Partisan Media and Political Discussion as Regulators of Identity

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Abstract

Using the Reinforcing Spirals Model as a framework, this study employed an intensive longitudinal design to explore the effects of partisan media use and discussion on variability and change in partisan identity. Findings suggest that in-party communication promotes stability by reducing variability in identity strength, while also contributing to the strengthening of identity. Identity exhibited a tendency to decay among the strongly identified, absent other influences. Non-affirming communication, in contrast, was associated with increased variability.

Partisan Media and Political Discussion as Regulators of Identity

The field of communication research has historically equated the concept of an effect with changes in attitudes or behaviors, often overlooking the significance of stability as a potential outcome of communication. This oversight may stem from sociological factors and the lack of a clear methodological framework for studying stability. Stability, or the lack of change, is a central aspect of communication effects that warrants further exploration, particularly in the context of individuals who appear resistant to change. This paper posits that stability can be an effect of communication and that it is essential to develop research designs that can distinguish between null results and the stabilization of attitudes due to communication. These ideas are applied in an intensive longitudinal study of political partisanship and communication.

Historically, communication research has acknowledged the limited influence of mediated communication on attitudes and behavior, as seen in the Erie County study by Lazarsfeld, Berelson, and Gaudet (1948). This study and others from the same era have been interpreted as evidence of minimal media effects. However, this interpretation may have been overly simplistic, as these studies also recognized the role of communication in reinforcing existing attitudes and behaviors. The concept of reinforcement has been used inconsistently in the literature, sometimes referring to stability and other times to the strengthening of attitudes. This paper seeks to clarify the concept of stability, distinguishing it from reinforcement, and to propose research designs and statistical tools that can adequately address stability as an outcome in communication research.

The Reinforcing Spirals Model (RSM) by Slater (2007, 2015) provides a theoretical framework that can accommodate stability as an individual-level outcome. The RSM posits that communication and related constructs are part of an endogenous system, with communication serving both as a cause and an effect. The model suggests that while some individuals may experience positive feedback loops leading to extremity, most people's attitudes and behaviors are stable due to self-regulating systems. The paper adopts a slight modification to the RSM to account for the natural decay of attitudes and identities, suggesting that active maintenance through communication is necessary to counterbalance this decay and maintain stability (Long, 2023). To test this hypothesis and the already-known aspects of the RSM, 21-day intensive longitudinal survey was conducted with measures of both communication and identity. Findings indicate that communication is, generally, destabilizing for identity. However, identify-affirming communication — media and interpersonal discussions with those who generally support one's own views — promote stability instead. Accounting for decay among those with stronger identities, identity-affirming communications both counterbalance the decay and reduce variation.

Conceptualizing Stability

Besides lack of change, stability can be understood by considering several sources of variation in a concept. Two key distinctions are between time-structured variability and net variability on one hand and development on the other (Nesselroade, 1991). Time-structured variability captures the extent to which deviations from an individual's norm at one point in time are related to deviations at a subsequent point in time. In other words, it reflects the degree to which variations are systematically related from one occasion to the next. For example, if an individual spends significantly more time than usual discussing politics with friends on a given day, time-structured variability would be evident if this increase is typically followed by a subsequent increase (or decrease) in political discussion on the following day. High levels of time-structured variability suggest that the individual's behavior is not well-regulated, as deviations tend to persist over time. Conversely, low levels of time-structured variability indicate that the individual quickly returns to their typical baseline, even if there are occasional departures from it. In statistical models, time-structured variability is captured via estimates of autocorrelation.

Net variability refers to the overall magnitude of variability, regardless of its temporal structure. It captures the frequency and extremity of deviations from an individual's average level, without considering whether these deviations are related to one another over time. An individual who consistently engages in a moderate amount of political discussion on a daily basis would exhibit low net variability, whereas an individual who mostly avoids political discussion but occasionally devotes large amounts of time to it would show high net variability. Importantly, net variability can be high even if time-structured variability is low. This would be the case if an individual's behavior fluctuates substantially from one occasion to the next, but these fluctuations are not systematically related to one another. In statistical analysis, net variability is akin to the error term (Nesselroade & Ram, 2004; Wang et al., 2012).

Both time-structured and net variability are distinct from development, which refers to lasting changes in an individual's average level of behavior over time. For example, an individual who gradually increases their overall level of political discussion over the course of several months would be showing development, even if they exhibit low levels of time-structured and net variability from one day to the next during this period. In other words, development reflects shifts in an individual's baseline, rather than fluctuations around that baseline. Although development is often the focus of research examining the impact of communication on attitudes and behaviors, a full understanding of stability and change requires the consideration of time-structured and net variability as well. With time-structured and net variability measured by autocorrelation coefficients and error terms, development corresponds to regression coefficients in the regression modeling context. Statistically analyzing all these forms of variation is best done in a single, multilevel regression model with within-person-demeaned predictors, as has been advocated in prior work (Hamaker et al., 2015; Wang et al., 2012).

Reinforcing Spirals and Using Communication for Stability

The Reinforcing Spirals Model (RSM; Slater, 2007, 2015) provides a useful theoretical framework for considering how communication can lead to stability rather than (or in addition to) change. The RSM treats both media use and phenomena like attitudes and identities that are often studied as outcomes of media use as part of an endogenous system. In other words, RSM argues that causal influences between media use and related constructs like identity are reciprocal and mutually reinforcing. A key claim of the RSM is that the effects of media use and related constructs like identity unfold over time through feedback loops. For instance, media use at one point in time may strengthen the accessibility of a particular identity, which in turn leads to more identity-congruent media use at a later point in time, further reinforcing the identity. Over time, this cyclical process may result in increasingly strong identities and highly selective, identity-focused patterns of media use.

However, the RSM also suggests that such "positive" feedback loops are not inevitable and indeed are not the norm. In most cases, the social system is complex, exposing people to a variety of influences that may counteract or attenuate the effects of identity-congruent media use. Thus, the RSM predicts that most people will not end up in a state of extremely selective exposure and polarized identities. Instead, they will tend to maintain a relative equilibrium in which their media use is just enough to sustain their current level of identity, but not so high as to generate a spiral of increasing identity strength and selectivity. Although both communication and psychological variables like attitudes and identities are essentially volitional, communication is arguably more constrained by opportunity structures like one's social network, partly explaining the apparently high stability of communication behaviors over time (Scharkow, 2019).

This homeostatic tendency is a major component of the RSM's explanation for the high levels of stability observed in both media use and identity over time (Alwin & Krosnick, 1991; Scharkow, 2019). The model suggests that individuals are motivated to maintain a relatively steady state, engaging in just enough identity-congruent media use to counteract the destabilizing effects of external influences. This dynamic process may help to explain why measures of both media selectivity and identity strength tend to exhibit high levels of rank-order stability, even if there are short-term fluctuations around each individual's average level. Long (2023) recently argued that identities and attitudes should be expected to decay when not actively maintained, presumably through communication.

Social Identity and Partisanship

Political partisanship is increasingly conceptualized as a social identity, reflecting an individual's sense of belonging and attachment to a political party (e.g., Huddy et al., 2015). The social identity approach suggests that individuals derive a sense of self-worth and meaning from their membership in valued social groups, including political parties. When an individual identifies strongly with a party, that partisan identity becomes an important part of their self-concept, shaping their attitudes, behaviors, and perceptions of the social world. This makes partisanship more than simply a calculated choice to match one's well-formed policy preferences or ideology to the available candidates and parties (Dias & Lelkes, 2022). Indeed, identification with a party may sometimes even lead to policy preferences rather than the other way around (e.g., Carsey & Layman, 2006).

However, partisan identity is not a unitary construct; it can vary along multiple dimensions. One key dimension is identity strength, which reflects the degree to which an individual feels a strong sense of belonging and commitment to their party. Individuals with strong partisan identities are more likely to view the world through a partisan lens, to exhibit bias in their processing of political information, and to engage in behaviors that support their party and its candidates. In contrast, individuals with weak partisan identities may be more open to considering alternative viewpoints and less motivated to engage in party-supporting behaviors. This is nothing particular to partisanship, but rather is consistent with research on social identities in general (Huddy, 2001).

Importantly, identity strength is distinct from the direction or extremity of an individual's ideology. An individual can identify strongly as a Democrat or Republican without necessarily endorsing extreme partisan positions, and an individual with moderate policy views can nonetheless have a strong partisan identity (Mason, 2018). Identity strength reflects the centrality and importance of partisanship to an individual's self-concept, rather than the specific content of their partisan beliefs. Moreover, identity strength is not a fixed, trait-like characteristic; it can vary over time and across contexts (Tucker et al., 2019). An individual's sense of partisan identity may be strengthened in response to threats to their party's status or values, and it may be weakened in response to intra-party conflicts or dissatisfaction with party leaders. The dynamic nature of identity strength suggests that it may be shaped by ongoing patterns of political communication and social interaction (Hobbs, 2019).

Studying the variability of identity strength can provide insight into the psychological processes underlying partisanship. Individuals with stable, strongly held partisan identities may exhibit different patterns of cognition and behavior than those with weaker or more variable identities. For example, strong, stable partisans may be more resistant to persuasion and more likely to engage in motivated reasoning when processing political information, whereas those with weaker or more fluctuating identities may be more open to influence and more evenhanded in their judgments. Examining the interplay between communication, identity strength, and political attitudes and behavior can thus shed light on the complex dynamics of partisanship in contemporary politics.

Predictions

Unless otherwise specified, relationships between variables are conceived at the within-person level. If X causes Y, this should — in this framework — be revealed as changes in X associating with changes in Y for each person. Or, in other words, if one had many observations of a single person, the relationships would still be in evidence even without other people for comparison. The usefulness of studying larger numbers of people comes from the fact that one expects people to be heterogeneous and we can average over the within-person results to account for both known and unknown contingencies in the causal processes.

As discussed previously, there are multiple types of variation that may occur and therefore separate predictions for each. One is development, which refers to lasting changes to the mean-level of a construct. Although the duration of the study is not long, changes in development can be characterized as trends that persist across measurement occasions. These are the usual “media effects” (although this study also considers interpersonal communication as well). The other type of change is variability, which has to do with the extent to which there are ephemeral changes in a construct of interest. Variability has to do with the magnitude and persistence of short-term changes in a construct, whatever the cause of the change. With these distinctions in mind, the following hypothesis is offered:

H1: Identity-affirming communication will predict decreased variability of identity strength.

The RSM suggests not only stability but reinforcement — that is, increases in identity strength — as a consequence of identity-affirming communication. As mentioned, it is possible to analytically separate variability from development. Therefore, it is predicted:

H2: Identity-affirming communication will predict increases in identity strength.

In other words, identity-affirming communication promotes development. One thing to consider is that the relationship suggested by H2 could be contingent on identity strength itself. For someone whose partisan identity is weak, the predominant effect of identity-affirming communication may be to increase strength of identity rather than stability. This is consistent with the proposed decay component of RSM. The weakly-identified are subject to little time decay, meaning the identity-enhancing effects of the communication should not be counteracted. Stronger identifiers, according to this logic, are likely to need identity-affirming communication just to retain a constant level of identity strength. This idea is proposed as a research question.

RQ1: Does the extent to which identity-affirming communication promotes variability and development of identity strength depend on the level of identity strength?

Relatedly, the idea that stronger identities are subject to over-time decay (Long, 2023) without any active maintenance is amenable to testing in this framework. Empirically, over-time trends in identity at the person level can be estimated as well as whether those trends depend on the level of another variable, such as mean level of identity strength. If identity strength trends downward for those with stronger average identities, this would be supportive of the decay concept. This would only be expected after accounting for the influence of communication, which is predicted to increase identity strength (H2).

H3: Those with stronger identities will have a negative time trend, net of other factors.

Last is a question about identity-relevant, but not necessarily identity-affirming, communication. In politics, if one assumes that a program like network news is not partisan, then the expected impact is not clear in this framework. As a catch-all, I will refer to political communication that is not identity-affirming as identity-*relevant*.

RQ2: How do the effects of identity-relevant, but not identity-affirming, communication compare with those of identity-affirming communication?

Methods

An intensive longitudinal survey is used to explore these predictions and questions, in which daily measurements of the key constructs are collected over a period of weeks. As discussed in the preceding sections, relatively long series of repeated measurements compared to what is typically available in this research area are essential for gaining insight to the dynamics of identity and communication. The hypothesized effects are likely to occur on a relatively short timescale compared to the long time lags between measurements in traditional panel studies. The biggest tradeoff of this design is sample quality, as the subjects are undergraduate students enrolled at a large research university in the United States. This is a reasonable tradeoff for cost-efficient access to such an intensive design, but it is a tradeoff nonetheless. One potential upside of a student sample is that it may exhibit higher volatility than usual when it comes to strength of political identification, thereby increasing statistical power to detect the hypothesized processes. Research on the RSM originated in part on research on highly-susceptible populations (Slater, Henry, Swaim, & Cardador, 2004) and this can be seen as an extension of that approach.

Overview

Participants were required to be U.S. citizens and at least 18 years old to ensure that they have sufficient stake in the U.S. political system and most institutional forms of participation available to them. At first, interested respondents took an introductory survey that is approximately 10 minutes long. This initial survey measured stable constructs as well as those that may be worth knowing but not to the extent that they need to be measured each day. In addition, the initial survey contained several more comprehensive measurements of the key concepts that are included in the daily surveys. After the first survey, participants filled out an approximately 2- to 3-minute survey with measures of identity strength and identity-relevant communication each day for 20 days. Participants received encouragement to complete surveys each day regardless of whether they responded on the previous day or any number of previous days. With many measurements in a short time span, the prior expectation was that dropping participants with a single non-response (as is typical in panel studies) would reduce the sample size dramatically — perhaps to zero. At any rate, missing data in such designs is common and retaining respondents with missing responses is considered a best practice (Ji et al., 2018). Other elements of the design, to be described in the coming sections, were designed with reducing respondent burden as a key priority. In an intensive longitudinal design, if some aspect of the questionnaire is difficult or annoying to respond to, it does not just affect that questionnaire's responses but also the likelihood of receiving a response in subsequent days. Participants were compensated with course credit through the department's research participation program; the amount of credit was based on the amount of participation.

Data collection began on January 30th, 2020 and the final responses were collected on April 17th, 2020. Participants could begin at any time during the ongoing semester as long as there were enough days remaining to receive 20 daily surveys. The surveys were programmed and distributed via "formr," a survey design and distribution framework created to accommodate complex designs like this one (Arslan et al., 2019). formr hosted the questionnaires on the web — with access restricted by personalized links that were sent via email and text message — and automated the process of re-sending questionnaires at pre-specified intervals. After taking the introductory survey, respondents were sent an email each day at 8:00 AM containing a link to that day's daily survey along with an update on their current progress in the study (how many days they have participated, how many remain, and the number of credits earned). Responses had to be entered before midnight or else are considered missing for the day. Those who provided a cell phone number in the introductory survey were also sent a text message each morning with a link to take the survey[1]. The goal was to have the survey filled out in the morning, ideally before any political communication. If the communication measures referred to the *present day*, and were administered later in the day, it would be difficult to pick a time that

[1] This was managed with the aid of a service called Twilio, which allows sending these messages from a local number used exclusively for this study.

respondents are both likely to be done talking about politics and watching/reading/listening to content about politics *and* apt to respond before the day is out. The chosen strategy risks having effects dissipate overnight, but should better minimize non-response and under-reporting. The median time to complete the daily surveys was 87 seconds, while the 10^{th} percentile completion time was 45 seconds and the 90^{th} percentile was 460 seconds. The mean of over 9 minutes is greatly influenced by a handful of cases in which respondents apparently completed the survey long after visiting the webpage. For the introductory survey, the median response took 8 minutes with an approximate range of 5 to 15 minutes.

For a research task as demanding as daily surveys over such a period of time, some non-response is expected and was indeed observed. Some subjects completed only the introductory survey and no others, which was explicitly offered as an option in recruitment materials. It is not possible to conduct meaningful analyses of those with just a single observation. Those who participated at least 3 times were retained for analysis with missing responses multiply imputed. An extensive discussion of the strategy and its motivations is included in Appendix A2.

Measures

All question wordings are included in Appendix A1 and were presented in that same order in the daily questionnaires (discussion, media, identification). Respondent characteristics like age, gender, and so on were collected in the introductory survey. In that first survey, respondents responded to a conventional categorical party identification item. First, they were asked, "generally speaking, do you think of yourself as a…" with response options "Republican," "Democrat," "Independent," and "Something else." Those who choose "something else" (or skipped the first question) were given a forced choice follow-up asking, "Do you generally think of yourself as a little closer to the Republicans or Democrats?" Those who did not choose one or the other were notified that their continued participation required a choice. The final sample was composed of 69% Democrats and 31% Republicans. 38% of respondents initially chose "Independent" or "Something else." All descriptive statistics refer to the 270 respondents who supplied sufficiently complete data to be retained for analysis and only the complete, non-imputed responses. For measures that are repeated, the descriptive statistics refer to the average of respondent averages; that is, a respondent with 22 responses is not weighted any more than a respondent with only 3 since the statistics are calculated based on each of their own mean responses.

After this, and on each of the daily surveys, partisan strength was measured by items adapted from the partisan identity scale developed by Huddy and colleagues (2015; Bankert et al., 2017). Unlike the validation studies for this measure, respondents receive measures for the same identity throughout the entirety of the study (rather than clarifying each day that they remain Republican/Democrat), a decision more justifiable given the short duration. To reduce memory effects as well as the length of the questionnaire, only a random subset of the items for the identity strength questionnaire was administered each day. This is a form of planned missingness, a procedure designed to reduce respondent burden and in this case increase validity in narrowly-spaced repeated measurements (Silvia et al., 2014). Because the individual items vary significantly in their means and to reduce measurement error, the responses were combined into a single response score using a graded response model, a type of item response theory model. The graded response model is also inherently able to deal with the planned missingness in the scale (Dai et al., 2021). The scale scores are approximately centered at 0 with unit variance ($M = -0.02$, $SD = 0.99$).

Each day, respondents were asked to estimate the amount of time they spent talking with others about news or politics the previous day. The total average was just over 25 minutes (M = 25.6, SD = 36.24, Median = 14.00), the majority of which was with co-partisans (M = 15.98, SD = 27.11, Median = 7.50), with out-partisans (M = 5.93, SD = 11.09, Median = 1.79) and people with either no partisanship or support a minor party (M = 10.86, SD = 11.09, Median = 3.40) rounding out the time spent in discussion. In models, a variable for the total amount of time spent in discussion is used to represent the general effect of discussion, separate from in-party discussion. Respondents were likewise asked to estimate the amount of time spent engaging with news or political media in the previous days. The total average was slightly more than half an hour (M = 34.54, SD = 47.85, Median = 18.73). Respondents spent the most time with sources that support one's own party (M = 17.21, SD = 28.81, Median = 7.38) followed by time using non-partisan sources (M = 10.86, SD = 18.96, Median = 3.40) and sources supporting the other party (M = 6.46, SD = 16.52, Median = 1.48). Models include a variable for the total amount of time spent using media to establish a baseline effect of media use aside from specifically in-party media sources.

As implied by the descriptive statistics, these measures of communication are strongly right/positive skewed. To make the measures more amenable to analysis, two methods were used. The first was Winsorizing the measures (Tukey & McLaughlin, 1963; Wilcox, 2005), which means replacing extreme values with a less extreme one. In this case, any value beyond the 99.5th percentile of responses — 300 minutes (5 hours) for both measures — was replaced with the value of the 99.5th percentile. Upon close inspection, some of these values were likely entered in error, but rather than delete them (a procedure known as trimming) they are more conservatively Winsorized instead. The reported descriptive statistics are of the Winsorized data.

Additionally, to attenuate the still-present right skew, a natural log transformation was applied to the communication measures before analysis[2].

Several other constructs were measured in the first survey that serve as controls in models to help address confounding for between-subjects comparisons. These include age (M = 21.34, SD = 3.55), race and ethnicity (83% white, 12% Black, 5% Asian, 5% Hispanic, 1% Middle Eastern/North African in a measure that allowed for multiple selections), and gender (73% women). Respondents were asked 4 questions meant to tap aspects of ideology. These items assessed attitudes about the extent government should be involved in the provision of healthcare, whether the government should provide more or fewer services, whether the defense budget should be increased or decreased, and whether it is the government's responsibility to improve the socioeconomic position of racial and ethnic minorities. These items, measured on a scale from 1 to 7, were combined into a single measure that will be referred to as "issue alignment" and scaled such that higher values correspond with more ideological alignment with the respondent's preferred party (M = 4.93, SD = 1.23). In other words, a Republican respondent who gave the strongest "limited government" responses on each item would have a score of 7 while a Democrat giving the same answers would have a score of 1. Respondents were also asked if they had ever voted in an election in the United States; 56% said they had.

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[2] Because many values are 0 and the log of 0 is undefined, the computation takes the form of $\log(x + 1)$ where x is the value being transformed. This has the useful property of retaining 0 as 0 since $\log(1) = 0$. The underlying logic of doing this transformation, besides the practical modeling concerns, is that (for instance) the substantive difference between 0 minutes of communication and 60 minutes of communication is presumably greater than the difference between 240 minutes and 300 minutes.

Analysis Plan

For analysis, multilevel AR(1) model is used (Hamaker et al., 2018; Hedeker et al., 2012). This is conceptually similar to a cross-lagged panel model, but it disaggregates the within-person from between-person effects as is done in the approach econometricians call fixed effects modeling (Bell & Jones, 2015). Such models can be estimated using Markov Chain Monte Carlo (MCMC) simulation, which allows for arbitrarily complex regression models in a computationally intensive, Bayesian framework.

Time-structured variability refers to the autocorrelation of deviations from the mean from one occasion to the next and the other regards the magnitude of those deviations. The best way to probe the effect on the autocorrelation, for which values close to 0 reflect more stability, is to include interaction terms between key predictors and the autocorrelation term. For instance, consider a model with identity strength as the outcome variable. An interaction between the lagged value of identity strength and identity-affirming communication estimates the extent to which identity-affirming communication affects the autocorrelation of identity strength. This is, in this framework, a primarily between-subject phenomenon — that is, what affects this kind of stability is not where a person is relative to his or her norms, but the actual level of the variables. For instance, the hypothesis is that a high level of affirming communication should contribute to stability. This does not mean added stability is expected when a person who engages in zero communication decides one day to spend a few minutes watching the news. Rather, someone who usually spends a good deal of time engaging in communication is expected to demonstrate more stability regardless of their day-to-day changes.

Hypotheses regarding development, or longer-lasting changes in the mean levels of an outcome, are tested with the main effects in these models and are conceptually equivalent to the typical kind of media effects. A positive main effect does not literally mean that the effect is long lasting, but empirically shows that changes in the predictors are associated with changes in the outcome beyond what can be explained by the outcome's mean level and overall trend. These effects are investigated solely by focusing on the within-person effects, which can be interpreted causally under assumptions that are weaker than for between-person effects and in cross-sectional designs. Models also include the time variable, since accurate estimates for variability (autocorrelation and residual variance) depend on the outcome variables being stationary conditional on the predictors. This means, in effect, that the models are a variant of growth curve models.

Finally, to assess effects on net variability, the error term itself is the outcome variable of an accompanying model that is estimated jointly with the model that estimates effects on the level of identity strength. As a multilevel model, each subject has their own average level of variability and predictors are entered into the model to predict each subject's net variability. Within-person predictors also allow for inference about the antecedents of occasion-level net variability; for instance, whether an increase in media consumption yesterday predicts instability in identity the following day. This ability to model the error term is the most distinctive part of the modeling approach used in this study (Hamaker et al., 2018).

MCMC estimation does not provide the analyst with the usual tools of statistical inference like test statistics, *p* values, and the like, but approximations are available. Simple methods of doing so include 95% credibility intervals, which are a Bayesian counterpart to confidence intervals that are interpreted as having a 95% probability of containing the true value. Likewise, posterior probabilities, which are Bayesian counterparts for *p* values, have the intuitive interpretation of being the probability the parameter is greater/less than 0 (Makowski et al., 2019). The key to interpretation of posterior probabilities is that a 95% posterior probability is equivalent in interpretation to a one-sided *p* value of .05, although Bayesian analyses tend to be more conservative. The existence of an effect will be assessed primarily using the posterior probability, using the 95% credibility interval as an additional indicator of uncertainty.

The models are estimated using the R package "brms" (Bürkner, 2018), which interfaces with the MCMC estimation software "Stan" (Carpenter et al., 2017) using the No-U-Turn sampler. It is important when doing Bayesian inference to report the prior distributions used in estimation (Depaoli & van de Schoot, 2017), which reflect prior knowledge (or lack thereof) about the values to be estimated. Conventionally, one centers the prior distributions on parameters like regression coefficients to 0 in order to state a prior belief of a null effect. This places the burden on the data to demonstrate non-zero effects. For the regression estimates and the random effect deviations, a normal prior distribution centered at 0 with a standard deviation of 1 is specified. This is a "weakly informative" prior (Gelman et al., 2008) in that it places a gentle constraint on the estimates to stay within plausible values but allows the model to estimate more extreme parameters if they are clearly justified by the data. For estimation, 2 MCMC chains of 2000 iterations each are used, of which half are considered warmups and discarded. This is done on each of the imputed datasets, then the chains are combined to create a single model with 50 chains for each parameter (2 chains for each of 25 datasets). Computation was performed on the [BLINDED FOR PEER REVIEW HIGH-PERFORMANCE COMPUTING CLUSTER].

Results

To reiterate, 3 types of effects are investigated: development, time-structured intraindividual variability, and net intraindividual variability. Table 1 summarizes results for hypotheses and Table 2 summarizes results relevant to research questions. Tables 3 and 4 show full results for the regression model. As a note on terminology, although the term "identity-affirming" communication has been used when discussing theory, the measured variables will be referred to as "in-party" discussion and media to more clearly convey exactly what was measured. Before diving into the specific results, some background on the modeling approach is necessary for proper context.

The distinctive feature of multilevel models is that coefficients can, if the analyst allows, vary by level (in this case, the levels are respondents). These varying coefficients are generally called "random effects." By convention, the intercept of multilevel models is always modeled as a random effect and each participant's intercept can be interpreted as an (conditional) estimate of their mean of the dependent variable, net of the predictor variables. As expected, participant intercepts for identity strength vary even after accounting for control variables, with an estimated standard deviation of 0.68 (95% CI [0.62, 0.75], posterior probability >99.9%), consistent with a conceptualization of strength as being at least partly trait-like. Another random effect in the model is for time, allowing each participant to have their own underlying growth curve over the course of the study (SD = 0.02, 95% CI [0.01, 0.02], posterior probability >99.9%).

In the estimation of random effects, one does not typically just allow each random effect to vary but also allows them to correlate with one another because failing to do so can cause estimation problems and may also produce incorrect results. Although these correlations are often considered substantively uninteresting, for these purposes there are theoretically relevant random effect correlations. H3 argued that one explanation for why the mutual reinforcement of identity and media use does not inevitably lead to extremity is that there may be an inherent pull toward moderation for those with high identity strength. In this model, each participant has their own estimate of both identity strength (the random intercept) and of their time trend (the random growth curve) after accounting for other variables. The correlation between these is -.26 (95% CI [-.40, -.11], posterior probability 99.7%), suggesting that people with high average identity strength do have a tendency to lose strength over time *if* other factors like communication are assumed to be 0. This is unlikely to be a ceiling effect because the measure is designed to prevent ceiling effects. It is unlikely to be a regression to the mean effect because the correlation is between the time trend and the overall mean, not the first measure of strength. Note also that this does not necessarily mean that people with relatively high identity strength actually did tend to see an over-time decrease in identity strength, because this estimate is only net of the other variables, many of which affect the level of identity strength. Finally, the average time trend across participants is 0, meaning this negative correlation translates to a negative time trend for strongly identified participants in absolute terms. All this is to say that H3 is supported by the data.

RQ1 asks whether the effect of in-party communication on identity strength is itself moderated by identity strength. In other words, RQ1 asks whether people with higher or lower identity strength have different susceptibility to influence from communication. To test the dependence of effects on identity strength, the normal strategy — including an interaction term — is not viable, since it is not computationally feasible to include the observed mean level of identity strength as a regressor when the random intercept is nearly equivalent to the observed mean. Instead, the effects of in-party discussion and media use are estimated as random effects, which could then correlate with the random intercept in the same way just discussed for the growth curves. There was little indication for the effects of in-party media depending on the level of identity strength (r = -.19, 95% CI [-.55, .21], posterior probability 82.2%) and no evidence for in-party discussion (r = .02, 95% CI [-.30, .34], posterior probability 45.0%). In short, there is not evidence to conclude that the effects of communication on variability are dependent on the average level of identity strength.

Contrary to the prediction of H1, no predictor appeared to affect the time-dependent variability of identity strength, which is operationalized as interaction terms with the lagged value of identity strength (also included in Table 3). This could partly be explained by the fact that the autocorrelation term itself was not clearly distinct from 0 (B = 0.08, 95% CI [-0.00, 0.17], posterior probability 97.2%), meaning that deviations from one's typical level of identity strength on one day do not clearly carry over to the next day or get overcompensated and cause lower-than-normal levels on the next day. This is generally interpreted as evidence of stability in the sense that a person self-regulates well. This finding may raise the question: Do participants, as a whole, just not exhibit this kind of variability? The evidence suggests that some do. The model includes a random effect for the autocorrelation coefficient and results indicate that participants differ from one another significantly in terms of their own autocorrelation from one occasion to the next. The individual-specific autocorrelation has standard deviation of 0.14 (95% CI [0.09, 0.19], posterior probability >99.9%). This is evidence that some participants do have non-zero autocorrelation coefficients, but across participants they are not consistently positive or negative. Substantively, it is most likely that many self-regulate well (meaning their autocorrelation is 0), but some non-trivial proportion do not. What the data do not show is what the underlying factors associated with better or worse self-regulation are. Another clue that communication may play a role: If these interaction terms are omitted from the model, then there is significant, positive autocorrelation. This means it appears that these variables do affect time-dependent variability *in aggregate.*

H2 predicts that in-party communication will lead to increases in identity strength. The model detects a positive effect of in-party discussion (B = 0.03, 95% CI [0.01, 0.06], posterior probability 99.3%), indicating that increases in discussion with supporters of the same party is associated with greater identity strength on the next day. The estimate for in-party media is similar (B = 0.04, 95% CI [0.01, 0.06], posterior probability 99.8%). H2 is supported by the analysis. Addressing RQ2 about general effects of communication besides in-party sources, the model shows a negative effect of media (B = -0.02, 95% CI [-0.03, -0.00], posterior probability 98.9%). Discussion, however, did not clearly have an effect (B = -0.01, 95% CI [-0.03, 0.01], posterior probability 91.1%). Note, however, that the estimates for media and discussion are nearly equivalent to one another. As within-subject effects, these can be reasonably interpreted as causal. Full results are in Table 3.

Turning to net intraindividual variability, the other part of H1, there are several effects of note (see Table 4 for all details). At the between-person level, in-party discussion is associated with decreased variability (B = -0.22, 95% CI [-0.39, -0.06], posterior probability 99.6%). The estimate for in-party media is also negative but statistically indistinct from 0 (B = -0.07, 95% CI [-0.25, 0.07], posterior probability 83.7%). Relevant to RQ2, the single largest predictor of net variability is the total amount of discussion (B = 0.39, 95% CI [0.25, 0.52], posterior probability >99.9%). This swamps the collective effects of nearly all other variables in the model. The total amount of media, however, shows no apparent association with net variability (B = -0.01, 95% CI [-0.12, 0.10], posterior probability 58.7%). At the within-person level, which is more easily interpreted as causal, H1 is supported by negative coefficients for in-party discussion (B = -0.08, [-0.13, -0.04], posterior probability >99.9%) and for in-party media (B = -0.04, 95% CI [-0.08, -0.00], posterior probability 97.5%). This means in substantive terms that when the amount of in-party communication increases, the level of identity strength is significantly more predictable (i.e., stable) the next day. And informing RQ2, positive coefficients for the within-person total amount of discussion (B = 0.11, 95% CI [0.08, 0.14], posterior probability >99.9%) and total amount of media (B = 0.07, 95% CI [0.04, 0.11], posterior probability >99.9%) suggest that non-affirming communication functions effectively the opposite way of in-party communication.

Discussion

Consistent with expectations, both discussion with and media use from sources supporting one's own party were found to promote stability in identity strength by reducing net intraindividual variability. In other words, on days following higher levels of identity-affirming communication, participants' sense of partisan identity tended to be closer to their typical baseline. This finding aligns with the RSM's notion of a homeostatic system in which identity-congruent communication helps to maintain a steady equilibrium.

The stabilizing effect of in-party communication appears to operate primarily by counteracting short-term fluctuations rather than by altering longer-term trajectories. Contrary to predictions, neither in-party discussion nor media use had a detectable impact on the autocorrelation of identity strength from one day to the next. This suggests that although affirming communication may prevent departures from one's average level of identity, it does not necessarily make those departures more or less persistent when they do occur. It's possible that the timescale of the study was too short to capture this kind of variability. Among other explanations, it is important to note that the average respondent already exhibited time-structured stability (as evidenced by a zero estimated autocorrelation), so it would logically not be possible for these other variables to further increase it towards zero.

As hypothesized, both in-party discussion and media use were also found to directly increase the overall level of partisan identity strength. This developmental effect is more in line with the usual conception of communication influence and provides further evidence for the mutual reinforcement between communication behaviors and psychological attachment to parties. Interestingly, while in-party media strengthened identity as expected, media use more broadly appeared to have the opposite effect when controlling for in-party exposure. This finding, although not explicitly predicted, is consistent with the idea that non-affirming communication may introduce challenges to one's partisan worldview.

Perhaps the most novel finding of the study concerns the inherent decay of partisan identity among the most strongly identified. As predicted based on recent theorizing, individuals with higher average levels of identity strength exhibited negative time trends, suggesting a gradual weakening of partisanship in the absence of other influences. This result helps to explain why the RSM's mutual reinforcement process does not inevitably lead to extremity — even as identity-affirming communication increases identity strength, a countervailing force seems to pull the highly committed back towards more moderate levels of attachment over time. Partisan communication, then, may serve to counteract this natural decay rather than to drive a never-ending spiral of polarization. On balance, this may explain the relative individual-level stability observed in partisanship in the United States (Tucker et al., 2019).

Taken together, these findings help explain the role of communication in shaping the dynamics of partisan identity in greater detail than simply saying that there are effects or non-effects. Identity-affirming discussion and media use appear to play a stabilizing role, reducing variability and counteracting short-term decay, even as non-affirming communication introduces a degree of instability. At the same time, affirming communication also contributes to a strengthening of identity in an absolute sense. Examining these processes over a period of weeks reveals patterns that may be obscured in designs with longer lags between measurements. Furthermore, this study adds to the growing literature on the RSM, helping show how its assertions can be essentially correct without needing to model all the potential causes of identity homeostasis.

Limitations of the study should be noted. The sample of college students, while offering benefits in terms of capturing a dynamic period of political development, may not be representative of the broader public. The self-report measures of communication, although commonly used, are vulnerable to bias and error. And the duration of the study, while longer than most repeated-measures designs, is still relatively short for detecting some of the more gradual changes suggested by the RSM. Future research could address these limitations by using more diverse samples, behavioral measures of media use, and extended longitudinal designs.

Despite these limitations, the current study makes a valuable contribution by applying novel theoretical and methodological approaches to the question of partisan media effects. By disaggregating different forms of change and stability, and by situating these dynamics within the framework of the RSM, this study helps to clarify the complex ways in which communication both reinforces and challenges our political identities over time. As scholars continue to grapple with questions of selective exposure, polarization, and democratic functioning, approaches like the one demonstrated here will be essential for untangling the web of causal influences linking media to the self.

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Table 1: Summary of Support for Hypotheses

Hypothesis	Type of Effect	Summary of Results
H1: In-party communication will decrease variability of identity strength.	Net variability	**Talk**: Supported **Media**: Weak support
H1: In-party communication will decrease variability of identity strength.	Time-structured variability	**Talk**: Not supported **Media**: Not supported
H2: In-party communication will increase identity strength.	Development	**Talk**: Supported **Media**: Supported
H3: Those with stronger identities will have a negative time trend, net of other factors.	Decay	Supported

Table 2: Summary of Results Pertaining to Research Questions

Research Question	Type of Effect	Summary of Results
RQ1: Does the extent to which in-party communication promotes variability and development of identity strength depend on the level of identity strength?	Net variability	**Talk**: No **Media**: No
RQ1: Does the extent to which in-party communication promotes variability and development of identity strength depend on the level of identity strength?	Development	**Talk**: No **Media**: No
RQ2: How do the effects of non-in-party communication compare with those of in-party communication?	Development	**Talk**: No effect **Media**: Decreases identity strength
RQ2: How do the effects of non-in-party communication compare with those of in-party communication?	Net variability	**Talk**: Increases variability of identity strength **Media**: Increases variability of identity strength at within-person level

Table 3: Regression Results for Effects on Mean Level of Identity Strength

	Estimate	95% CI	Post. Prob.
Within-subject effects			
Strength (t – 1); autocorrelation	0.08	[-0.00, 0.17]	97.2%
In-party talk	0.03	[0.01, 0.06]	99.3%
In-party media	0.04	[0.01, 0.06]	99.8%
Total talk	-0.01	[-0.03, 0.01]	81.5%
Total media	-0.02	[-0.03, -0.00]	98.9%
Effects on time-dependent variability			
In-party talk	-0.01	[-0.12, 0.11]	56.7%
In-party media	-0.01	[-0.10, 0.08]	51.8%
Total talk	0.04	[-0.05, 0.13]	80.6%
Total media	-0.01	[-0.08, 0.06]	58.4%
Between-subject effects			
In-party talk	0.45	[0.21, 0.69]	>99.9%
In-party media	0.12	[-0.08, 0.30]	88.9%
Total talk	-0.19	[-0.39, 0.02]	96.1%
Total media	-0.01	[-0.18, 0.16]	52.4%
Republican	0.15	[-0.06, 0.37]	91.4%
Gender (woman)	0.26	[0.08, 0.46]	99.6%
Issue alignment	0.11	[0.03, 0.20]	99.5%
Race/ethnicity (White)	-0.24	[-0.53, 0.04]	94.9%
Race/ethnicity (Hispanic)	-0.24	[-0.61, 0.14]	89.5%
Race/ethnicity (Black)	-0.06	[-0.39, 0.26]	64.1%
Age	-0.03	[-0.06, -0.01]	99.4%
Voted before	0.15	[-0.03, 0.32]	94.8%
Survey number	0.00	[-0.00, 0.00]	68.5%
Intercept	-0.16	[-0.93, 0.64]	65.7%

Note: “Post. Prob.” refers to posterior probability, which readers can interpret approximately as 1 – *p* value.

Table 4: Regression Results for Effects on Residual Variance of Identity Strength

	Estimate	95% CI	Post. Prob.
Within-subject effects			
In-party talk	-0.08	[-0.13, -0.04]	>99.9%
In-party media	-0.04	[-0.08, -0.00]	97.5%
Total talk	0.11	[0.08, 0.14]	>99.9%
Total media	0.07	[0.04, 0.11]	>99.9%
Between-subject effects			
Intercept	-1.41	[-1.92, -0.92]	>99.9%
In-party talk	-0.22	[-0.39, -0.06]	99.6%
In-party media	-0.07	[-0.20, 0.07]	83.7%
Total talk	0.39	[0.25, 0.52]	>99.9%
Total media	-0.01	[-0.12, 0.10]	58.7%
Republican	0.00	[-0.13, 0.14]	51.0%
Gender (woman)	0.14	[0.02, 0.26]	98.9%
Issue alignment	0.01	[-0.05, 0.06]	61.7%
Race/ethnicity (White)	-0.12	[-0.30, 0.06]	90.9%
Race/ethnicity (Hispanic)	0.09	[-0.16, 0.34]	76.9%
Race/ethnicity (Black)	-0.06	[-0.27, 0.14]	72.8%
Age	0.01	[-0.01, 0.02]	75.7%
Voted before	-0.11	[-0.22, 0.01]	97.1%

Note: “Post. Prob.” refers to posterior probability, which readers can interpret approximately as 1 – *p* value.

Appendix A1. Daily Questionnaire Measures

Political Discussion

1. **Yesterday,** how much did you talk (online or offline) about news or politics?
   [ ] hours [ ] minutes

   And about what percentage of that time was with people who…

   a. Are Republicans, support Republicans, or have a conservative point of view
      _____ %

   b. Are Democrats, support Democrats, or have a liberal point of view
      _____ %

   c. Do not support Republicans or Democrats and do not have a particularly conservative or liberal point of view
      _____ %

Political Media

1. **Yesterday,** how much time did you spend reading, watching, listening to, or hearing about the news or political content, including posts you saw on social media?
   [ ] hours [ ] minutes

   And about what percentage of that time was the content from sources that…

   a. Sources that tend to favor the Republican party or conservative viewpoints. Examples of sources like this include *FOX News, Breitbart News, The Daily Wire/Ben Shapiro.*
      _____ %

   b. Sources that tend to favor the Democratic party or liberal viewpoints. Examples of sources like this include *MSNBC*, *Huffington Post*, *Mother Jones*.
      _____ %

   c. Sources that do not tend to favor one political party or ideology over another. Examples of sources like this include *USA Today, Politico, Yahoo! News*.
      _____ %

Political Identification

In the first questionnaire only:

1. Generally speaking, do you think of yourself as a…
    a. Republican
    b. Democrat
    c. Independent
    d. Something else
2. [If not a. or b. in Q1] Do you generally think of yourself as a little closer to the Republicans or Democrats?
    a. Closer to Republicans
    b. Closer to Democrats

On both the first and subsequent questionnaires:

3. Please rate your level of agreement with the following statements. Response choices are Strongly Disagree, Disagree, Disagree Somewhat, Agree Somewhat, Agree, Strongly Agree
    a. If I talk about [Republicans/Democrats] today, I would say "we" instead of "they."
    b. I am interested in what other people think about [Republicans/Democrats].
    c. If someone criticizes [Republicans/Democrats], it would feel like a personal insult.
    d. I have a lot in common with supporters of [Republicans/Democrats].
    e. If [Republicans/Democrats] do badly in a new opinion poll, it will ruin my day.
    f. If I meet someone who supports [Republicans/Democrats], I will feel connected with that person.
    g. If I talk about [Republicans/Democrats] today, I will refer to them as "my party."
    h. If someone praises [Republicans/Democrats], it will make me feel good.

Note: These items are based on the scale validation study by Bankert and colleagues (2017).

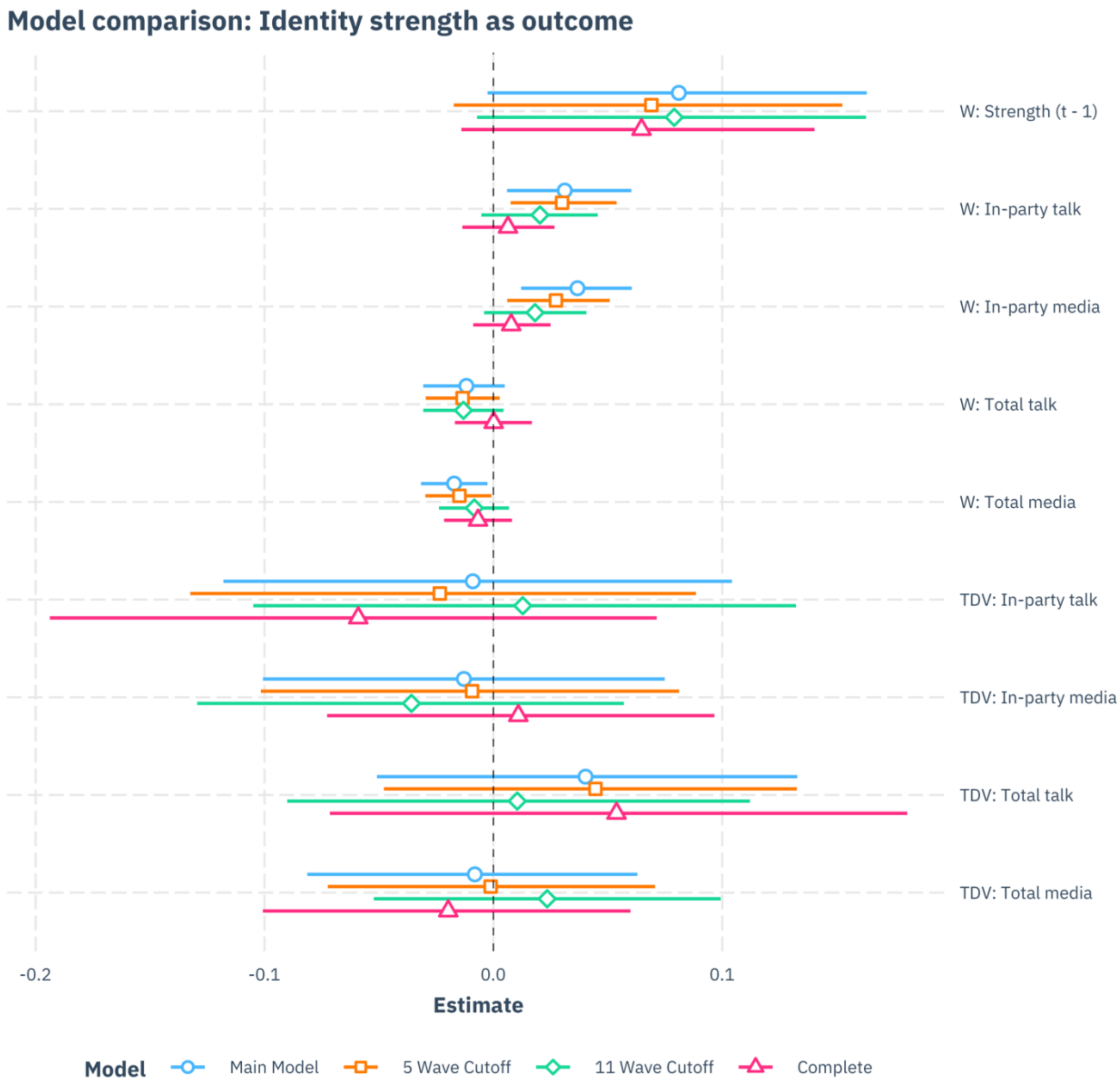
Appendix A2. Missing Data Strategy

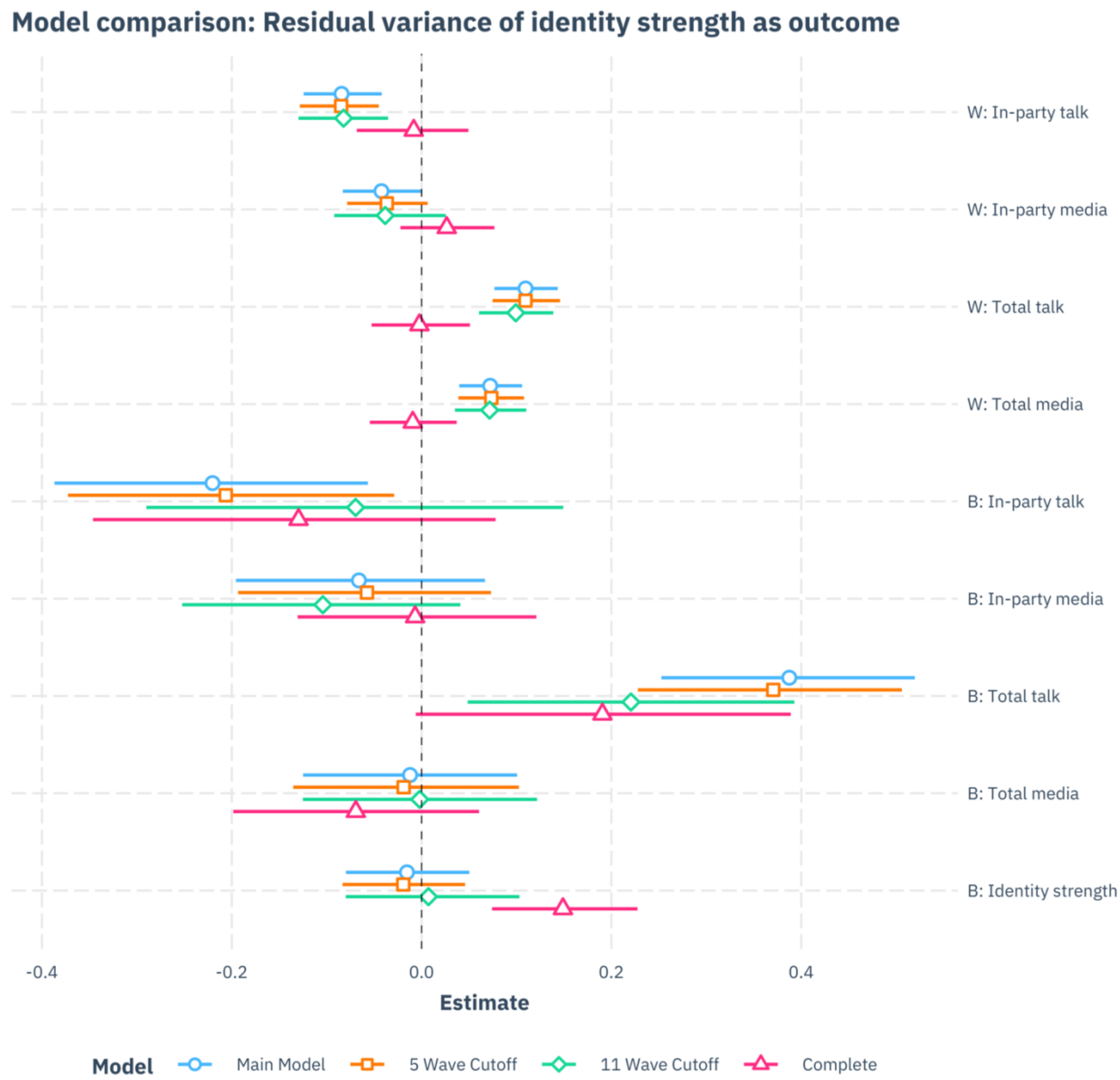
As previously mentioned, an expected feature of these data is a high level of missingness. Without expensive incentives, most participants will not respond each day. Although the deletion of missing data is rarely advised in quantitative research, the problems are arguably more acute in longitudinal designs when the use of lagged variables make such data losses compound over time. To address the missing data, multiple imputation procedures implemented in the Amelia software package (Honaker et al., 2011) which has several features designed specifically for longitudinal data that allow the imputation procedures to consider time trends, lagged values, and so on (Honaker & King, 2010). A full explanation of multiple imputation is beyond the scope of this paper, but the basic procedure is that a statistical model makes probabilistic predictions about what values would have been observed if the respondent had taken the survey and imputes them into the data. To account for the uncertainty in these probabilistic predictions, multiple imputed datasets are created with different plausible values for the missing observations. Analyses are then run on each imputed dataset and the results of the analyses are combined after the fact to capture the variation in potential results. Although for simple analyses only a small number (e.g., 5) of imputed datasets are necessary, larger numbers are suggested for Bayesian estimation (e.g., 20 to 100; Zhou & Reiter, 2010). The analyses reported here are based on 25 imputed datasets. Appendix A3 includes visual comparisons of model results using multiply imputed and complete data.

The main causes of missing data are skipped surveys and attrition. Recent research suggests that skipped surveys should be imputed using multiple imputation procedures (Ji et al., 2018) and dropping participants who fail to meet a certain level of participation can in some cases be worse than doing no accounting for missing data at all and analyzing only the observed cases (Jacobson, 2020). There are few guidelines or clear justifications available in the literature for choosing a threshold of completion under which all participant data should be dropped (Trull & Ebner-Priemer, 2020), but the findings of Jacobson (2020) indicate that more inclusive standards are best. Ji and colleagues (2018) used simulations to find satisfactory performance without any threshold and 30% of all observations across participants missing. Jacobson, Chow, and Newman (2019), using a related modeling approach to the one here, find strong results even when 70% of all observations are missing. The goal of the missing data procedures, then, is to not omit participants who participate less since their non-participation may be related to important variables. If those participants are not informative, then they should just add noise to the statistical estimates. With this in mind, all participants who completed at least 3 surveys were included in analyses and all their missing responses were imputed. Appendix A3 also includes a visual comparison of regression results when different inclusion cutoffs are chosen. These exclusions shrunk the final sample from 369 to 270. It should be noted that recruitment materials made clear to participants that participation beyond the initial survey was not required, so some likely only planned to take the initial survey and not pursue further participation. After the exclusions, just under 35% of all possible observations remained missing and were therefore imputed.

Appendix A3. Comparing Results from Multiply Imputed and Complete Data

Note: in figures, “W” refers to within-subject effects and “B” refers to between-subject effects.




Model comparison: Residual variance of identity strength as outcome
W: In-party talk
W: In-party media
W: Total talk
W: Total media
B: In-party talk
B: In-party media
B: Total talk
B: Total media
B: Identity strength
-0.4
-0.2
0.0
0.2
0.4
Estimate
Model
Main Model
5 Wave Cutoff
11 Wave Cutoff
Complete