(0.026)
Observations	441	441
Adjusted R2	0.304	0.304
Residual Std. Error	0.275 (df=425)	0.275 (df=425)
F Statistic	13.806***(df=15; 425)	13.815*** (df=15; 425)

Note. *p < 0.1; **p < 0.05; ***p < 0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. In-app post-treatment attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk, are coded such that higher values represent receiving more messages or longer messages.

Table E3. Predicting follow-up attitudes using message count and length

	Dependent variable: Follow-up attitudes	
	Message count	Word count
Personal Narration	–0.001	0.00001
	(0.002)	(0.00002)
Evidence	–0.0003	–0.00002
	(0.002)	(0.0002)
Incorrect Label	–0.010	–0.010
	(0.009)	(0.009)
No Label	0.008	0.007
	(0.010)	(0.010)
Topic: Immigration	–0.028***	–0.028***
	(0.008)	(0.008)
Pre-treatment attitudes	0.769***	0.770***
	(0.022)	(0.022)
Democrat	0.025***	0.025***
	(0.009)	(0.009)
Strong Partisan	0.026***	0.026***
	(0.008)	(0.008)
Female	0.001	0.001
	(0.008)	(0.008)
Age (In Years)	0.0003	0.0003
	(0.0003)	(0.003)
College	0.011	0.011
	(0.008)	(0.008)
White	0.007	0.006
	(0.010)	(0.010)
Partner's pre-treatment distance	0.032	0.033
	(0.023)	(0.022)
Junk	0.0003	0.00000
	(0.001)	(0.00002)
Number of messages in conversation	0.0001	0.0001
	(0.0002)	(0.0002)
Constant	0.112***	0.112***

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	(0.026)	(0.026)
Observations	1,066	1,066
Adjusted R2	0.624	0.624
Residual Std. Error	0.126 (df=1050)	0.126 (df=1050)
F Statistic	118.778*** (df=15, 1050)	118.911*** (df=15, 1050)

Note. *p < 0.1; **p < 0.05; ***p < 0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Follow-up attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk, are coded such that higher values represent receiving more messages or longer messages.

Table E4. Predicting perceptions of sender's persuasive influence using narration

	Dependent variable: Perceptions of sender's persuasive influence		
	(1)	(2)	(3)
Narration (Binary)	0.035	0.045*	0.044*
	(0.024)	(0.024)	(0.024)
Evidence (Binary)	–0.069**	–0.056**	–0.056**
	(0.022)	(0.022)	(0.022)
Incorrect Label	0.00	0.004	0.004
	(0.028)	(0.027)	(0.027)
No Label	0.022	0.023	0.023
	(0.027)	(0.027)	(0.027)
Topic: Immigration	–0.008	–0.004	–0.004
	(0.023)	(0.023)	(0.023)
Democrat		–0.006	–0.006
		(0.020)	(0.020)
Strong Partisan		0.007	0.007
		(0.021)	(0.021)
Female		0.019	0.019
		(0.021)	(0.021)
Age (In Years)		–0.002***	–0.002***
		(0.002)	(0.002)
College		–0.086***	–0.086***
		(0.021)	(0.021)
White		–0.062**	–0.062**
		(0.027)	(0.027)
Junk (Binary)			0.006
			(0.024)
Number of messages in conversation			0.0002
			(0.001)
Constant	0.471***	0.650***	0.639***
	(0.030)	(0.055)	(0.059)
Observations	829	829	829
Adjusted R2	0.009	0.040	0.038
Residual Std. Error	0.297 (df=823)	0.293 (df=817)	0.293 (df=815)
F Statistic	2.825** (df=5; 823)	4.195*** (df=11; 817)	3.563*** (df=13, 815)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Perceptions of sender's persuasive influence are coded such that positive values represent higher ratings that one's partner had influenced their views. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Table E5. Predicting in-app post-treatment attitudes using narration

	Dependent variable: In-app post-treatment attitudes		
	(1)	(2)	(3)
Narration (Binary)	–0.007	–0.017	–0.025
	(0.028)	(0.027)	(0.028)
Evidence (Binary)	0.005	–0.00005	–0.020
	(0.026)	(0.025)	(0.026)
Incorrect Label	–0.007	–0.008	–0.008
	(0.029)	(0.029)	(0.030)
No Label	0.010	0.001	–0.031
	(0.030)	(0.029)	(0.030)
Topic: Immigration	–0.043	–0.063	–0.078
	(0.040)	(0.039)	(0.067)
In-app pre-treatment attitudes	0.483***	0.421***	0.503***
	(0.047)	(0.053)	(0.064)
Democrat		0.107***	0.099***
		(0.030)	(0.035)
Strong Partisan		0.032	0.002
		(0.027)	(0.029)
Female		–0.027	–0.028
		(0.025)	(0.027)
Age (In Years)		0.003***	0.003**
		(0.001)	(0.001)
College		0.029	–0.002
		(0.025)	(0.026)
White		–0.054*	–0.044
		(0.029)	(0.031)
Partner's in-app pre-treatment distance			0.005
			(0.044)
Junk (Binary)			–0.032
			(0.026)
Number of messages in conversation			–0.0003
			(0.001)
Constant	0.392***	0.289***	0.308***
	(0.046)	(0.074)	(0.096)

Observations	542	542	441
Adjusted R2	0.216	0.251	0.307
Residual Std. Error	0.296 (df=535)	0.289 (df=529)	0.275 (df=425)
F Statistic	25.866*** (df=6; 535)	16.123*** (df=12; 529)	13.998*** (df=15; 425)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. In-app post-treatment attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Table E6. Predicting follow-up attitudes using narration

	Dependent variable: Follow-up attitudes		
	(1)	(2)	(3)
Narration (Binary)	0.0009	0.006	0.008
	(0.008)	(0.008)	(0.009)
Evidence (Binary)	0.005	0.005	0.009
	(0.008)	(0.007)	(0.008)
Incorrect Label	–0.008	–0.010	–0.008
	(0.009)	(0.009)	(0.009)
No Label	0.011	0.010	0.009
	(0.009)	(0.009)	(0.10)
Topic: Immigration	–0.023***	–0.026***	–0.029***
	(0.008)	(0.008)	(0.008)
Pre-treatment attitudes	0.788***	0.758***	0.769***
	(0.021)	(0.022)	(0.022)
Democrat		0.027***	0.024***
		(0.008)	(0.009)
Strong Partisan		0.027***	0.024***
		(0.008)	(0.009)
Female		0.002	0.002
		(0.007)	(0.008)
Age (In Years)		0.0003	0.0003
		(0.0003)	(0.0003)
College		0.009	0.010
		(0.007)	(0.008)
White		0.004	0.005
		(0.010)	(0.010)
Partner's pre-treatment distance			0.034
			(0.022)
Junk (Binary)			–0.004
			(0.008)
Number of messages in conversation			0.00005
			(0.0002)
Constant	0.151***	0.127***	0.106***
	(0.020)	(0.025)	(0.026)

Observations	1,164	1,164	1,066
Adjusted R2	0.615	0.622	0.625
Residual Std. Error	0.126 (df=1157)	0.125 (df=1151)	0.126 (df=1050)
F Statistic	310.267*** (df=6; 1157)	160.508*** (df=12; 1151)	119.241*** (df=15; 1050)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Follow-up attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Table E7. Predicting perceptions of sender's persuasive influence with treatment labeling interaction

	Dependent variable: Perceptions of sender's persuasive influence
Personal Narration (Binary)	0.062*
	(0.034)
Incorrect Label	0.035
	(0.043)
No Label	0.021
	(0.042)
Evidence (Binary)	–0.057**
	(0.023)
Topic: Immigration	–0.003
	(0.023)
Democrat	–0.006
	(0.020)
Strong Partisan	0.006
	(0.021)
Female	0.019
	(0.022)
Age (In Years)	–0.003***
	(0.001)
College	–0.085***
	(0.021)
White	–0.061**
	(0.028)
Junk (Binary)	0.006
	(0.024)
Number of messages in conversation	0.0002
	(0.001)
Personal Narrative x Incorrect Label	–0.053
	(0.054)
Personal Narrative x No Label	0.003
	(0.053)
Constant	0.637***
	(0.059)

Observations	829
Adjusted R2	0.038
Residual Std. Error	0.293 (df=813)
F Statistic	3.186*** (df=15; 813)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Perceptions of sender's persuasive influence are coded such that positive values represent higher ratings that one's partner had influenced their views. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Figure E1. Linear predictions of perceptions of sender's persuasive influence by reception of personal narrative and treatment labeling condition

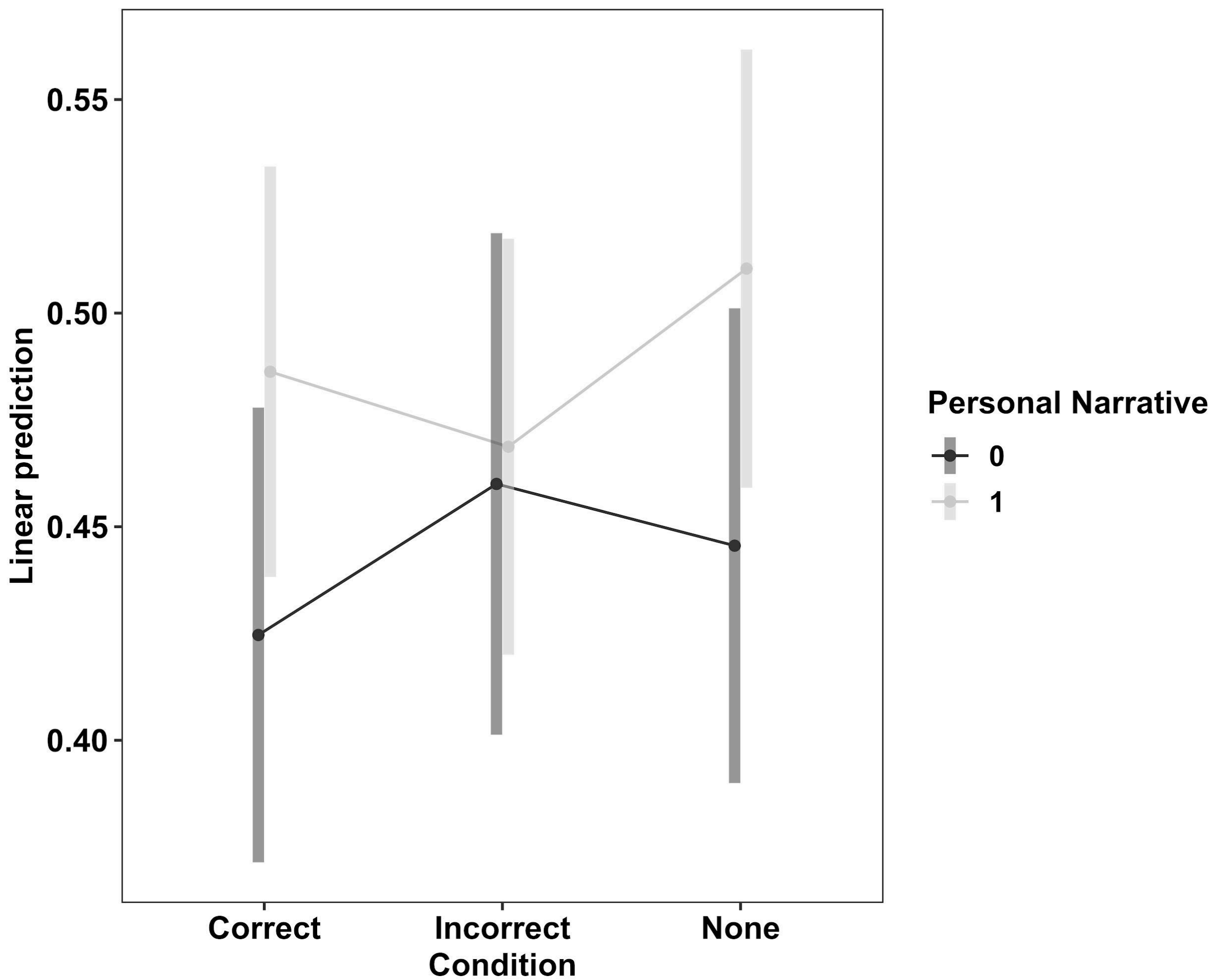

Table E8. Predicting in-app post-treatment attitudes with treatment labeling interaction

	Dependent variable: In-app post-treatment attitudes
Personal Narration (Binary)	–0.021
	(0.037)
Incorrect Label	–0.039
	(0.052)
No Label	–0.024
	(0.048)
Evidence (Binary)	–0.021
	(0.027)
Topic: Immigration	0.504***
	(0.064)
In-app pre-treatment attitudes	–0.075
	(0.068)
Democrat	0.096***
	(0.035)
Strong Partisan	0.001
	(0.029)
Female	–0.029
	(0.027)
Age (In Years)	0.003**
	(0.001)
College	–0.002
	(0.026)
White	–0.042
	(0.032)
Partner's in-app pre-treatment distance	0.006
	(0.044)
Junk (Binary)	–0.032
	(0.027)
Number of messages in conversation	–0.0004
	(0.001)
Personal Narrative x Incorrect Label	0.055
	(0.061)

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Personal Narrative x No Label	–0.010
	(0.065)
Constant	0.309***
	(0.093)
Observations	441
Adjusted R2	0.305
Residual Std. Error	0.275 (df=423)
F Statistic	12.334*** (df=17; 423)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. In-app post-treatment attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

Figure E2. Linear predictions of in-app post-treatment attitudes by reception of personal narrative and treatment labeling condition

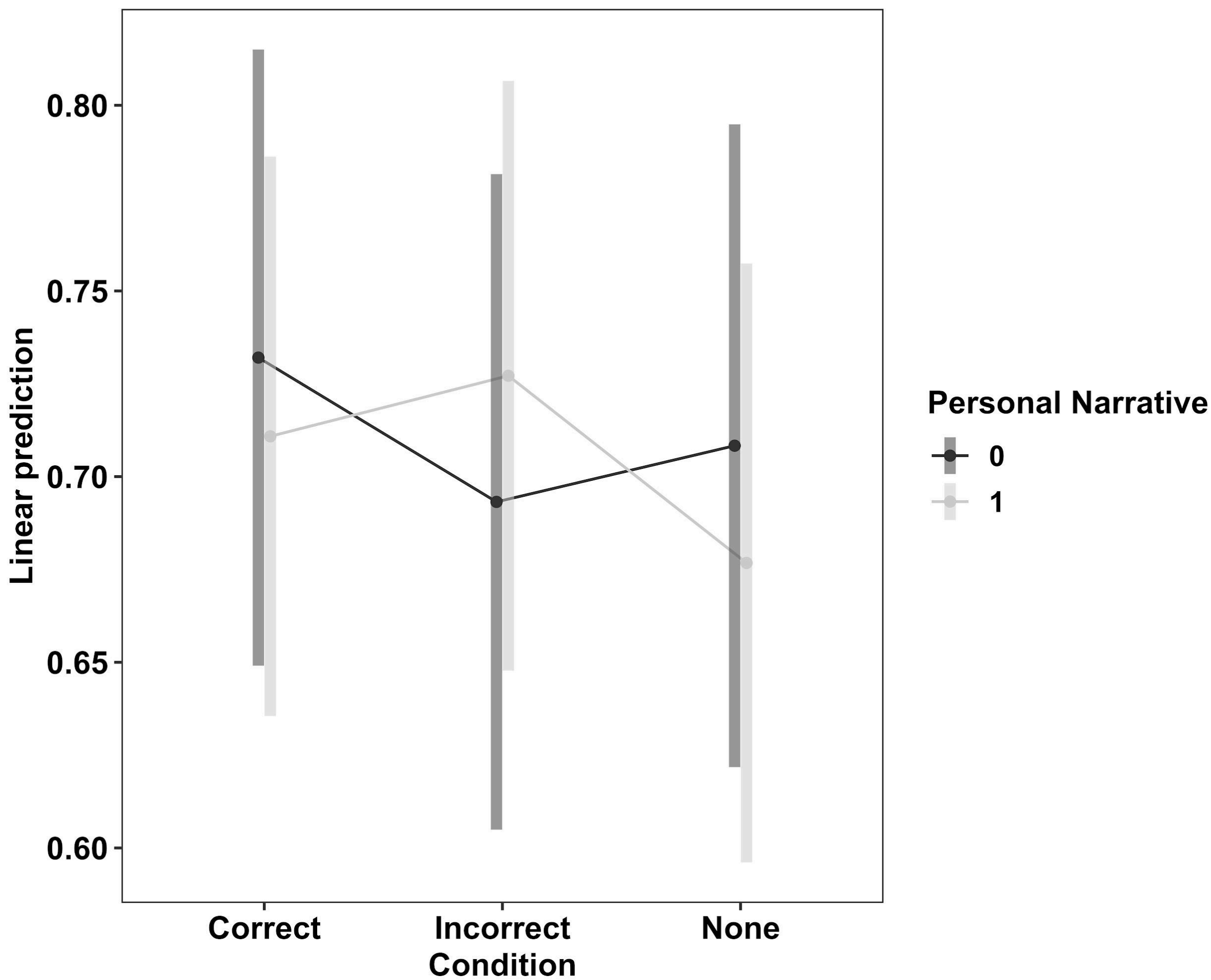

Table E9. Predicting follow-up attitudes with treatment labeling interaction

	Dependent variable: Follow-up
Personal Narration (Binary)	–0.015
	(0.014)
Incorrect Label	–0.028*
	(0.015)
No Label	0.008
	(0.015)
Evidence (Binary)	0.011
	(0.008)
Topic: Immigration	0.770***
	(0.022)
Pre-treatment attitudes	–0.029***
	(0.008)
Democrat	0.024***
	(0.009)
Strong Partisan	0.026***
	(0.008)
Female	0.002
	(0.008)
Age (In Years)	0.0003
	(0.0003)
College	0.010
	(0.008)
White	0.006
	(0.010)
Partner’s pre-treatment distance	0.034
	(0.022)
Junk (Binary)	–0.005
	(0.008)
Number of messages in conversation	0.0001
	(0.001)
Personal Narrative x Incorrect Label	0.037*
	(0.020)

Personal Narrative x No Label	0.001
	(0.020)
Constant	0.118***
	(0.028)
Observations	1,066
Adjusted R2	0.626
Residual Std. Error	0.126 (df=1048)
F Statistic	105.655*** (df=17; 1048)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Follow-up attitudes are coded such that positive values represent more extreme views after the conversation. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

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Figure E3. Linear predictions of follow-up attitudes by reception of personal narrative and treatment labeling condition

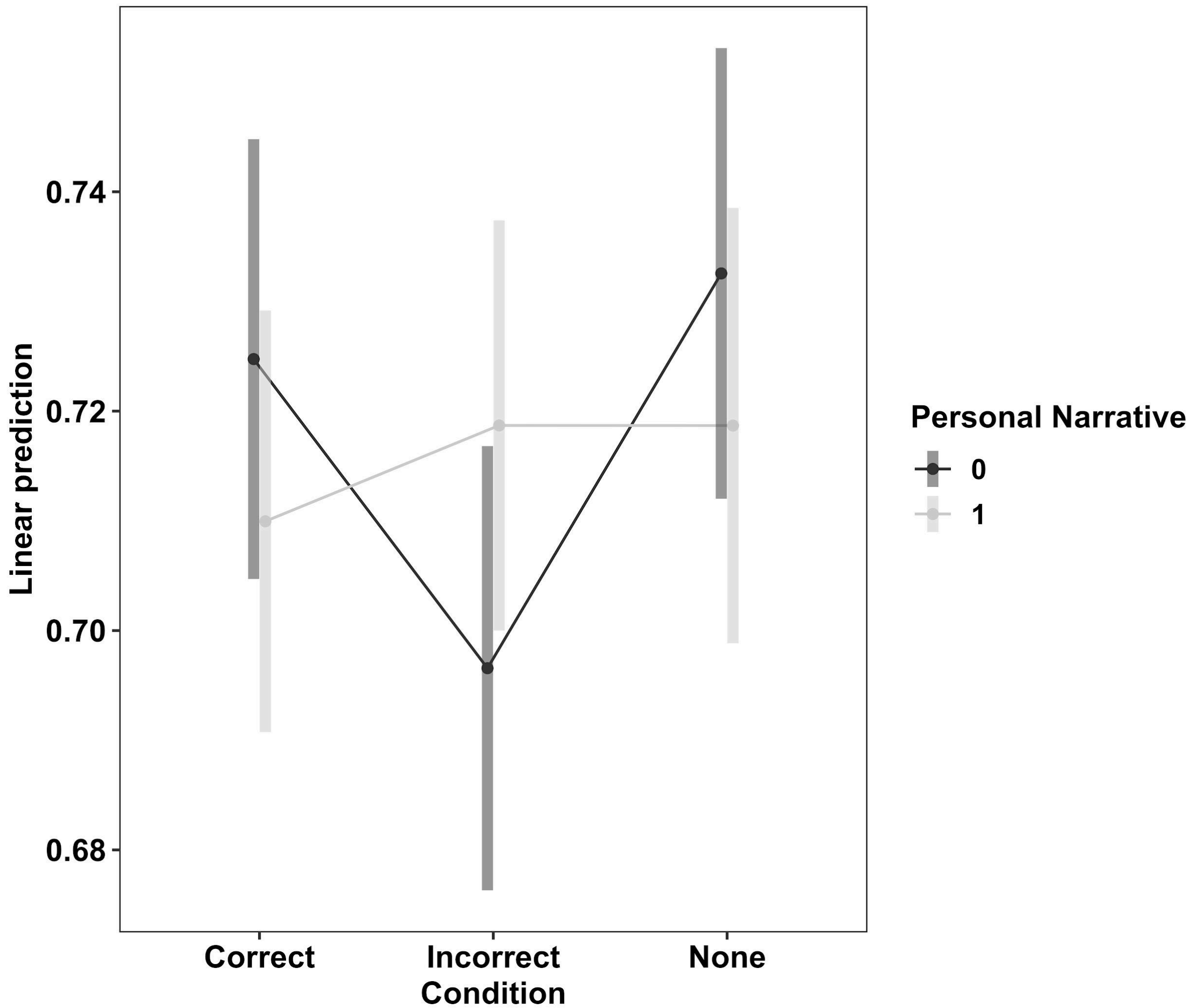
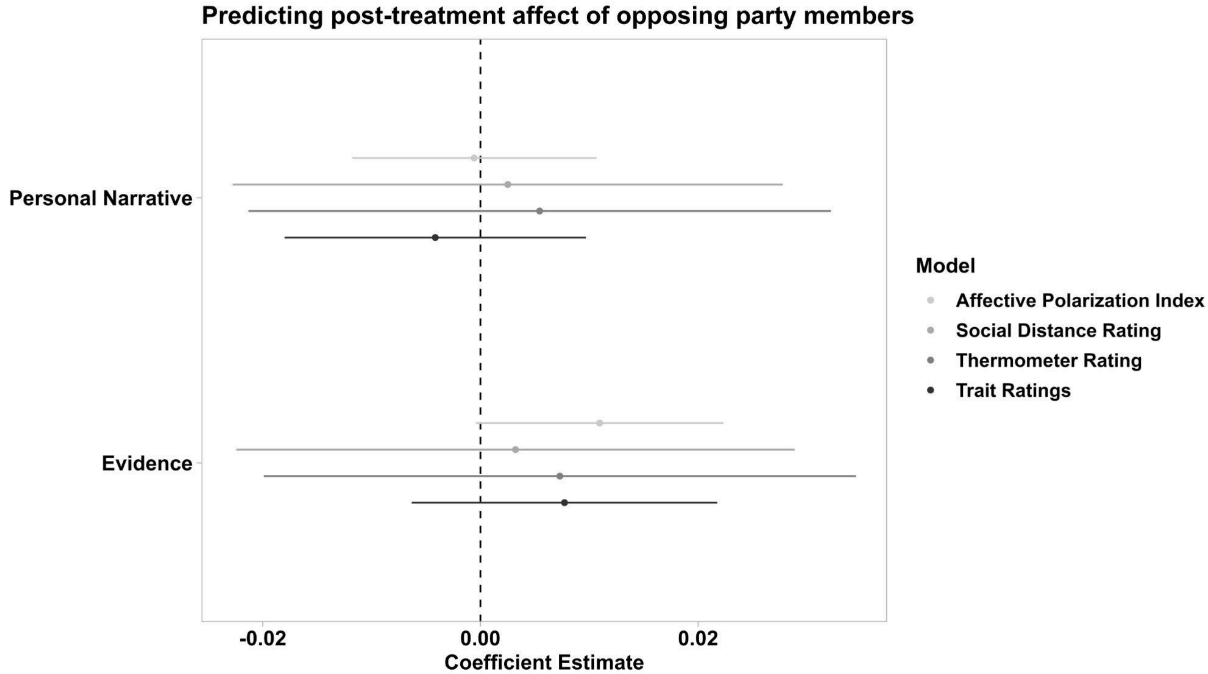


Figure E4. Predicting affective polarization by personal narrative reception



Note. OLS coefficients and significance tests were conducted. Positive values on the x-axis denote having more positive viewpoints of opposing party members. Estimates are calculated using a linear regression model that controls for baseline covariates (treatment labeling condition, topic, gender, age, race/ethnicity, college, political identity, and partisan strength) and clusters *SE*s by dyad. Predictors include an affective polarization index of social distance, thermometer, and trait ratings of the opposing party members. Higher values represent more positive views about opposing party members.

Table E10. Predicting Enjoyment of Conversation by reception of Personal Narrative

	Dependent variable: Enjoyment of Conversation
Personal Narration (Binary)	0.037*
	(0.019)
Incorrect Label	–0.032
	(0.020)
No Label	–0.039*
	(0.023)
Evidence (Binary)	–0.006
	(0.023)
Topic: Immigration	–0.013
	(0.020)
Democrat	–0.045***
	(0.017)
Strong Partisan	0.027
	(0.019)
Female	0.036*
	(0.020)
Age (In Years)	0.002***
	(0.001)
College	–0.069***
	(0.018)
White	–0.011
	(0.023)
Junk (Binary)	0.002
	(0.022)
Number of messages in conversation	0.0003
	(0.001)
Constant	0.768***
	(0.055)
Observations	829
Adjusted R2	0.047
Residual Std. Error	0.250 (df=815)
F Statistic	4.108*** (df=13; 815)

Note. *p<0.1; **p<0.05; ***p<0.01. OLS coefficients and significance tests. P-values are for two-tailed tests. *SE*s clustered by dyad. Persuasive techniques, as well as the control variable for junk messages, are coded such that higher values represent receiving more persuasive messages.

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References

Arceneaux, Kevin, and Ryan J. Vander Wielen. 2017. *Taming Intuition: How Reflection Minimizes Partisan Reasoning and Promotes Democratic Accountability*. New York: Cambridge University Press.

Combs, Aidan, Graham Tierney, Brian Guay, Friedolin Merhout, Christopher A. Bail, D. Sunshine Hillygus, and Alexander Volfovsky. 2023. "Reducing Political Polarization in the United States with a Mobile Chat Platform." *Nature Human Behaviour* 7 (9): 1454–61.

Dias, Nicholas, and Yphtach Lelkes. 2022. "The Nature of Affective polarization: Disentangling Policy Disagreement from Partisan Identity." *American Journal of Political Science* 66 (3): 775–90.

Mason, Lilliana. 2018. *Uncivil agreement: How Politics Became Our Identity.* Chicago: University of Chicago Press.