# Live-Text Surveys in Probability Panels: Completion Rates, Representativeness, and Subsequent Panelist Engagement

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## ABSTRACT

We assess the effectiveness of live-text surveys as a contact and interviewing mode within a nationally representative probability panel. We compare a live-text protocol, in which consenting panelists respond to questions one by one over via text message, to a longer push-to-Web protocol in which a link to the survey is sent via email and text. Our quasi-experimental design compares two surveys sampled from the same probability panel with similar topics and launch dates, but different data collection protocols.

Over its full field period, the push-to-Web protocol achieved nearly twice the response rate as the live-text protocol; however, when limiting to responses received within the first 16

hours (the length of the live-text field period), the live-text response rate exceeded the push-to-Web response rate. The demographic profile of respondents was similar between the two protocols, with the live-text protocol slightly improving the representation of panelists without a college degree.

Aside from the outcomes of the specific surveys in question, we also consider effects on panelists' response to subsequent surveys within the panel. The live-text protocol had no effect on the propensity to unsubscribe from the panel or to report a high satisfaction with their panelist experience. Live-text respondents were slightly less likely to complete subsequent push-to-Web surveys, suggesting that a small subset of panelists may prefer the live-text protocol once exposed to it.

Results suggest that live-text surveys should be considered as a data collection methodology within probability panels when a short field period is of paramount importance. When a longer field period is available, considerations of response rates, coverage, and subsequent panelist engagement weigh in favor of the traditional push-to-Web protocol.

## 1. INTRODUCTION

### 1.1. Background

Historically, random digit dialing (RDD) with computer-assisted telephone interviewing (CATI) was the standard approach to collecting probabilistic samples of U.S. households, particularly when a short field period (several days or less) was required. In the past decade, declines in RDD response rates to the single digits (Kennedy and Hartig 2019), and the resulting increase in costs, have driven adoption of alternative sampling frames and data collection methodologies (Kennedy et al. 2023). Alternatives that rely on mailing as the primary contact mode—such as address-based sampling (ABS)—can obtain significantly higher response rates; however, best practices for these include costly design features such as prepaid incentives and

follow-up mailings, as well as longer field periods to ensure the delivery of all mailings (Harter et al. 2016; Olson et al. 2019). Online opt-in panels can obtain large samples at a very low cost and with a fast turnaround, but their non-probabilistic recruitment methodologies increase the risk of selection bias (Cornesse et al. 2020) and contamination by fraudulent respondents (Kennedy et al. 2021; Mercer and Lau 2023).

Practitioners faced with the need to reconcile short field periods, probabilistic recruitment, and relative affordability have increasingly turned to **probability panels** as a sampling frame and/or **text messaging** as a contact mode. A probability panel is a collection of persons who have been recruited via a probabilistic sample—typically ABS or RDD—and agreed to receive periodic surveys (Callegaro and DiSogra 2008; Rao et al. 2010; Scherpenzeel and Toepoel 2012; Callegaro et al. 2014; DiSogra and Callegaro 2016; McPhee et al. 2022). Like their opt-in counterparts, probability panels typically rely on online interviewing (Bosnjak et al. 2016), though some include mixed-mode capabilities (Rookey et al. 2008; Bretschi et al. 2023). Panelists may be notified of new surveys via emails, text messages, phone calls, customized mobile apps, and/or an online portal. All of these contact modes are compatible with short field periods.

Text messaging entails sending a written message to a respondent's cellular phone via Short Message Service (SMS) or Multimedia Messaging Service (MMS). There are two primary ways to operationalize surveys via text messaging (Conrad et al. 2017): **text-to-Web surveys** and **live-text surveys**. Text-to-Web entails sending a link that the respondent must click to access the survey via their phone's Web browser. Thus, text messaging functions similarly to a push-to-Web email or mailing: the text message is the *contact* mode and pushes the respondent to a separate *response* mode (the online survey instrument).

With live-text surveys, text messaging is both the contact and the response mode: the respondent receives and responds to questions one-by-one within their texting application. As discussed below, live-text surveys can often obtain responses within a very short timeframe. A tradeoff is that the question-by-question approach is susceptible to breakoffs, so live-text surveys typically need to be kept short, with practitioners recommending no more than 15-25 questions (Collins 2024). When using SMS, the length of each question, including response options, is limited to 160 characters (Marlar 2017).

In principle, text messaging can be used with any sampling frame for which cell phone numbers are available for some or all units. However, U.S. regulations restrict unsolicited contacts to cellular numbers. The Telephone Consumer Protection Act (TCPA) prohibits the use of automatic dialing technologies to either call or text cellular numbers without prior consent (Lavrakas et al. 2010). Therefore, samples of "unconsented" phone numbers—such as RDD samples—generally require peer-to-peer (P2P) texting in which interviewers manually send texts.

With panels, consent can be obtained as part of the registration process, which allows for faster and more cost-effective text-based surveys by making automated texting feasible. For non-text-consented panelists, alternative contact information (e.g., email addresses) can be collected to allow survey invitations to be sent via other channels. Thus, on a probability panel, non-text-consented individuals can be included in survey samples, so long as non-text-based contact and interviewing modes are available for a given survey.

### 1.2. Scope of study

In this paper, we examine the effectiveness of a live-text contact protocol as a means of administering short, very-quick-turnaround surveys within a probability panel. We compare the

live-text protocol to a more common push-to-Web protocol in which both email and text invitations provide a link to an online survey instrument. We exploit a quasi-experiment in which two surveys on similar topics—each using one of these protocols—were administered nearly concurrently within a national probability panel.

We first compare the two contact protocols with respect to the outcomes of the specific surveys in question. Specifically, we evaluate differences in response rates, response timeliness, and the demographic representativeness of respondents. Comparisons of demographic representativeness are of particular interest because the coverage of the live-text protocol, unlike the push-to-Web protocol, is inherently limited to the subset of panelists who consent to receiving text messages. With this, we aim to contribute to the limited extant literature on the optimal approach to leveraging text messaging within probability panels.

Second, we track panelist response behavior and engagement metrics *after* the surveys in questions. Due to the significant investment required for probabilistic recruitment, it is important to consider the impact of alternative contact and interviewing protocols on panelists' willingness to remain on the panel and continue responding to surveys. We evaluate the impact of exposure to the live-text protocol, relative to the push-to-Web protocol, on panelists' propensity to respond to future surveys, to request to leave the panel, and to report being satisfied with their panel experience.

## 2. PRIOR RESEARCH

To date, there is limited published literature evaluating the impact of text messaging as a contact mode, or comparing live-text to push-to-Web protocols, within probability panels. Importantly, we did not identify any prior studies of the impact of alternative texting protocols on subsequent engagement and survey participation by panelists.

Among consented Gallup panelists and recontact sample (all probability-based), Marlar (2017) compared text-to-Web and live-text protocols, finding little difference in contact rates, but higher breakoff rates with the live-text approach. Brenner et al. (2022) found similar results within an opt-in panel.

McGeeney and Yan (2016) tested the addition of text-to-Web contacts to a baseline email-to-Web protocol within a probability panel, finding that it improved response timeliness but did not change the final response rate or demographic representativeness. They did not test a live-text approach. Similar results have been observed in non-U.S. panels, both probability-based (De Bruijne and Wijnant 2014; Toepel and Lugtig 2018) and opt-in (Mavletova and Couper 2014).

Outside the panel context, evaluations of live-text and text-to-Web surveys have generally proceeded separately, with little research directly comparing the two. As an exception, Collins (2024) found in several randomized experiments that live-text exhibited higher contact rates, but higher breakoff rates that increase with survey length, with 15 – 25 questions being the approximate "breakeven" after which text-to-Web shows higher final response rates. Though weighted substantive estimates did not differ between the conditions, the live-text samples tended to show lower design effects, implying greater representativeness with respect to weighting variables. Standalone evaluations of text-to-Web contacts have been conducted on non-panel samples, in both U.S. and non-U.S. contexts, by Bosnjak et al. (2008); Hansen and Pedersen (2012); Woo et al. (2015); Andreadis (2020); Kim and Couper (2021); Bucher and Sand (2022); Soszynski and Bliss (2023); Cabrera-Alvarez and Lynn (2024); Christian et al. (2024); Kistler et al. (2024); and Kocar (2024).

Evaluations of the live-text approach have stressed its utility at collecting highly timely data. For example, Hoe and Grunwald (2015) found that 78% of live-text responses were obtained within 4 hours of launch. Similarly, Spiegelman et al. (2024) found that attempting a live-text interview before sending a paper questionnaire both increased the overall response rate and reduced the median time-to-response to less than one day, compared to 13 days with an email-to-Web contact. Accordingly, live-text or similar protocols have been adopted for real-time health or behavioral monitoring studies; as examples, see Anhøj and Møldrup (2004); Kuntsche and Robert (2009); Johansen and Wedderkopp (2010); Andrews et al. (2011); Berkman et al. (2011); Moreno et al. (2012); Brenner and DeLamater (2013); and Garcia et al. (2014). Schober et al. (2015) stress potential advantages for measurement quality, finding live-text respondents less likely than phone respondents to provide rounded or non-differentiated answers. Live-text interviewing has also been evaluated as an alternative to face-to-face interviewing in developing countries, where mobile penetration is high (Lau et al. 2019a); see West et al. (2015); Johnson (2016); Lau et al. (2019b); Haas et al. (2022); and Gellar et al. (2023).

Text messaging has also been studied as a mode of delivering prenotification or reminder messages for surveys in other modes, without a direct means of completing or accessing the survey via text. These have generally shown little effect on response rates when tested with U.S. phone-based surveys (Brick et al. 2007; Steeh et al. 2007), though positive effects have been observed outside the U.S. (Virtanen et al. 2007; Dal Grande et al. 2016).

## 3. DATA AND METHODS

See the Appendix for a PRICSSA item checklist and the wording of all questions used in this analysis.

### 3.1. SSRS Opinion Panel recruitment and empanelment

This analysis uses data from the SSRS Opinion Panel (henceforth, the "Panel"), a probability panel of approximately 50,000 (as of this writing) U.S. adults ages 18 and older.

Approximately 87% of Panel members were recruited via ABS. ABS recruitment uses stratified random samples of U.S. addresses from the United States Postal Service's Computerized Delivery Sequence file. The data collection methodology has varied across cohorts, but the current protocol entails:

- An initial mailing with a prepaid $1 cash incentive and a push-to-Web invitation letter.
- A reminder postcard.
- A final reminder mailing with a push-to-Web invitation letter.

In addition to a URL and passcode for the online survey, the ABS invitation letters and postcards include a toll-free number at which respondents can complete the survey via CATI with a live interviewer.

A further 6% of Panel members were recruited via samples of prepaid cell phone numbers from the cell phone RDD frame. Prepaid cell recruits are initially contacted via outbound dialing and/or P2P text-to-Web messages. The remaining 7% were recruited via a weekly RDD tracker that was discontinued in 2022.

The recruitment survey invitations do not mention the Panel but simply ask the respondent to complete a survey, for which they are offered a $10 post-incentive, which is paid regardless of whether respondents agree to join the Panel. The offer to join the Panel is presented about halfway through the survey; respondents from historically lower-response-rate subgroups are offered a bonus incentive if they join. Empaneled respondents are asked for consent to

receive text messages related to Panel surveys; those who decline consent are retained as panelists and subsequently contacted only via email or phone. All panelists, regardless of the mode by which they complete the registration survey, are offered a choice of their preferred mode (online or live-interviewer CATI) and language (English or Spanish) for future surveys.

At the time of the surveys whose results are reported here, the overall Panel recruitment response rate was 6.5% (AAPOR Response Rate 3) with a 73.6% retention rate. Approximately 89% of panelists complete surveys online. Approximately 61% of all panelists are text-consented.

**3.2. SSRS Opinion Panel surveys**

After empanelment, panelists become eligible for sampling into surveys. Survey-level sampling uses a probability proportional to size (PPS) methodology described in the Appendix.

Nearly all Panel surveys use a push-to-Web contact protocol for online panelists. This protocol includes both text-consented and non-text-consented panelists. All sampled online panelists receive an initial invitation email with a link to the survey and an incentive offer. Nonresponding panelists receive multiple reminder emails, with the exact number depending on the field period. Additionally, text-consented online panelists receive one or more text-to-Web reminders with a link to the survey. Upon completion, online panelists receive an instant incentive via an emailed link to an electronic gift card.

A live-text protocol is occasionally used for short surveys. Only text-consented panelists are eligible for sampling into these surveys. Panelists are sent a text message asking if they are willing to complete a short survey for a specified incentive amount. Those who respond affirmatively are then sent questions one-by-one, providing numeric responses to each (e.g., "1" for "Yes"). As with push-to-Web surveys, completers receive instant electronic incentives.

Within a live-text protocol, reminder texts may or may not be used depending on the length of the field period and observed response patterns.

### 3.3. Analytic data and methods

This analysis uses 5,775 panelists who were invited into one or both of the following surveys:

- A *Washington Post* poll conducted March 4 – 5 using a live-text protocol.[1]
- A CNN poll conducted March 6 – 10 using a push-to-Web protocol.[2]

We refer to these surveys as the "target surveys" to distinguish them from earlier or later surveys for which the panelists may have been sampled.

Both target surveys asked about perceptions of President Trump's performance early in his second term. The live-text poll emphasized economic policy, focusing on recently announced tariffs. The push-to-Web poll asked about economic policy and several other issue areas. Following the Panel's standard procedures, neither survey's sponsor was mentioned in the questionnaire or invitation materials.

Table 1 summarizes key design features of each survey. Note that, while panelists sampled for these surveys constitute the analytic sample, the analysis in this paper relies entirely on Panel paradata and profile variables; no client-sponsored questions are used for this analysis.

We treat this pair of surveys as a quasi-experiment due to their similar topics and nearly concurrent fielding dates. Of course, the ideal would have been to administer these surveys as a true experiment with the contact protocol randomized and all other features held constant. In

[1] Full results available at https://www.washingtonpost.com/politics/interactive/2025/trump-tariffs-poll-us-economy.
[2] Full results available at https://www.cnn.com/2025/03/12/politics/cnn-poll-trump-economy.

practice, this was not possible, as they were sponsored by different clients with different questionnaires and scheduling requirements.

Table 1. Design features of surveys used for analysis

| Characteristic | Push-to-Web survey | Live-text survey |
|---|---|---|
| Time in field | 89 hours | 16 hours |
| Dates in field | March 6 - 10, 2025 | March 4 - 5, 2025 |
| Topic | Views on presidential performance (multiple policy areas) | Views on presidential performance (economic policy) |
| Eligibility criteria | U.S. adults ages 18+<br>Text-consented and non-text-consented panelists<br>Online and CATI panelists | U.S. adults ages 18+<br>Text-consented panelists<br>Online panelists |
| Number of respondents[1] | 935 | 1,009 |
| Number of questions[2] | 98 | 11 |
| Invitation/reminder protocol: online panelists | 1 initial invitation email<br>1 reminder text (text-consented panelists only)<br>Up to 4 reminder emails | 1 initial invitation text<br>No reminders |
| Invitation/reminder protocol: CATI panelists | Outbound calling (up to 5 attempts) | Not applicable |
| Interviewing mode | Online survey instrument (online panelists)<br>Live-interviewer CATI (CATI panelists) | Automated text |
| Interviewing languages | English, Spanish | English, Spanish |

[1] Respondent count for push-to-Web survey includes only first released replicate.

[2] Excludes intro, screening, and incentive blocks. Includes questions that were hidden for some respondents due to skip patterns.

As with any quasi-experimental design, several limitations should be noted up front. First, the field periods were not exactly concurrent, so this design cannot control for any effects of the day of week or time that the survey was launched. Second, the live-text survey was much shorter (with respect to the number of questions) than the push-to-Web survey. Both of these represented approximately typical questionnaire lengths for Panel surveys that use their respective protocols; in light of the research discussed above, we consider a limited questionnaire length to be an inherent component of the live-text protocol. However, because we did not administer a similarly short survey using the push-to-Web protocol, this analysis cannot disentangle the effect of the contact protocol itself from that of the length of the survey. Finally, in the push-to-Web sample, all sample members who were texted were also emailed. While we can differentiate between respondents who completed via an emailed link and a texted link, we do not observe the counterfactual response patterns that would have been obtained with an email-only protocol (e.g., how many text-to-Web respondents would have otherwise completed via the emailed link). Therefore, we can compare the push-to-Web protocol as a whole to the live-text protocol, but we do not disentangle the effect of text-to-Web contacts within the push-to-Web protocol.

Both samples were selected using the Panel's standard PPS methodology. The samples were selected independently, and about 340 panelists were, by chance, sampled for both. Design weights were assigned to all sampled panelists, reflecting their probabilities of recruitment into the Panel and selection for the survey-level sample. Respondents' weights were calibrated to population benchmarks for demographics and party affiliation; however, because this analysis focuses on data collection outcomes rather than population estimates, only uncalibrated design weights are used in this analysis.

For both surveys, additional replicates were released during field to reach the target number of completes. For the live-text survey, the additional replicates were released about three hours into field, so we retain these replicates in the analytic sample. For the push-to-Web survey, the additional replicates were released 2 – 3 days into field; since these replicates faced a substantially shortened field period and reminder protocol, we exclude them from the analysis.

The live-text sample was limited to online, text-consented panelists. The push-to-Web sample included non-text-consented panelists. It also included CATI panelists who were contacted via outbound dialing; but, since 92% of respondents completed online, we refer to it as a push-to-Web survey for brevity.

For most analyses presented here, which are considering operational outcomes such as response rates and subsequent panelist engagement, we restrict the push-to-Web sample to online, text-consented panelists to avoid confounding comparisons by differences in the eligibility criteria. The exception is when analyzing the demographics of the responding samples (Tables 3 and 4 below). For that analysis, we include the non-text-consented and CATI panelists in the push-to-Web sample. This is because the restriction of coverage to text-consented panelists is an inherent limitation of the live-text protocol that might, *a priori*, be expected to negatively affect demographic representativeness. Including the non-text-consented panelists in the push-to-Web sample ensures that any effect of the coverage limitation on demographic representativeness is accounted for in this analysis.

All panelists were assigned a baseline response propensity (RP) score, which we use as a control variable in some analyses. The baseline RP score is the panelist's modeled probability of responding to their next survey (in this case, the target survey), based on panelist-level profile data and their response history to all *prior* surveys for which they have been sampled. The

baseline RP score does not incorporate any information about the target survey itself; it is, effectively, an aggregation of information known *prior* to the target survey about the panelist's willingness to complete surveys. As nearly all surveys on the Panel use a push-to-Web protocol, it implicitly reflects the modeled probability of response conditional on receiving the push-to-Web protocol. The Appendix provides additional information about the construction of this variable.

## 4. RESULTS

### 4.1. Survey-level response rates

Table 2 shows the weighted distribution of each sample by its final disposition.

Table 2. Invited sample by disposition, push-to-Web vs. live text survey

| | Percent of invited sample | | | | Standard errors | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Push-to-Web survey | | | | Push-to-Web survey | | | |
| **Disposition** | **Live-text survey** | **Text-consented online** | **Non-text-consented online** | **CATI panelists** | **Live-text survey** | **Text-consented online** | **Non-text-consented online** | **CATI panelists** | ***p* value[1]** |
| Complete | 25.6% | 43.1% | 49.5% | 28.0% | 0.7% | 1.5% | 1.9% | 3.9% | 0.00 |
| Started survey, incomplete | 1.5% | 2.0% | 2.6% | 0.0% | 0.2% | 0.4% | 0.6% | 0.0% | 0.29 |
| Overquota | 0.1% | 0.1% | 0.2% | 0.0% | 0.1% | 0.1% | 0.1% | 0.0% | 0.63 |
| Did not start survey | 72.8% | 54.9% | 47.7% | 72.0% | 0.7% | 1.5% | 1.9% | 3.9% | 0.00 |
| *Invited sample size (unweighted)* | *3951* | *1209* | *795* | *163* | | | | | |
| *AAPOR Response Rate 1 (survey-level)* | *25.6%* | | *43.6%* | | | | | | |
| *Cumulative response rate[2]* | *1.2%* | | *2.1%* | | | | | | |

[1] From a *t* test of the difference in the specified percentage between the live text sample and the text-consented push-to-Web sample.

[2] Equal to the product of the panel recruitment response rate (AAPOR Response Rate 3), the panel retention rate, and the survey-level response rate.

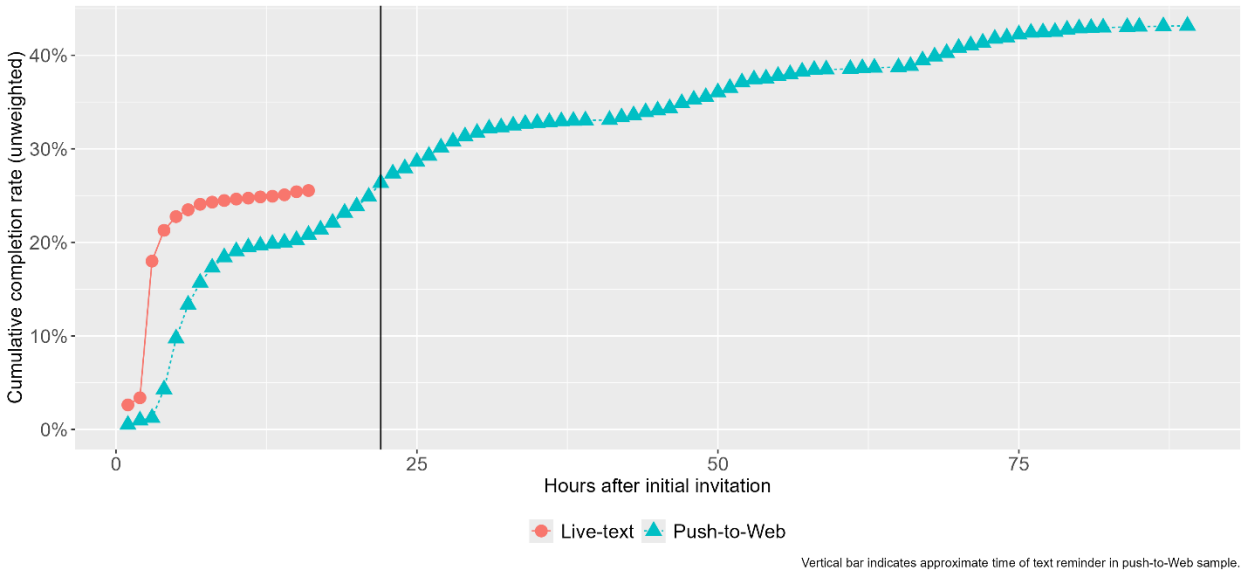
NOTE: Estimates are design-weighted unless otherwise noted.

Among text-consented panelists, the push-to-Web protocol achieved significantly higher completion rates (43.1%) compared to the live-text survey (25.6%). Nearly all of the difference in nonresponse was attributable to those who did not start the survey: a significantly larger proportion of respondents in the live-text survey did not start the survey (72.8%) compared to the text-consented push-to-Web sample (54.9%). Considering the samples as a whole, survey-level and cumulative response rates were higher for the push-to-Web relative to the live-text sample.

**4.2. Timing of completion**

Figure 1 shows cumulative operational completion rates (the unweighted percentage of the sample completing the survey) as of each hour after the launch of data collection for each target survey. Consistent with prior research, the live-text protocol obtained responses at a much faster pace than the push-to-Web protocol. With the live-text protocol, most responses were received within three hours of launch; and, although it remained open for 16 hours, completion largely leveled off after six hours. Although the push-to-Web protocol obtained a higher final completion rate over its full field period, it would have yielded a lower completion rate with a comparable 16-hour field period (21% vs. 26%), with an even larger gap at six hours (13% vs. 23%).

*Figure 1: Cumulative completion rates by hour of data collection*




### 4.3. Demographic representativeness

Table 3 shows the design-weighted demographic distributions of all respondents for each sample. Design weights are applied to correct for differences in the sample design between the two studies, which affected the unweighted demographic composition of the samples. While both samples' weights were ultimately calibrated to match the distribution of the U.S. adult population by demographics, party identification, and (in the case of the live-text poll) recalled 2024 vote, the uncalibrated design weights are used to assess the success of each protocol at obtaining a demographically representative set of respondents. These distributions are compared to external population benchmarks, where available.

In addition to the descriptive bivariate comparisons, the table includes the coefficients from the following logistic regression, estimated on the combined set of respondents to the live-text and push-to-Web surveys:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum \beta_k X_k$$

where $p$ is the probability that the respondent is in the live-text sample and $X_k$ is the vector of predictors shown in the table. This allows for a multivariate assessment of the variable(s) that differentiate live-text from push-to-Web respondents.

Table 3. Demographics of responding sample, push-to-Web vs. live text survey, all respondents

| | | | Percent of push-to-Web respondents[2] | | Percent of live-text respondents | | Logistic regression coefficients[3] | | |
|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **Category** | **Benchmark percentage[1]** | **Percent** | **Standard error** | **Percent** | **Standard error** | **Coefficient** | **Standard error** | ***p* value** |
| Age | 18 - 29 | 19.8% | 14.7% | 1.1% | 14.0% | 1.1% | | | |
| | 30 - 49 | 33.7% | 34.3% | 1.7% | 34.5% | 1.5% | 0.04 | 0.15 | 0.81 |
| | 50 - 64 | 23.7% | 24.6% | 1.6% | 24.7% | 1.4% | 0.01 | 0.16 | 0.94 |
| | 65+ | 22.8% | 26.3% | 1.6% | 26.9% | 1.4% | -0.01 | 0.17 | 0.96 |
| | Missing | NA | 0.1% | 0.1% | 0.0% | 0.0% | -12.11 | 0.85 | 0.00 |
| Gender | Male | 48.9% | 47.2% | 1.8% | 46.6% | 1.6% | | | |
| | Female | 51.1% | 51.2% | 1.8% | 52.7% | 1.6% | 0.01 | 0.10 | 0.90 |
| | Other | NA | 0.4% | 0.2% | 0.1% | 0.1% | -1.55 | 1.22 | 0.20 |
| | Missing | NA | 1.2% | 0.4% | 0.6% | 0.3% | -0.62 | 0.58 | 0.29 |
| Race/ethnicity | White, non-Hispanic | 60.8% | 67.0% | 1.6% | 66.8% | 1.5% | | | |
| | Black, non-Hispanic | 12.1% | 8.1% | 0.8% | 8.1% | 0.9% | -0.10 | 0.17 | 0.58 |
| | Hispanic | 17.9% | 14.1% | 1.1% | 13.9% | 1.1% | -0.03 | 0.15 | 0.84 |
| | Other, non-Hispanic | 9.3% | 8.9% | 1.1% | 9.6% | 1.0% | 0.18 | 0.18 | 0.33 |
| | Missing | NA | 2.0% | 0.5% | 1.5% | 0.4% | 0.07 | 0.41 | 0.87 |
| Educational attainment | High school diploma or below | 37.9% | 30.9% | 1.5% | 33.9% | 1.6% | | | |
| | Some college or Associate's degree | 26.3% | 25.0% | 1.6% | 25.1% | 1.4% | -0.14 | 0.13 | 0.27 |
| | Bachelor's degree or higher | 35.8% | 43.2% | 1.8% | 40.3% | 1.6% | -0.26 | 0.12 | 0.03 |
| | Missing | NA | 0.9% | 0.3% | 0.7% | 0.3% | -0.37 | 0.59 | 0.53 |
| Party identification | Democratic | 30.2% | 28.4% | 1.6% | 35.2% | 1.5% | | | |
| | Republican | 29.9% | 33.5% | 1.7% | 31.0% | 1.5% | -0.47 | 0.18 | 0.01 |
| | Independent or other | 39.9% | 38.1% | 1.7% | 33.7% | 1.5% | -0.40 | 0.13 | 0.00 |
| | Missing | NA | 0.0% | 0.0% | 0.1% | 0.1% | 14.55 | 1.02 | 0.00 |
| Voter registration status | Registered to vote | 76.9% | 80.3% | 1.3% | 84.0% | 1.2% | | | |
| | Not registered to vote | 23.1% | 19.7% | 1.3% | 16.0% | 1.2% | -0.22 | 0.23 | 0.32 |
| | Missing | NA | 0.0% | 0.0% | 0.0% | 0.0% | | | |

Table 3. Demographics of responding sample, push-to-Web vs. live text survey, all respondents

| Characteristic | Category | Benchmark percentage[1] | Percent of push-to-Web respondents[2] Percent | Standard error | Percent of live-text respondents Percent | Standard error | Logistic regression coefficients[3] Coefficient | Standard error | *p* value |
|---|---|---|---|---|---|---|---|---|---|
| Recalled 2024 vote[4] | Harris | 48.3% | 35.8% | 1.7% | 39.0% | 1.6% | | | |
| | Trump | 49.8% | 36.4% | 1.7% | 36.6% | 1.6% | 0.17 | 0.16 | 0.29 |
| | Other | 1.9% | 2.0% | 0.5% | 2.7% | 0.5% | 0.49 | 0.34 | 0.16 |
| | Did not vote | NA | 25.8% | 1.5% | 21.7% | 1.3% | 0.02 | 0.22 | 0.94 |
| Internet use frequency | Almost constant | 41.8% | 41.6% | 1.7% | 42.3% | 1.6% | | | |
| | Less frequent | 58.2% | 57.6% | 1.7% | 57.3% | 1.6% | -0.02 | 0.11 | 0.82 |
| | Missing | NA | 0.8% | 0.4% | 0.4% | 0.2% | -0.85 | 0.75 | 0.26 |
| Language of survey completion | English | NA | 98.1% | 0.4% | 98.3% | 0.3% | | | |
| | Spanish | NA | 1.9% | 0.4% | 1.7% | 0.3% | -0.06 | 0.33 | 0.85 |

[1] Benchmarks are for U.S. adults ages 18+. Benchmark source is the 2024 National Public Opinion Reference Survey for party identification and Internet use frequency; the Federal Election Commission for recalled 2024 vote; the 2022 Current Population Survey Voting and Registration Supplement for voter registration status; and the March 2024 Current Population Survey Annual Social and Economic Supplement for all other characteristics. NA indicates external benchmark not available.

[2] Includes both text-consented and non-text-consented online and CATI respondents.

[3] From a logistic regression estimated on the combined set of respondents to the two surveys, where the dependent variable is an indicator of response to the live-text survey. Coefficients not shown for the reference category.

[4] Recalled 2024 vote is populated for only a subset of the analytic sample (*n* = 1,308). Panelists with missing data were imputed using hot-deck imputation with party identification and voter registration status as boundary variables. Benchmark for recalled 2024 vote is the certified national popular vote, among voters.

NOTE: Estimates are design-weighted. All characteristics are self-reported. *n* = 935 for push-to-Web survey and 1,009 for live text survey.

In general, despite the differing response rates, the two protocols obtained respondents with a similar demographic profile. Based on the multivariate analysis, education and party identification were the primary differentiators between the two sets of respondents. Live-text respondents were less likely to hold a college degree, and therefore their educational distribution was closer to the Current Population Survey benchmark. Live-text respondents were more likely to identify as Democratic and less likely to identify as Republican or Independent. Using the Pew Research Center's 2024 National Public Opinion Reference Survey as the benchmark for party identification, the two-party distributions diverged from the population by similar magnitudes but different directions—the push-to-Web respondents showed a 5-point Republican margin, and the live-text respondents a 4-point Democratic margin, compared to an approximately even split in the population.

Table 4 shows the same results but limits the push-to-Web sample to respondents obtained within 16 hours of launch. In this way, we simulate the composition of the sample that would have been obtained if the push-to-Web protocol were used for a comparably short-turnaround survey. Note that this approach assumes that no email or text reminders would be used within this hypothetical shortened push-to-Web protocol, as the first reminders were sent approximately 22 hours after launch.

Table 4. Demographics of responding sample, push-to-Web vs. live text survey, respondents within 16 hours of launch

| | | | Percent of push-to-Web respondents[2] | | Percent of live-text respondents | | Logistic regression coefficients[3] | | |
|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **Category** | **Benchmark percentage[1]** | **Percent** | **Standard error** | **Percent** | **Standard error** | **Coefficient** | **Standard error** | ***p* value** |
| Age | 18 - 29 | 19.8% | 13.7% | 1.5% | 14.0% | 1.1% | | | |
| | 30 - 49 | 33.7% | 34.4% | 2.4% | 34.5% | 1.5% | 0.04 | 0.18 | 0.82 |
| | 50 - 64 | 23.7% | 23.4% | 2.1% | 24.7% | 1.4% | 0.06 | 0.21 | 0.79 |
| | 65+ | 22.8% | 28.3% | 2.4% | 26.9% | 1.4% | -0.03 | 0.22 | 0.87 |
| | Missing | NA | 0.3% | 0.2% | 0.0% | 0.0% | -14.84 | 0.97 | 0.00 |
| Gender | Male | 48.9% | 44.7% | 2.5% | 46.6% | 1.6% | | | |
| | Female | 51.1% | 53.6% | 2.5% | 52.7% | 1.6% | -0.10 | 0.13 | 0.43 |
| | Other | NA | 0.2% | 0.2% | 0.1% | 0.1% | -1.18 | 1.52 | 0.43 |
| | Missing | NA | 1.5% | 0.5% | 0.6% | 0.3% | -0.98 | 0.65 | 0.13 |
| Race/ethnicity | White, non-Hispanic | 60.8% | 69.0% | 2.3% | 66.8% | 1.5% | | | |
| | Black, non-Hispanic | 12.1% | 8.0% | 1.1% | 8.1% | 0.9% | -0.15 | 0.21 | 0.48 |
| | Hispanic | 17.9% | 10.4% | 1.4% | 13.9% | 1.1% | 0.05 | 0.19 | 0.81 |
| | Other, non-Hispanic | 9.3% | 11.1% | 1.7% | 9.6% | 1.0% | -0.06 | 0.21 | 0.79 |
| | Missing | NA | 1.7% | 0.6% | 1.5% | 0.4% | 0.23 | 0.55 | 0.68 |
| Educational attainment | High school diploma or below | 37.9% | 30.3% | 2.2% | 33.9% | 1.6% | | | |
| | Some college or Associate's degree | 26.3% | 22.0% | 2.2% | 25.1% | 1.4% | -0.01 | 0.17 | 0.97 |
| | Bachelor's degree or higher | 35.8% | 47.3% | 2.6% | 40.3% | 1.6% | -0.30 | 0.15 | 0.04 |
| | Missing | NA | 0.4% | 0.3% | 0.7% | 0.3% | 0.52 | 0.82 | 0.53 |
| Party identification | Democratic | 30.2% | 26.9% | 2.2% | 35.2% | 1.5% | | | |
| | Republican | 29.9% | 36.8% | 2.5% | 31.0% | 1.5% | -0.70 | 0.23 | 0.00 |
| | Independent or other | 39.9% | 36.3% | 2.5% | 33.7% | 1.5% | -0.45 | 0.17 | 0.01 |
| | Missing | NA | 0.0% | 0.0% | 0.1% | 0.1% | 15.49 | 1.04 | 0.00 |
| Voter registration status | Registered to vote | 76.9% | 83.6% | 1.8% | 84.0% | 1.2% | | | |
| | Not registered to vote | 23.1% | 16.4% | 1.8% | 16.0% | 1.2% | -0.03 | 0.28 | 0.92 |
| | Missing | NA | 0.0% | 0.0% | 0.0% | 0.0% | | | |

Table 4. Demographics of responding sample, push-to-Web vs. live text survey, respondents within 16 hours of launch

| | | | Percent of push-to-Web respondents[2] | | Percent of live-text respondents | | Logistic regression coefficients[3] | | |
|---|---|---|---|---|---|---|---|---|---|
| **Characteristic** | **Category** | **Benchmark percentage[1]** | **Percent** | **Standard error** | **Percent** | **Standard error** | **Coefficient** | **Standard error** | ***p* value** |
| Recalled 2024 vote[4] | Harris | 48.3% | 36.1% | 2.5% | 39.0% | 1.6% | | | |
| | Trump | 49.8% | 38.5% | 2.5% | 36.6% | 1.6% | 0.23 | 0.21 | 0.28 |
| | Other | 1.9% | 2.6% | 0.9% | 2.7% | 0.5% | 0.26 | 0.41 | 0.54 |
| | Did not vote | NA | 22.7% | 2.1% | 21.7% | 1.3% | 0.02 | 0.27 | 0.94 |
| Internet use frequency | Almost constant | 41.8% | 41.0% | 2.5% | 42.3% | 1.6% | | | |
| | Less frequent | 58.2% | 57.9% | 2.5% | 57.3% | 1.6% | -0.02 | 0.14 | 0.90 |
| | Missing | NA | 1.1% | 0.7% | 0.4% | 0.2% | -1.15 | 0.90 | 0.20 |
| Language of survey completion | English | NA | 100.0% | 0.0% | 98.3% | 0.3% | | | |
| | Spanish | NA | 0.0% | 0.0% | 1.7% | 0.3% | 15.73 | 0.26 | 0.00 |

[1] Benchmarks are for U.S. adults ages 18+. Benchmark source is the 2024 National Public Opinion Reference Survey (Pew Research Center 2024) for party identification and Internet use frequency; the Federal Election Commission (2025) for recalled 2024 vote; the 2022 Current Population Survey Voting and Registration Supplement for voter registration status (Flood et al. 2022); and the March 2024 Current Population Survey Annual Social and Economic Supplement (Flood et al. 2024) for all other characteristics. NA indicates external benchmark not available.

[2] Includes both text-consented and non-text-consented online and CATI respondents.

[3] From a logistic regression estimated on the combined set of respondents to the two surveys, where the dependent variable is an indicator of response to the live-text survey. Coefficients not shown for the reference category.

[4] Recalled 2024 vote is populated for only a subset of the analytic sample ($n$ = 987). Panelists with missing data were imputed using hot-deck imputation with party identification and voter registration status as boundary variables. Benchmark for recalled 2024 vote is the certified national popular vote, among voters.

NOTE: Estimates are design-weighted. All characteristics are self-reported. $n$ = 451 for push-to-Web survey and 1,009 for live text survey.

Results are largely consistent with those shown in Table 3. Among respondents obtained within 16 hours of launch, most demographic differences between push-to-Web and live-text respondents were not statistically significant in the multivariate analysis. However, the differences that did exist when including the full push-to-Web field period were generally larger when limiting to a comparable field period. The early push-to-Web respondents were more college-educated than the live-text respondents, to a greater extent than when considering the full field period. Early push-to-Web respondents skewed Republican to a greater extent, with about a 10-percentage-point Republican advantage in the two-party margin. Additionally, no responses in Spanish were obtained in the first 16 hours of the push-to-Web field period.

**4.4. Impact on subsequent panelist engagement**

We now turn to the impact of exposure to a live-text survey on panelists' subsequent engagement with Panel surveys. We test for effects on the following outcomes:

- Whether the panelist responded to the next survey for which they were sampled after the target survey(s).
- Whether the panelist responded to *any of* the next *three* surveys for which they were sampled after the target survey(s). Panelists who fail to complete multiple consecutive surveys are eventually removed from the Panel, so we use "panelist retention" as a shorthand for this outcome.
- Whether the panelist proactively requested removal from the Panel (unsubscribed) within 3 months of the target survey(s).
- Whether the survey rated their experience on the Panel as "Excellent" or "Very good" the next time they were asked about it. Most push-to-Web surveys on the Panel end by asking panelists to rate their experience on a five-point scale. This question is not asked after

live-text surveys; therefore, to allow for comparability between the live-text and push-to-Web surveys, we compare responses to the first presentation of the question *after* the target survey(s).

We estimate logistic regression models of the following form:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 TEXT + \sum \beta_k X_k$$

where $p$ is the probability of the specified outcome, *TEXT* indicates panelists sampled for the live-text survey (including those sampled for both the push-to-Web and live-text surveys), and $X_k$ is a vector of controls. We include the following controls:

- Linear and quadratic terms for the panelist's baseline RP.
- Linear and quadratic terms for the number of days between the target survey and the next survey invitation.

Our primary research question for this analysis is whether *exposure* to the live-text protocol affects subsequent panelist engagement. Therefore, these regressions are estimated on all panelists sampled for one or both target surveys, regardless of whether they completed the target survey(s). The primary coefficient of interest is that on *TEXT*, which is shown in Table 5 (see the Appendix for full regression tables, including coefficients for control variables).

Table 5. Regression coefficients for subsequent panelist behavior

| | Intercept | | | Exposure to live-text survey[1] | | |
|---|---|---|---|---|---|---|
| **Outcome** | **Coefficient** | **Standard error** | ***p* value** | **Coefficient** | **Standard error** | ***p* value** |
| Responded to next survey[2] | -0.26 | 0.10 | 0.01 | -0.09 | 0.10 | 0.37 |
| Responded to any of next 3 surveys[3] (retention) | 1.20 | 0.13 | 0.00 | -0.25 | 0.14 | 0.07 |
| Unsubscribed from Panel within next 3 months[2] | -6.59 | 0.76 | 0.00 | 1.01 | 0.74 | 0.17 |
| Rated Panel "Excellent" or "Very good" on next survey[4] | 2.20 | 0.15 | 0.00 | -0.22 | 0.17 | 0.20 |

[1] Includes those sampled for both live-text and push-to-Web survey. Reference category is push-to-Web survey only.

[2] Among panelists invited to either survey with at least 1 subsequent survey invitation, $n$ = 4,624.

[3] Among panelists invited to either survey with at least 3 subsequent survey invitations, $n$ = 3,614.

[4] Among all panelists invited to either survey with at least 1 subsequent survey completion, $n$ = 2,440.

NOTE: Coefficients are from logistic regressions estimated on text-consented online panelists invited to either or both surveys, with the specified outcome as the dependent variable. Reference category is panelists invited to push-to-Web survey only. All regressions control for baseline response propensity and time until next survey. Coefficients for control variables are shown in Tables A.1 - A.4 of the Appendix. Estimates are unweighted.

Relative to the push-to-Web protocol, exposure to the live-text protocol was not significantly associated with the propensity to unsubscribe from the Panel or to report a high satisfaction rating when next asked.

Results related to future survey completion are more nuanced. When predicting response to the immediate next survey, the coefficient on *TEXT* is negative but non-significant. However, the negative coefficient reaches marginal significance when predicting response to one of the next three surveys ($p < 0.1$). Holding the numeric controls (baseline RP and time to next survey) at their means, exposure to the live-text survey reduces the predicted retention rate from 79% to 74%.

Notably, all panelists sampled for the target survey(s) received the push-to-Web protocol for their first three post-target surveys. This suggests two potential explanations for the effects of live-text exposure on future completion.

- **Persistent nonresponse**: The live-text protocol showed a lower response rate (Table 2). It is possible that, once a panelist does not respond to a survey, they continue to not respond even after the protocol switches back to push-to-Web.
- **Protocol switching**: Among those who do respond to the live-text protocol, some may stop responding to subsequent push-to-Web surveys, perhaps because they find they prefer the live-text protocol.

To help disaggregate these effects, we re-estimate the retention model, adding two predictors: (1) an indicator for non-completion of the target survey and (2) an interaction between this indicator and *TEXT*. We retain the controls for baseline RP and days until the next survey. Table 6 shows key coefficients from this modified regression.

Table 6. Coefficients for retention regression with controls for target survey completion

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | 3.54 | 0.48 | 0.00 |
| Exposure to live-text survey[1] | -0.99 | 0.52 | 0.06 |
| Nonresponse to target survey[2] | -3.01 | 0.50 | 0.00 |
| Interaction: exposure to live-text X nonresponse to target survey | 1.02 | 0.55 | 0.06 |

[1] Includes those sampled for both live-text and push-to-Web survey. Reference category is push-to-Web survey only.
[2] Reference category is response. Those sampled for both live-text and push-to-Web are counted as respondents if they responded to either or both.
NOTE: Coefficients are from logistic regressions estimated on text-consented online panelists invited to either or both surveys and to at least 3 subsequent surveys ($n$ = 3,614). Dependent variable is response to any of next 3 surveys. All regressions control for baseline response propensity and time until next survey. Coefficients for control variables are shown in Table A.5 of the Appendix. Estimates are unweighted.

Among respondents to the target survey, the coefficient on *TEXT* is again negative and marginally significant ($p < 0.1$). However, the interaction term with target survey nonresponse is positive ($p < 0.1$) and implies that the coefficient on *TEXT* is approximately zero among target survey nonrespondents. In other words, controlling for baseline RP, nonrespondents to the live-text and push-to-Web survey were equally likely to complete one of their next three surveys;

while live-text respondents were slightly less likely than push-to-Web respondents to complete one of their next three surveys.

Table 7 shows how these relationships manifest in practice.

Table 7. Mean baseline response propensity, and percent completing 1 of next 3 surveys, by target survey protocol and completion status

| Target survey completion status | Target survey protocol | Mean baseline response propensity | Percent completing 1 of next 3 surveys |
|---|---|---|---|
| Response | Push-to-Web only | 0.82 | 0.98 |
| | Live-text or both | 0.84 | 0.96 |
| Nonresponse | Push-to-Web only | 0.27 | 0.32 |
| | Live-text or both | 0.42 | 0.47 |

NOTE: Estimates are unweighted

Consider first the nonrespondents under each protocol. On average, live-text nonrespondents had a higher baseline RP than push-to-Web nonrespondents. Recall that the baseline RP is effectively an aggregation of the panelist's response history prior to the target survey, and nearly all of the prior surveys on which the RP models were trained used the push-to-Web protocol. Therefore, we would expect the set of nonrespondents to a lower-response-rate protocol to include some panelists who have had relatively high prior response rates.

Live-text nonrespondents also had a higher probability of completing one of their next three surveys than push-to-Web nonrespondents. This is consistent with the patterns observed in Table 6: controlling for baseline RP, the live-text protocol had no effect on retention among target survey nonrespondents. Therefore, once re-exposed to the push-to-Web protocol, completion rates among live-text nonrespondents "bounced back" to levels consistent with their prior response history to push-to-Web surveys. This suggests that the higher nonresponse to the live-text surveys is not persistent.

On the other hand, the patterns among live-survey respondents are consistent with a protocol-switching explanation. Despite a slightly higher baseline RP, live-text respondents were slightly *less* likely than push-to-Web respondents to complete one of their next three surveys, consistent with the negative coefficient in Table 6. This suggests that there is a subset of panelists who, once they complete via the live-text protocol, are unwilling to resume completing push-to-Web surveys. However, this subset is quite small: those who completed the target survey, but not one of the next three surveys, constituted about 4% of live-text respondents and 1% of those invited to the live-text survey. Hence, the effect on overall retention, while marginally statistically significant, is small in practical terms.

## 5. DISCUSSION

### 5.1. Impact on survey-level outcomes

Our first research question focused on comparisons of survey-level outcomes within a probability panel between live-text and push-to-Web protocols (the latter including both email- and text-to-Web contacts). Broadly, live texting appears to be a viable method of collecting short-turnaround data from a probability panel. While the push-to-Web response rate over the full 89-hour field period was nearly twice the 16-hour live-text response rate (43.6% vs. 25.6%), live-text responses were much more "front-loaded": after 16 hours (the length of the live-text field period), the push-to-Web response rate remained several percentage points below the live-text response rate (20.8%).

Despite the differing response rates, the responding sample compositions were broadly similar. To the extent that there were significant differences, the live-text sample aligned slightly more closely with the U.S. adult population. In particular, the live-text protocol slightly improved the representation of non-college-educated panelists. This difference was larger when

comparing to push-to-Web respondents obtained within a comparable 16-hour field period. Similarly, over the comparable 16-hour field period, live-text respondents aligned more closely with the partisan distribution of U.S. adults.

There remain some disadvantages to the live-text protocol. First, the lower survey-level response rate implies a cumulative response rate—which must be reported under American Association for Public Opinion Research (2023) standards for probability panel samples—of about 1%, similar to modern RDD samples. Second, live-text coverage is inherently limited to text-consenting panelists. Despite this coverage limitation, our results suggest that live-text respondents are demographically similar to push-to-Web respondents. However, the possibility remains that some attitudes (e.g., towards online privacy) or behaviors (e.g., frequency of texting) may differ between consenters and non-consenters in ways that could bias substantive estimates from some surveys. This represents an inherent risk of relying on a live-text protocol, with the salience of the risk likely varying by the topic of the survey.

With this in mind, applying a "fit for purpose" framework (Santos 2014; Dever et al. 2021), the benefit-risk tradeoff is likely most favorable to the live-text protocol in situations where the speed of data collection is paramount. Examples could include assessing the public response to fast-breaking news events, preference between political candidates at the end of an election cycle, or other measures for which true population values could conceivably change within the span of several days. In contrast, when a longer field period is available—that is, when measuring outcomes that are unlikely to change over several days—higher cumulative response rates and more complete coverage would tend to weigh in favor of the push-to-Web protocol.

### 5.2. Impact on subsequent panelist engagement

Our second research question assessed the impact of exposure to the live-text protocol, relative to the much more common push-to-Web protocol, on panelists' participation in subsequent surveys and other measures of panelist engagement and satisfaction. We detected no effect on the propensity to actively opt out of the Panel or to self-report a favorable rating of the panelist experience.

However, we found evidence that panelists sampled for a live-text survey were marginally less likely to participate in future push-to-Web surveys. Notably, live-text nonrespondents completed subsequent push-to-Web surveys at similar rates as before, suggesting that the higher nonresponse to the live-text protocol was not persistent. Rather, the decline in future participation occurred among *respondents* to the live-text protocol, suggesting that there exists a small group of panelists who, once exposed to this protocol, are unwilling to return to a push-to-Web protocol.

Given the expense of replenishing attritted panelists with new probabilistic recruits, this pattern provides a further reason to limit the use of the live-text protocol to situations in which a short field period is an overriding priority. While this group of "protocol switchers" appears to be small, follow-up research should consider potential interventions to reactivate them for subsequent push-to-Web surveys. In particular, qualitative research to understand the reason for some panelists' preference for the live-text protocol could inform the design of such interventions.

### 5.3. Limitations and directions for future research

As discussed in Section 3, the two surveys used for this analysis did not constitute a true experiment. While they were administered within several days of each other, covered similar

topics, and had the same target population, they were different surveys with different field dates and different questions. Although the samples were independently selected using probabilistic procedures, and design weights were applied to correct for sample design differences, the quasi-experimental design implies that confounding remains possible. For example, a comparison between two samples that launched at different times cannot account for day-of-week or time-of-day effects on response behavior.

This quasi-experimental design captures the results of each protocol *as a whole*. Differences in individual design features—particularly in the timing and frequency of reminders—are inherent to each protocol, and we cannot differentiate the impact of these individual features from each other or from panelists' general preferences between protocols. For example, in the push-to-Web protocol, the text messages were used as reminders rather than initial invitations; it is possible that responses would have been obtained more quickly in this protocol had a text message been used for the initial invitation. As another example, the push-to-Web protocol was in the field for considerably longer (89 hours vs. 16 hours). In this analysis, we roughly simulated a comparable field period by evaluating push-to-Web responses received in the first 16 hours of field. However, a short-turnaround push-to-Web protocol would likely vary in other ways (e.g., email and text reminders would likely be more front-loaded), which this analytic approach cannot account for. Thus, further research into live-text vs. push-to-Web outcomes, using a factorial design to randomize both the overall protocol and individual design features, would be beneficial.

Similarly, differences in the length of the survey—98 questions in the push-to-Web survey vs. 11 in the live-text survey—are a potential confounder. As noted above, we consider a short survey to be an inherent requirement of the live-text protocol, based on prior research by

Collins (2024); it is unlikely that this protocol would ever be used for a 98-question survey. However, it remains to be determined how a shorter push-to-Web survey would perform in a quick-turnaround setting. We hypothesize that the live-text survey would still outperform, as nearly all nonresponse in both protocols was attributable to non-starts rather than breakoffs (see Table 2). However, this represents another direction for follow-up research.

Our evaluation of respondent composition in Tables 3 and 4 is limited to demographics available from the panelist profile. The distributions of benchmarkable demographics are indicative of general sample representativeness; ultimately, however, demographic differences can be corrected via weight calibration. Ideally, we would compare the two protocols with respect to weighted substantive estimates, after calibrating the weights, as Collins (2024) did in a non-panel setting. This was not possible for this analysis, because the two surveys used different questionnaires with no items asked in sufficiently comparable ways. Therefore, such a comparison would be a priority in a controlled experiment.

Finally, this analysis considered push-to-Web and live-text as wholly separate protocols. Our findings suggest the possibility that they could complement each other in useful ways—for example, live-text appears to slightly mitigate the underrepresentation of panelists without college degrees in responding samples. Therefore, further research could test the utility of combining them into a single contact protocol for probability panelists. Potential approaches could include a choice protocol in which panelists can opt to respond either way; a sequential protocol in which live texting is used as a nonresponse follow-up after a series of push-to-Web contacts; or an adaptive design in which different protocols are targeted to identifiable subgroups of the panel (Schouten, Peytchev, and Wagner 2018). Such testing would need to consider the operational challenges raised by a combined approach. For example, either the push-to-Web

survey would need to be short enough to be compatible with a live-text version; or the live-text version would need to include only a subset of items, in which case responses to push-to-Web-only items would need to be imputed for live-text respondents. However, to the extent that each protocol appeals to different subsets of the population, a combined approach could be worth testing.

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# SUPPLEMENTAL METHODOLOGICAL INFORMATION

## A.1. Within-Panel sampling methodology

Within-Panel sampling uses a modified probability proportional to size (PPS) approach where the measure of size is a panelist's calibrated weight. The full sampling algorithm for a particular survey is as follows:

- A Panel-wide weight for each panelist is constructed as follows:
    - A design weight is assigned reflecting the panelist's original selection probability for their recruitment cohort.
    - The design weight is adjusted for nonresponse to the recruitment survey and attrition from the Panel.
    - The resulting weight is calibrated to population benchmarks for U.S. adults ages 18+.
- The active Panel is subset to the target population for the survey.
- The filtered Panel may be divided into strata based on substantive profile variables relevant to the survey.
- Within each stratum, substrata are created by dividing the Panel into approximately equal-sized quantiles defined by the Panel-wide weight.
- The sample size for each substratum is calculated by allocating the stratum-level sample in proportion to the median of the Panel-wide weight. Specifically, for each substratum $h$ within stratum $g$, let $m_{g,h}$ be the median of the Panel-wide weight, and let $n_g$ be the target sample size for stratum $g$. Then the sample size for substratum $h$ is:

$$n_{g,h} = \max\left[1, ROUND\left(n_g * \frac{m_{g,h}}{\sum_{h \in g} m_{g,h}}\right)\right]$$

- A simple random sample of the specified size is selected within each substratum.

## A.2. Construction of baseline response propensity (RP) score

The baseline RP score is a score ranging from 0 to 1 reflecting the panelist's modeled probability of completing their next survey, based on their profiled demographics and their aggregated response history (if any). It is assigned using random forests.

Two random forest models were developed: the "new panelist" model, used to score panelists for whom the target survey was their first survey since recruitment; and the "existing panelist" model, used to score panelists for whom the target survey was their second or later survey.

For both models, the training samples and dependent variables were created so as to not incorporate any information about the target survey itself, creating a baseline measure of RP at the time the panelist was sampled for the target survey.

For the new panelist model, the training sample was existing panelists, that is, those for whom the target survey was their second or later survey. For each of these panelists, the dependent variable was a binary indicator of whether they responded to their first survey. Because panelists have no prior response history as of their first survey, the predictors consisted of panelist-level profile variables:

- Preferred survey mode (Web or CATI)
- Preferred survey language (English or Spanish)
- Text consent status
- Age
- Gender
- Race/ethnicity
- Educational attainment

- Party identification
- Voter registration status
- Internet use frequency

For the existing panelist model, the training sample was existing panelists for whom the target survey was their third or later survey. For each of these panelists, the dependent variable was a binary indicator of whether they responded to the survey *immediately preceding* the target survey. The predictors consisted of the same panelist-level profile variables listed above, plus the following:

- Number of prior surveys
- Cumulative completion rate to all prior surveys
- Disposition of the immediate prior survey (non-open, breakoff, complete, or terminate)
- Number of days since the prior survey

After training both models, the predictors were defined for the target survey in the same manner as for the prior survey used for training. The models were then applied to the target survey to create the baseline measure of RP.

## A.3. Full regression tables

Table A.1. Full regression coefficients: response to next survey

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | -0.26 | 0.10 | 0.01 |
| Exposure to live-text survey[1] | -0.09 | 0.10 | 0.37 |
| Baseline response propensity | 124.01 | 3.32 | 0.00 |
| Baseline response propensity ^ 2 | -6.17 | 2.59 | 0.02 |
| Days until next survey | 1.09 | 2.72 | 0.69 |
| Days until next survey ^ 2 | 7.46 | 2.73 | 0.01 |

[1] Reference group is push-to-Web only.

Table A.2. Full regression coefficients: response to any of next 3 surveys (retention)

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | 1.20 | 0.13 | 0.00 |
| Exposure to live-text survey[1] | -0.25 | 0.14 | 0.07 |
| Baseline response propensity | 143.15 | 4.31 | 0.00 |
| Baseline response propensity ^ 2 | -1.27 | 3.21 | 0.69 |
| Days until next survey | -2.93 | 3.32 | 0.38 |
| Days until next survey ^ 2 | -3.43 | 3.10 | 0.27 |

[1] Reference group is push-to-Web only.

Table A.3. Full regression coefficients: unsubscribed from Panel within next 3 months

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | -6.59 | 0.76 | 0.00 |
| Exposure to live-text survey[1] | 1.01 | 0.74 | 0.17 |
| Baseline response propensity | -73.12 | 21.91 | 0.00 |
| Baseline response propensity ^ 2 | -12.82 | 15.67 | 0.41 |
| Days until next survey | -11.40 | 16.06 | 0.48 |
| Days until next survey ^ 2 | 5.56 | 15.15 | 0.71 |

[1] Reference group is push-to-Web only.

Table A.4. Full regression coefficients: rated Panel as "Excellent" or "Very good" on next survey

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | 2.20 | 0.15 | 0.00 |
| Exposure to live-text survey[1] | -0.22 | 0.17 | 0.20 |
| Baseline response propensity | 23.18 | 2.69 | 0.00 |
| Baseline response propensity ^ 2 | 4.43 | 2.76 | 0.11 |
| Days until next survey | 1.64 | 3.36 | 0.63 |
| Days until next survey ^ 2 | 3.29 | 3.34 | 0.32 |

[1] Reference group is push-to-Web only.

Table A.5. Full regression coefficients: response to any of next 3 surveys (retention), with controls for target survey completion

| Term | Coefficient | Standard error | *p* value |
|---|---|---|---|
| Intercept | 3.54 | 0.48 | 0.00 |
| Exposure to live-text survey[1] | -0.99 | 0.52 | 0.06 |
| Nonresponse to target survey[2] | -3.01 | 0.50 | 0.00 |
| Baseline response propensity | 127.59 | 4.48 | 0.00 |
| Baseline response propensity ^ 2 | -2.89 | 3.35 | 0.39 |
| Days until next survey | -1.96 | 3.44 | 0.57 |
| Days until next survey ^ 2 | -2.80 | 3.14 | 0.37 |
| Exposure to live-text survey X nonresponse to target survey | 1.02 | 0.55 | 0.06 |

[1] Reference group is push-to-Web only.

[2] Reference category is response. Those sampled for both live-text and push-to-Web are counted as respondents if they responded to either or both.

## A.4. PRICSSA item checklist

Table A.6. PRICSSA item checklist

| Item | Response |
|---|---|
| 1.1. Data collection dates | Push-to-Web: March 6 - 10, 2025<br>Live-text: March 4-5, 2025 |
| 1.2. Data collection modes | Push-to-Web: online (via push-to-Web emails and text messages) and live-interviewer phone.<br>Live-text: real-time text messaging. |
| 1.3. Target population | U.S. adults ages 18+. |
| 1.4. Sample design | Panel recruitment: stratified single-stage sample (address-based or random-digit dialing).<br>Panel surveys: stratified probability proportional to size. |
| 1.5. Survey response rates | See Table 2. |
| 2.1. Missingness rates | Missing rates for demographic variables are shown in Tables 3 - 4. Missing was treated as its own category except for recalled 2024 vote, which was imputed using hot-deck imputation. |
| 2.2. Observation deletion | Some sample replicates excluded from push-to-Web survey; see Section 3.3 for details. Other deletions varied by analysis; see table notes. |
| 2.3. Sample sizes | Varied by analysis; see tables. |
| 2.4. Confidence intervals/standard errors | See tables. |
| 2.5. Weighting | Varied by analysis; see tables. |
| 2.6. Variance estimation | Design-weighted analyses used Taylor Series linearization. |
| 2.7. Subpopulation analysis | Not applicable. |
| 2.8. Suppression rules | No estimates were suppressed. |
| 2.9. Software and code | All analyses were performed in R, using the *survey* package for design-based analyses. Replication code for all analysis is included with the supplementary online materials. |
| 2.10. Singleton problem | Not applicable. |
| 2.11. Public/restricted data | Not applicable. Contact authors for replication data (requires a data use agreement). |
| 2.12. Embedded experiments | There were no embedded experiments. |

## A.5. Question wording

### *A.5.1. Panel experience rating*

RATE2. In general, how would you rate your experience as a member of the SSRS Opinion Panel?

1 Poor
2 Fair
3 Good
4 Very good
5 Excellent
998 **[PN: IF CATI:]** (DO NOT READ) Don't know
999 **[PN: IF CATI:]** (DO NOT READ) Refused
999 **[PN: IF WEB:]** Decline/Web blank

### *A.5.2. Panel demographics*

DOB_YEAR. In what year were you born?

___ [RANGE: 1900- CURRENTYEAR-18)]

DOB_MONTH. In what month were you born?

1 January
2 February
3 March
4 April
5 May
6 June
7 July
8 August
9 September
10 October
11 November
12 December
999 **[PN: IF CATI:]** (DO NOT READ) Don't Know/Refused
999 **[PN: IF WEB:]** Web Blank

GENDER. Are you:

001 Male
002 Female
003 **[PN: IF WEB:]** I describe myself another way (SPECIFY)
003 **[PN: IF CATI:]** You describe yourself another way (SPECIFY)
999 **[PN: IF CATI:]** (DO NOT READ) Prefer not to answer
999 **[PN: IF WEB:]** Prefer not to answer

Z10. Are you of Hispanic or Latino origin or descent?

001 Yes
002 No
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** Prefer not to answer

RACEMULTI. Which of the following describes your race? You can select as many as apply.

001 White
002 Black or African American
003 Asian
004 Native American/American Indian/Alaska Native
005 Native Hawaiian/Other Pacific Islander
006 NO CODE 6
007 Another Race (Please type in) _____
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** Prefer not to answer

EDUC. What is the highest level of school you have completed or the highest degree you

001 **NO CODE 1**
002 Less than high school graduate
003 High school diploma or GED or alternative credential
004 Some college credit, no degree
005 Associate's degree (for example: AA, AS)
006 Bachelor's degree (for example: BA, BS)
007 **NO CODE 7**
008 Master's degree, Professional degree beyond a bachelor's degree, or Doctorate degree (for example: PhD, EdD)
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** Prefer not to answer

POLPARTY. Generally speaking, do you usually think of yourself as…?

001 A Republican
002 A Democrat
003 An Independent
997 Something else (NOT SPECIFIED)
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** *Web Blank*

REGVOTE. Are you registered to vote at your present address, or not?

001 Yes
002 No
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** *Web Blank*

VOTE2024. In talking to people about elections, we often find that a lot of people were not able to vote because they weren't registered, they were sick, or they just didn't have time. How about you, did you happen to vote in the 2024 presidential election?

001 Yes, did vote
002 No, did not vote
003 (PN: SUPPRESS) Under 18 in 2024
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** *Web Blank*

PRES2024. Which candidate did you vote for in the 2024 presidential election?

001 Kamala **[PN: IF CATI:** PRONO: "KAH-ma-la"**]** Harris
002 Donald Trump
003 Chase Oliver
004 Jill Stein
005 Robert F. Kennedy, Jr.
997 Another candidate (SPECIFY)
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** *Web Blank*

INTFREQ. About how often do you use the internet?

001 Almost constantly
002 Several times a day
003 About once a day
004 Several times a week
005 Less often
006 **(PN: SUPPRESS)** Not an internet user
999 **[PN: IF CATI:]** (DO NOT READ) Don't know/Refused
999 **[PN: IF WEB:]** *Web Blank*