Through a Live Elections Dashboard, Darkly: Managing Expectations and Trust in Progressive Vote Counting During the 2024 U.S. Election

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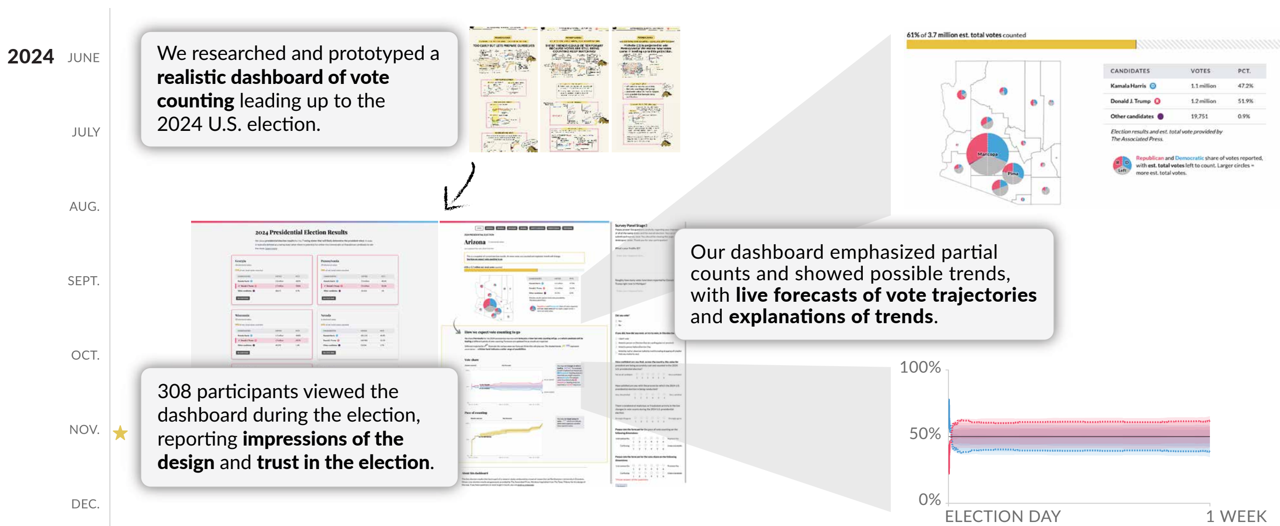

Figure 1: Summary of our design process and dashboard deployment.

Abstract

During U.S. elections, news outlets publish live dashboards to contextualize vote counting and manage public expectations. This proved challenging in 2020 amid election fraud allegations, sparking conversations about how data journalists might better visualize and explain live vote counting. To address this, we designed a dashboard to foster understanding of the progressive nature of vote counts and more realistic expectations of the vote counting timeline. We deployed it during the 2024 U.S. presidential election, showing it to 308 people with real results, and collected surveys and interviews on impressions and trust. We contribute: (1) a design process and framework for how audiences might form expectations around live data, (2) survey findings suggesting live forecasts slightly increased confidence in vote counting and slightly reduced belief in evidence of fraud, and (3) interview findings underscoring the importance of agency in viewing live data and tensions in the perceived usefulness of live forecasts.

CHI '26, Barcelona, Spain

ACM ISBN 979-8-4007-2278-3/2026/04
https://doi.org/10.1145/3772318.3793385

CCS Concepts

• **Human-centered computing** → **Empirical studies in visualization**; **User studies**.

Keywords

Dashboards, Progressive Visualization, Public-facing Visualizations, Real-time Interfaces, Forecast Communication, U.S. Elections, Vote Counting, Data Journalism, Trust

ACM Reference Format:
Mandi Cai, Grace Wang, Chloe R. Mortenson, Fumeng Yang, Erik C. Nisbet, and Matthew Kay. 2026. Through a Live Elections Dashboard, Darkly: Managing Expectations and Trust in Progressive Vote Counting During the 2024 U.S. Election. In *Proceedings of the 2026 CHI Conference on Human Factors*

in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain. ACM, New York, NY, USA, 18 pages. https://doi.org/10.1145/3772318.3793385

1 INTRODUCTION

"For now we see through a glass, darkly; but then face to face: now I know in part; but then shall I know even as also I am known."
— 1 Corinthians 13:12

"Accept data as a lens, not a mirror." — Al-Hazwani et al. [1]

On Election Day in the United States, mass audiences tune in to see votes cast and counted in real time [3] as they wait for winners to be called. Because votes in the U.S. trickle in gradually due to the country's decentralized voting system, the public is engaged in a continual process of shifting expectations about how the vote count is progressing and who might win the election. News outlets (specifically data journalists) serve as shepherds of this information, visualizing and contextualizing evolving vote counts to these audiences [13, 15, 43, 69, 80]—a task that requires ample institutional resources and challenging editorial decisions [13]. In 2020, this live elections coverage was further complicated by unfounded allegations of election fraud that decried "statistically unlikely" events in vote counts [24, 83]. Members of the public began linking certain visual trends in vote counts to fraud [53], sparking conversations among the data journalism community of how to improve their data coverage of elections, manage audience understanding of data over time, and support trust in elections [86].

Though there is a wide collection of live elections designs already employed (as cataloged by Cai and Kay [13]), there are still questions among data journalists around how to responsibly contextualize partial, dynamic data, e.g., real-time vote counts, during the data progression [13, 28, 48, 53, 65, 68]. Live elections dashboards are an example of a large-scale, public-facing instance of progressive data visualization, and there is sparse existing work exploring how to design information progressively in a complex environment for a general audience. There is also little to no empirical data on how audiences engage with these progressive designs and dashboards during real-world elections, and whether they can have a meaningful impact on trust in news outlets and in elections.

To explore these gaps, we embarked on an extensive design process—prototyping over months and interviewing 21 lay individuals —to build a realistic live dashboard of vote counting with the design objectives of **communicating that vote counts are partial**, **showing how counts may change over time**, and **explaining how processes of vote counting may create visual trends in the data** (Sec. 3). To guide designs, we envisioned the viewer as entering with prior expectations about the vote counting timeline and shifting their expectations over time as they watch live vote counts (Fig. 4), using past and present data to make inferences about the future. In our final designs, to highlight the progressive and partial nature of vote counts, we included visualizations of vote shares over time and emphasized the estimated number of votes outstanding (Fig. 5). To show possible trends in vote counts, we included live-updating forecasts of vote trajectories over time (Fig. 7). Lastly, to explain how events and processes in vote counting may lead to visual trends, we added text explanations of this next to the forecasts (Fig. 7).

These dashboards were deployed live during vote counting for the 2024 presidential election, with real election results from The Associated Press. We showed the dashboard to 308 participants, and surveyed them before, during, and after the election to assess whether components of our design had an impact on confidence and belief in evidence of fraud in the 2024 election (and to track overall trust in the election). Additionally, we interviewed 16 people from the 308 participants after the election to discuss their experiences with our dashboard and its components in depth. Our study contributes:

(1) Our design exploration and process, including a proposed framework of how audiences form expectations around live data that guided our process (Sec. 3)
(2) Findings from our surveys suggesting a small, positive effect of our live forecasts on confidence in vote count, and small, negative effect of live forecasts on belief in evidence of fraud in vote counts (Sec. 5)
(3) Findings from our post-election interviews highlighting the importance of agency when viewing live data, tensions in perceived usefulness of live forecasts, and the influence of external information and emotions on expectations (Sec. 6)

In our post-election interviews (Sec. 6), interviewees discussed using our dashboard as a "just the facts" reference point and felt it afforded them agency in monitoring data. Though they found the live forecasts trustworthy and successfully understood the uncertainty of swing states' results, interviewees felt the forecasts initially conveyed too much uncertainty. They also felt that, once it was clear Trump would win, the forecasts reflected what they already expected and did not offer new information. We identify tensions between perceived usefulness and the degree of uncertainty conveyed in forecasts, as well as a tension between perceived usefulness and trustworthiness. These impressions may be attributable to the quicker, more straightforward nature of the 2024 presidential election relative to 2020. Interviewees also viewed our dashboard through various lenses of external knowledge and emotions, which influenced their pre-election expectations and helped them reason through expectations as they watched the live data.

In our design implications (Sec. 7), we reflect on how designs of live data in contested spaces can address participant needs for agency and make design suggestions for live forecasts, calling for additional research on displays of public-facing forecasts. We also amend our framework for interpretations of live data from Fig. 4 to consider the role of participants' external knowledge and emotions in the evolution of election expectations. Finally, given the real-world nature of our study, we detail lessons learned from conducting a highly realistic study that embraces the entangled nature of an interface during a politically-charged, social event. Though this study was originally inspired by the problems that data journalists face, we believe it builds on existing work on public-facing dashboards and progressive visualization, and presents an example of how to design and contextualize evolving information in real-world settings when millions of people are changing their expectations simultaneously.

2 BACKGROUND

2.1 Contextualization of data over time, through dashboards and progressive visualization

Live dashboards of vote counting exist at the intersection of dashboard design and progressive visualization, because they broadcast election results as votes are processed and counted. Few [25] defines a dashboard as "a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance". Dashboards often show the latest, present snapshot of dynamic data over time [25, 70], but they can also show historical data or predictions about the future in conversation with current data. Some live dashboards of vote counting have incorporated forecasts that predict winners as votes are counted, and COVID-19 dashboards have included forecasts of trends in cases [11, 16, 92]. Progressive visualization concerns the creation of "intermediary visualization outputs while the data is still being processed" [4], and can be helpful for long-lasting, slow, or non-transparent computations. Progressive visualizations reckon with communicating the "meaningfulness" and uncertainty in partial results without misleading the user [4, 73]. We view dashboards as a broader class of interfaces that can employ progressive visualization to convey the outputs of ongoing processes, like vote counting.

Dashboards can have a contextual and narrative element to convey meaning or "insights", as dashboards published by news outlets do [13, 92], that treads more into the space of explanation, analysis, storytelling, and persuasion [34, 49, 74]. COVID-19 dashboard creators in Zhang et al.'s [91] study voiced that the main objective in creating visualizations on public-facing COVID-19 dashboards was to produce the "right" story, in order to help viewers understand the pandemic. But it is tricky to pin the right story when the visualizations are viewed by so many, and the underlying data is updating and shifting. Public-facing dashboards also reckon with how best to convey uncertainty in snapshots of situations that may shift moment by moment, e.g., when votes are counted progressively and election outcomes are uncertain [13]. For maintainers of public-facing dashboards, doing this for a general audience can be labor intensive [13, 91].

Challenges in progressive visualization, like participants anchoring on early, false patterns in the data progression [65], are also relevant to public dashboards maintained by news outlets. But studies of progressive visualization have typically explored its use in the context of expert data analysis and exploration [4, 52, 73], rather than for ongoing processes witnessed in the public sphere. There is potential for misinterpretation and misuse of the visualizations influenced by political messaging outside of the live data, as witnessed with both COVID-19 visualizations [47, 91, 92] and election visualizations [13, 20, 53, 83, 86]. Live dashboards of vote counting are embedded in a complex social and media context, shaped by the public's interests [92], making them a distinctive case of *public-facing* progressive visualization worth studying.

2.2 Data journalists' role in narrating data over time

The day-to-day job of a data journalist is often to perform data analysis on "raw" data in order to uncover stories relevant to the general public [21, 26, 58]. Publishing large interactive dashboards for viewers to explore the data themselves was a large part of early data journalism [58, 88]. Though there is existing research on the broad practices in data journalism, there is less work drilling down into how data journalists manage the public's interpretations of data in situations that unfold over time [30, 57]. Managing interpretations of evolving information risks eroding audience trust if a news outlet is perceived as "wrong", which occurred in 2016, when pre-election forecasts favoring Hillary Clinton in the news were followed by Donald Trump's win [31, 90]. It is safe to assume that data journalism, like news coverage broadly, primarily covers present or near-past events [59, 76], but this coverage reacting to the present can quickly become outdated. Predictive journalism has been adopted to assist the public with reasoning about possible future outcomes in uncertain, changing situations [2, 22, 60]. However, some journalists feel that predictions are more opinion than fact, too technically advanced to produce, or too difficult to communicate [13, 39].

2.3 Managing public trust in news media and elections

During the 2020 U.S. elections, news outlets and researchers warned the public that it may take longer to know the president-elect because of the expansion of mail-in voting amid the COVID-19 pandemic [18, 20, 27, 29, 44, 61, 84]. However, alternative perspectives about the 2020 election also circulated—commentators on channels like Fox News aired their overall skepticism of 2020 voting protocols, and a frequently cited visual cue of alleged election fraud was the late shift toward Joe Biden in line charts of votes in Pennsylvania (a claim that was debunked [14, 53]). Following the 2020 election fraud allegations, data journalists and news outlets broadly reflected on their role in live elections coverage, seeking to move beyond "horserace" reporting and prioritize pro-democracy coverage [5, 86]. With the decades-long decline in trust in news media over the latter half of the 20th century [32] and a recent decrease in trust in U.S. elections [20, 72], we decided to focus on trust as a dependent variable in our study—specifically, trust in news outlets and their live elections coverage, and trust in how votes are processed and counted in elections [72]—to understand if our presentation and contextualization of election results could affect trust in a positive way.

Though the intent of live elections coverage is often to correct misinterpretations [11] and improve trust in elections, there is limited empirical data showing what viewers' actual impressions are, motivating our decision to spotlight trust. Optimistically, research by Lockhart et al. [51] showed that telling voters about the vote counting process and legitimate reasons for potential delays ahead of the election could overall improve election trust.

2.3.1 *Primer on how elections are conducted and broadcast in the U.S..*

In the U.S., elections are conducted at the local level without a central elections authority to aggregate and report vote counts

[19]. Each locality follows its own local and state-level rules to process and count ballots [19, 56]. Third party organizations (like The Associated Press) collect and publish these local results across the nation and project unofficial winners of federal elections, which news outlets then publish to viewers [38, 62, 67]. The information published on election night is technically unofficial because vote counts are not certified until weeks later [7, 40].

3 DESIGN OF DASHBOARD

3.1 Design objectives

3.1.1 (A) INTERVIEWS *Interviewing data journalists and election analysts.* To construct our objectives, we initially began with open design questions outlined by Cai and Kay [13] in their design analysis of existing live elections dashboards and interview study with data journalists: *How can dashboards better emphasize uncertainty in partial, progressive data? What strategies are successful in correcting for illusion bias, when readers fall prey to false patterns during the progression of data? How can displays of real-time election results better inform readers of the vote counting, reporting, review, and certification processes?*

We then interviewed four election analysts and statisticians, who emphasized that rules governing when different types of ballots can be processed and counted are among the most critical factors to track in elections. One analyst described their organization's efforts to prepare the public to better understand how votes are reported and interpreted. We also spoke with two election and voting journalists, who highlighted how county- and municipality-level procedures shape the speed of vote counting, as well as the unique challenges posed by mail-in ballots. Together, these conversations—along with insights from Lockhart et al. [51]—directed us towards **foregrounding the progress and process of vote counting on the dashboard**.

3.1.2 (A) INTERVIEWS *Interviewing lay people.* However, these priorities were constructed from interviews with news and elections practitioners, not audience members. To explore viewer needs and ensure that our objectives aligned with viewers' goals for election dashboards, we interviewed 11 lay people from Prolific about their experiences watching live elections results from April to June 2024. The sample's median age was 40, with 6 men and 5 women; politically, 5 leaned Republican, 4 Democrat, and 2 Independent.

During interviews, participants were walked through different time points of a fictional election, and asked questions like *When you watch election results live, what do you pay attention to?* and *What is confusing to you about how votes are counted?* Participants were broadly confused about the timing of election results and winner projections, honing in on the mechanics and delayed reporting of mail-in voting. Some expressed suspicion about the delayed shift in Pennsylvania's 2020 election results toward Biden, even with the information that the shift was due to batches of Democratic-leaning mail-in ballots processed and reported later [48].

These themes of confusion in timing and trends in vote counting led us to envision our live dashboard as **teaching viewers about the vote counting process, rather than just communicating a current snapshot of votes**. We reasoned that if an individual only wants to know election outcomes, then they can tune back in when winners are projected. Watching the live process makes more sense if they are interested in seeing how votes are counted and reported over time across different geographies, demographics, and types of ballots. The invocation of certain trends in votes as evidence of election fraud also prompted us to think about what a "normal" vote counting timeline is to viewers—why are certain events or trends in the data perceived as deviating from the norm? Ideally, viewers should **have reasonable expectations of what vote count trajectories can look like and why**. A delayed shift in votes towards Biden is not necessarily indicative of fraud, even though interviewees felt that it was sudden and late. This ties back to the value of explaining vote counting processes (though we acknowledge that viewers will realistically still be curious about final election outcomes).

Building on the initial open design questions and needfinding interviews, we formulated the following design objective with actionable design goals (DG):

Main design objective: *Foster understanding of the progressive nature of vote counts and more realistic expectations of the vote counting timeline, by:*

- **DG1:** *Communicating that vote counts are partial*
- **DG2:** *Showing how counts may change over time*
- **DG3:** *Explaining how processes of vote counting may create visual trends in the data*

3.2 Prototyping designs

Data journalists have tried various methods of encoding and explaining evolving vote counts in their live elections dashboards [13], which we used as a starting template for our designs. By envisioning the actionable design goals as modules, we could focus on designing for one particular goal, and then lay out all of the modules on a dashboard to see how they fit together to communicate the main design objective.

3.2.1 ***DG1: Communicating that vote counts are partial***. Live elections dashboards often incorporate progress bars and textual descriptions of percentage counted to indicate that vote counting is incomplete [13]. Visual metaphors like unfogging a mirror or piecing together a puzzle reminded us that viewers are viewing votes that have already been cast, but require unveiling and piecing together to understand the meaning of. We brainstormed ways to embed the partial nature of vote counting directly into the visual presentation of results and sketched designs that **emphasized the proportion of votes already counted versus those still outstanding**, to couch any inevitable comparisons of at-the-moment Democratic and Republican vote shares.

3.2.2 ***DG2: Showing how counts may change over time***. Leading up to the 2020 election, news outlets offered explanations of trends in vote counts that audiences should be prepared to see [18, 44], given that vote counting was expected to take longer with the 2020 COVID-19 pandemic and the expansion of mail-in voting [61, 84]. To extend these options, we sketched modules incorporating text and visualization that **pointed out events and trends in vote counts from historical elections** (left, Fig. 2), suggesting to viewers that similar patterns might emerge in the upcoming election and that it could be premature to draw conclusions. Especially early on in vote counting, our knowledge about the winner is uncertain and people should not anchor on early red waves or blue waves [44].

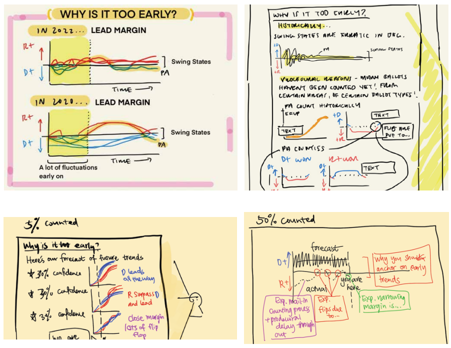

Figure 2: Sketches for DG2: *showing how counts may change over time.*

Larger outlets like The Washington Post also provided live elections forecasts on their results dashboards [11, 16] that showed fuzzy predictions of final election outcomes to try to prevent viewers from anchoring on early, misleading trends in vote counts. We prototyped designs of live-updating forecasts that would serve the same function as The Washington Post's, but to **set expectations for possible trajectories of vote counts instead of only final vote counts** (right, Fig. 2). We hypothesized that perhaps viewers may not immediately assume election malfeasance is the reason for certain trends if they are already aware that those trends are part of a "typical" vote counting timeline—following previous empirical evidence that forewarning the public that change is likely and acknowledging uncertainty as normal can have positive effects on trust [66].

3.2.3 ***DG3: Explaining how processes of vote counting may create visual trends in the data.*** We sketched modules **detailing state-specific vote counting protocols** and **highlighting notable events in vote counting timelines that were the result of how votes were processed and counted**. We were, however, confronted with a limitation in the data available to us for the 2024 presidential election—data on vote types reported over time (e.g., in-person, mail-in) was inconsistent and incomplete, which meant we would not be able to assess with certainty how the processing of different vote types affected the timing and trends in 2024 results. However, we could still include overall descriptions of how states planned to process votes differently or broad statements about how vote counting may take longer (an approach that NPR took in 2020 and 2022 [54, 55]).

3.2.4 ***Designing for stages of vote counting.*** We decided to mock up designs illustrating the vote count at **0% (no votes), 20% (early stage), and 80% (later stage, once a winner has likely been projected) completion**, making slight adjustments to the text and combinations of components to reflect the state of the race. To guide our designs across time, we imagined a framework (Fig. 4) in which the viewer is someone with prior expectations of how the election will pan out. This viewer gradually shifts their expectations of that outcome as they view live, progressive vote counts. We hypothesized that there might be specific "events" during vote counting, such as a surge in votes or a change in leading candidate, that draw people's attention and are pivotal in shifting expectations or raising suspicions about the election. As we laid out combinations of our modules into a full page design, we thought about which modules would be most effective (and at which percentage of total votes counted) for guarding against viewers' subjective expectations becoming too certain about an outcome.

In line with our design objectives, the desired outcome was that viewers, upon engaging with our dashboard, would be able to appropriately weigh the significance of current results given outstanding votes, be less likely to mistake trends created by vote counting processes as election malfeasance, and better understand vote counting procedures. We hoped that these desired outcomes would ultimately translate to greater trust in election processes while recognizing that party affiliation and political messaging might override such effects, leading us to test our design prototypes with lay people to assess initial reactions (Sec. 3.3).

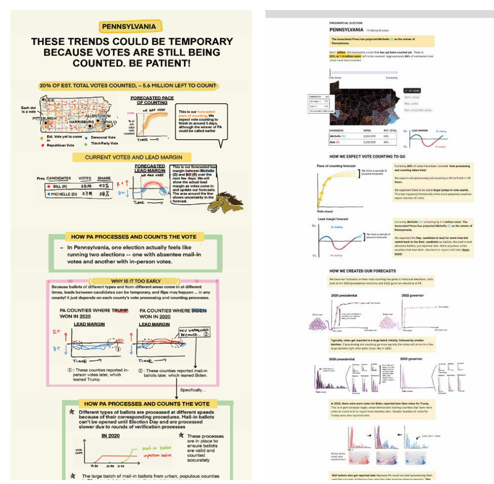

Figure 3: Prototypes of the full dashboard interface with modules for DG1, DG2, and DG3.

3.3 Prototype testing with participants

We chose design prototypes that addressed all of our design objectives and a wide range of visual designs at different percentages of votes counted, and tested them with 10 lay people from Prolific from July to September 2024. Participants had a median age of 46, with 6 men and 4 women; politically, 6 leaned Democrat, 3 Independent, and 1 Republican. Our designs evolved as we interviewed participants, so some saw version 1 (left, Fig. 3) and others saw version 2 (right, Fig. 3). With repeated exposure to our designs at 0%, 20%, and 80% of votes counted, participants (B3, B4, B5) **became more familiar with the different modules** and generally **recognized the message that it was too early to draw conclusions from current vote totals**. We also noticed the **role of our dashboard in confirming participants' existing expectations** (B9, B10),

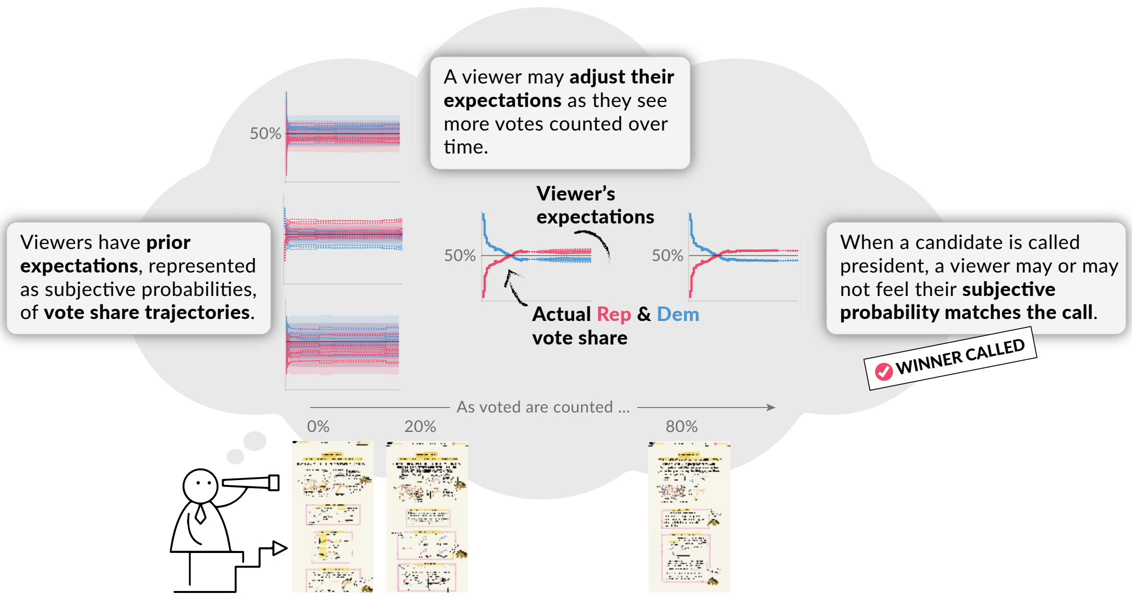

Figure 4: A framework for viewers' interpretations of live data that guided our dashboard design at different percentages of votes counted. The prototyped designs at each point are included in supplementary materials.

even in these early prototyping interviews. Specific insights from these interviews, and design modifications in response, include the following:

- Several interviewees (B2, B3, B5, B6) told us we should keep standard elements of live elections results displays, like a geographic map or table of vote counts, and to make the live vote counts salient.
  Design modification: *We kept a map and table of current vote totals at the top of the design. We also decided to visually highlight the percentage of outstanding votes at the top of our designs.*
- Participants (B3, B5, B6) preferred a simpler design that was not overwhelmed with textual and visual content and suggested aligning our messaging to a primary goal. B9 stated that there was value in stripping away the drama and just looking at the data.
  Design modification: *We chose to display a more concise set of design components that stayed consistent across all percentages of votes counted—pairing live forecasts of vote count trajectories (one of our more novel design components) with explanatory text about potential trends and their causes. We also reduced the textual explanations to concise, one-sentence blurbs.*
- B7 mentioned that some of our textual explanations cautioning viewers to be patient while viewing results sounded condescending, as if he was being talked to like a kid.
  Design modification: *We were mindful of language on the page and tried not to include text with a forceful, assertive tone.*
- Participants (B4, B5, B6) suggested we clarify how to read our live forecasts, improve the axis labeling, and visually distinguish the forecasts from live vote counts.
  Design modification: *We added a short description of what our live forecasts were encoding, changed the axis from margin of lead to total vote share, and clearly separated and titled the forecasts module.*

3.4 Final dashboard design

In our final designs, we decided to include an initial snapshot of the current election results as a county-level geographic map and a table (Fig. 5), a representation of the present that elections dashboards often prioritize. These are common features of existing live elections dashboards [13] requested by participants in Sec. 3.3. However, the rest of our design deviated from many other election dashboards in its explicit emphasis on progress and partiality in vote counts. We displayed ① **visualizations of vote totals over time** that showed where votes had been and how they had changed, a less common feature of existing dashboards [78]. To emphasize that vote counts are partial, we showed a visually salient ② **progress bar** with estimated percentage of votes counted at the top of the dashboard. Additionally, we modified a ③ **pie chart map** from The Texas Tribune [81] to include a live-updating slice of the proportion of outstanding votes left to count (estimated by The Associated Press [63]) in each state's county (Fig. 5).

To show participants possible future trajectories in vote counts, we displayed a ④ ⓐ **visualized forecast of the trajectory of vote share over time** between Harris and Trump and a ④ ⓑ **visualized forecast of the trajectory of pace of counting** (Fig. 6) for each state, both elements that (to our knowledge) are novel to live elections dashboards. Previous elections dashboards have showed forecasts only of the final outcomes [11, 77, 79]. To foster more understanding in how processes of vote counting manifest

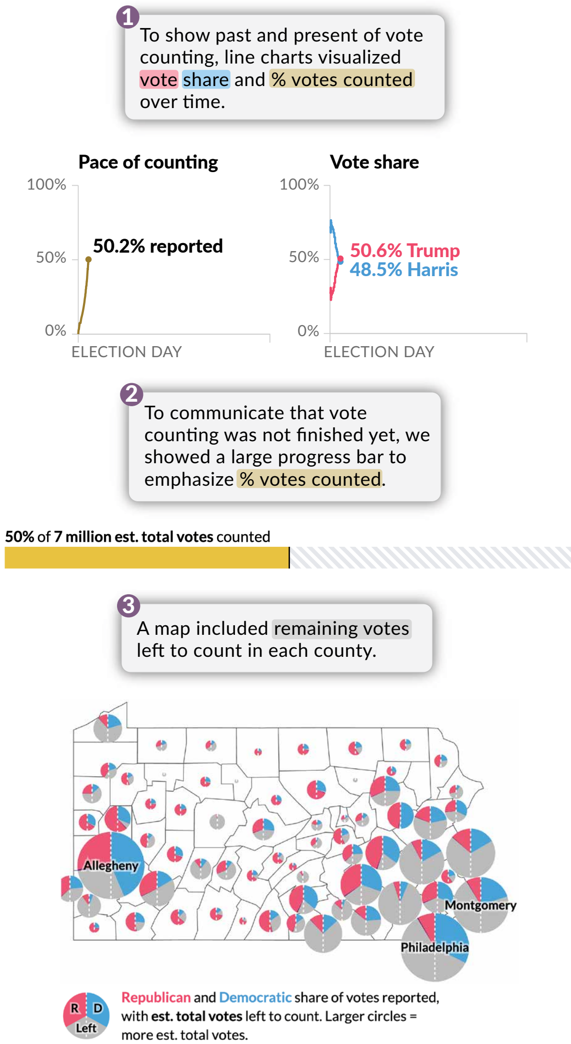

Figure 5: Components of our final design for DG1: *communicating that vote counts are partial.*

Figure 6: (Top) Live forecasts of vote share and pace of counting trajectories for DG2: *showing how counts may change over time.* (Bottom) Explanations of trends in vote counts for DG3: *explaining how processes of vote counting may create visual trends in the data.*

as visual trends, we showed 5 **text explanations** that described reasons behind shifts in vote trajectories (Fig. 6), after iterating on what text to include given the feedback in Sec. 3.3.

To model the trajectories in vote counts, we decomposed the trajectory into three quantities: for each county c in a state in a given election e, we modeled n (number of batches of votes reported), v (number of votes in each batch), and t (timing of each batch). We fit separate hierarchical Bayesian models of these quantities for each state using county-level demographic predictors (population, race, and education) and vote count trajectories from past elections, including the 2016 and 2020 presidential elections, and 2020 U.S. Senate, 2022 U.S. Senate, and 2022 governor elections when available for the state.[1] On Election Day, models were refit with live vote counts from the 2024 presidential election every 10 minutes after polls closed if there were updated vote counts for that particular state. We generated forecasts extending one week ahead, given that the 2020 presidential election required several days of counting before a winner was declared and the possibility that 2024 might unfold similarly.

We illustrated uncertainty in our predictions by visualizing and animating them as hypothetical outcome plots (HOPs)[2] (Fig. 8)—showing a different, discrete draw from the joint distribution of forecasted vote trajectories every two seconds—and displaying the 50%, 85%, and 95% credible intervals of possible outcomes to tell

[1]Full details of our forecast model, as well as the data pipeline to ingest live results from The Associated Press, selectively refit state-level models, and feed projections to the front end, are available in the supplementary materials.

[2]It was important that we communicate the uncertainty in our forecasts to illustrate the uncertainty inherent in the election, especially at early stages of vote counting, and to build trust among participants [35, 37, 41, 66].

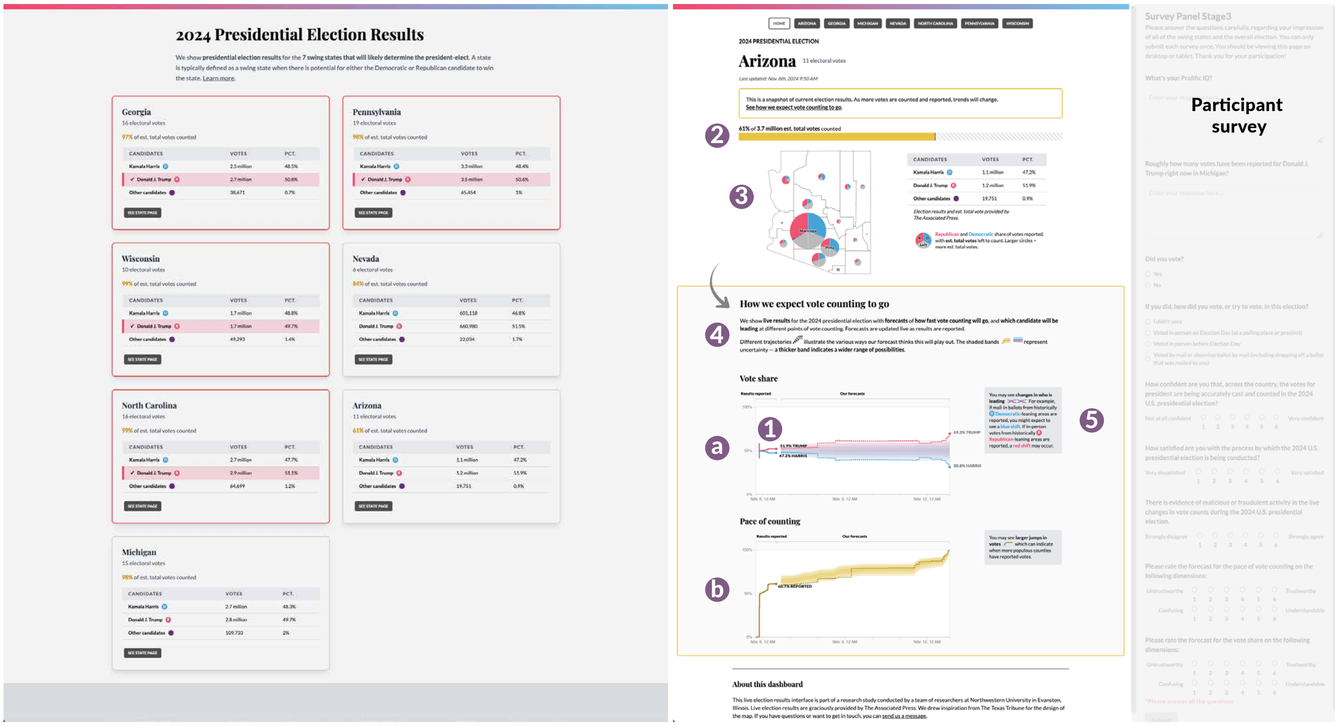

Figure 7: Final dashboard homepage and example of a swing state's results page (version with live forecasts and text explanation) during the 2024 presidential election.

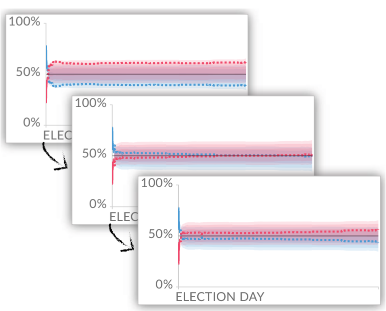

Figure 8: Hypothetical outcome plots for our live forecasts.

viewers where to expect uncertainty [42]. The forecasted sample trajectories could familiarize participants with the possibility that they may see increases and flips at different points of the vote counting process due to states' elections processes [20, 27, 29]. From poll close to at least four hours after votes first began coming in, our predicted trajectories of Democratic vote share and Republican vote share included the actual trajectories in each swing state, with the exception of Pennsylvania.[3]

Live elections results were sourced from The Associated Press, a reputable provider of election results to various news outlets [64], via their elections API. Because swing states are the most pivotal and uncertain races in a presidential election [75], we only showed presidential race results for the following swing states—Arizona, Georgia, Michigan, Nevada, Pennsylvania, Wisconsin, and North Carolina—and omitted election results for statewide and local races (Fig. 7). Donald Trump and Kamala Harris were the main contenders for the 2024 presidential election, so their vote totals were made most salient.

4 DEPLOYMENT DURING THE ELECTION

Our study engaged participants in three distinct phases: two weeks prior to, during, and one week following the 2024 presidential election. Protocols were reviewed and approved by the authors' university Institutional Review Board (IRB). We captured participants' baseline impressions before the election and evaluated the possible impacts of our dashboard once the election had concluded. Inspired by experience sampling [17, 82], we also chose to survey participants during the election as votes were counted (from when polls closed in swing states until a president was projected by The Associated Press) to capture trust of the election in the moment and impressions of memorable events, e.g., a notable flip or spike in votes for a candidate. Post-election semi-structured interviews were conducted to follow up on participants' survey responses and get richer descriptions of how they engaged with and were affected by our dashboard.

4.1 Experimental conditions

We initially recruited 795 adult participants from Prolific (not including the 21 previously interviewed) based in the U.S. who were

[3]Validation for the forecasts is included in supplementary materials.

English speakers and could engage with a website on a desktop computer. Around 20% of the 795 reported residing in swing states. The 795 participants were randomly assigned to one of four conditions to see a specific dashboard design:

(1) **no** forecasts + **no** explanation
(only components in Fig. 5, for **DG1**: *communicating that vote counts are partial*)
(2) **live** forecasts + **no** explanation
(components in Fig. 5 + Fig. 7.4, for **DG2**: *showing how counts may change over time*)
(3) **no** forecasts + **text** explanation
(components in Fig. 5 + Fig. 7.5, for **DG3**: *explaining how processes of vote counting may create visual trends in the data*)
(4) **live** forecasts + **text** explanation
(components in Fig. 5 + Fig. 7.4 + Fig. 7.5)

By assigning participants to different designs, we could disentangle the effects of the live forecast and text explanation components—features that were more experimental and suggestive of potential vote trajectories, in contrast to already reported counts.

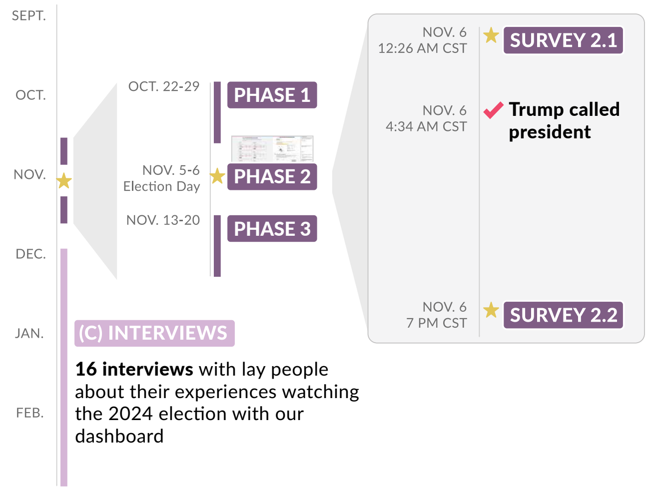

Figure 9: Timeline of deployment of dashboard during the election.

4.2 Surveys

PHASE 1 Two weeks before Election Day, participants answered questions related to their trust in election processes—their confidence, satisfaction, and belief in evidence of fraud—on a Likert scale from 1 to 6 and through qualitative free response.

- **Confidence in vote counting:** *How confident are you that, across the country, the votes for president are being accurately cast and counted in the 2024 U.S. presidential election?* (Not at all confident ↔ Very confident)
- **Satisfaction in election conduct:** *How satisfied are you with the process by which the 2024 U.S. presidential election is being conducted?* (Very dissatisfied ↔ Very satisfied)
- **Belief in evidence of fraud:** *There is evidence of malicious or fraudulent activity in the live changes in vote counts during the 2024 U.S. presidential election.* (Agree ↔ Disagree)

PHASE 2 Beginning after the first polls closed in Georgia on Election Day (the earliest swing state to close), participants were invited back to view their assigned version and answer a survey every day until a president was projected by The Associated Press. We only surveyed participants one additional day because Trump was projected president the day after Election Day. Participants received 1 USD per survey response. In this set of surveys, participants were again asked questions about their confidence in vote counting, satisfaction in election conduct, and belief in evidence of fraud in the live vote counts. If participants viewed live forecasts, they were asked about their trust and understanding of the forecasts.

- **Trust + comprehension of pace of counting forecast:** *Please rate the forecast for the pace of vote counting on the following dimensions:* (Untrustworthy ↔ Trustworthy) (Confusing ↔ Understandable)
- **Trust + comprehension of vote share forecast:** *Please rate the forecast for the vote share on the following dimensions:* (Untrustworthy ↔ Trustworthy) (Confusing ↔ Understandable)

The dashboard tracked participants' time spent on each page, mouse movements, and clicks as rough proxies for how often they engaged with the page. Out of the 795, 308 (39%) engaged with at least one of the swing state's results pages during the election, and 167 (21%) filled out at least one of the phase 2 surveys. (In these subgroups, a slightly larger share of participants saw the **no** forecasts + **no** explanation condition, and a slightly smaller share saw the **live** forecasts + **text** explanation condition.)

PHASE 3 In the last phase, beginning a week after the day a president was projected, participants were asked to fill out a final survey with similar questions as survey 2. Out of 795, 136 (17%) answered the phase 3 survey. Surveys for phase 2 and 3 were administered directly on the dashboard to encourage participants to revisit the dashboard.

4.3 Post-election interviews

(C) INTERVIEWS After the election, survey participants were invited back to complete an optional 60-minute semi-structured interview over Zoom for 12 USD about their experiences watching election results through our dashboards. We spoke to 16 people from December 2024 to February 2025.

4.4 Participant demographics

Among the 308 who engaged with at least one of the swing state's results pages, the median age was 49; 49% were male and 48% female; 73% identified as White, 13% Black, 7% Asian, and 6% other races, with 11% identifying as Hispanic; 36% held a four-year college degree and 32% had some college education; and politically, 51% leaned Democrat, 35% Republican, and 14% Independent. The demographic makeup was largely consistent across PHASE 2 and PHASE 3 responders, though PHASE 3 included a somewhat higher share of Democratic-leaning and four-year college participants. Compared to U.S. demographics from 2023 [12], white participants are overrepresented and Hispanic participants are slightly underrepresented in our participant pool. Our samples also lean more educated and

Democratic. Of the 16 people we interviewed for (C) INTERVIEWS , the median age was 53; 10 were men and 6 were women; 11 leaned Democratic, 4 leaned Republican, and 1 identified as Independent.

5 FINDINGS: SURVEYS

5.1 Analysis of survey measures

In our survey analysis, we consider the 167 participants who responded to at least one phase 2 survey. For the measure of confidence in how votes were cast and counted, we took the latest rating reported in phase 2 during the election if there were multiple survey responses. We modeled the Likert scale rating $y_{i,t}$ of each participant i at time t using a Bayesian multilevel linear regression model [46], generating 5000 posterior draws over two chains. R-hat values were below 1.01 and effective sample sizes exceeded 1000 across parameters, indicating model convergence. Our main predictors are survey phase, participant political party lean (Democratic, Independent, Republican), presence of a live forecast, presence of a text explanation, and interaction effects between these variables.[4]

$$y_{i,t} \sim \mathcal{N}(\mu_{i,t}, \sigma_\epsilon) \tag{1}$$

$$\begin{aligned} \mu_{i,t} = (\beta_0 + \gamma_i) + \beta_1 Phase_t + \beta_2 PartyLean_i + \\ \beta_3 Phase_t PartyLean_i + \\ \beta_4 Forecast_i Phase_t + \beta_5 Explanation_i Phase_t + \\ \beta_6 Forecast_i Phase_t PartyLean_i + \\ \beta_7 Explanation_i Phase_t PartyLean_i \end{aligned} \tag{2}$$

$$\gamma_i \sim \mathcal{N}(0, \sigma_\gamma) \tag{3}$$

5.2 Effects of live forecasts and explanations

Visualized in Fig. 10, our analysis suggests that live forecasts *possibly* had a **small effect on confidence in vote counting** (0.43, 95% CI = [-0.03, 0.9]), increasing confidence somewhere between 0 and 1 point on the scale. If live forecasts had an impact, it was small. Our analysis also suggests that live forecasts possibly had a **small negative effect on belief in evidence of fraud** in vote counting (-0.6, 95% CI = [-1.09, -0.1]), decreasing belief somewhere between 0 and 1 point on the scale. We did not observe a meaningful effect of our text explanations on confidence (-0.11, 95% CI = [-0.57, 0.35]), or belief in evidence of fraud (0.09, 95% CI = [-0.39, 0.59]).

We emphasize that these analyses and results are still exploratory. Deep-rooted attitudes like trust in contested political contexts are impacted by a host of alternative factors outside our dashboard design, which is illustrated in the following section (Sec. 5.3) and in our post-election interview themes (Sec. 6.3).

5.3 Effects of political partisanship

Given the tendency for people to trust forecasts and elections more when their candidate wins [36, 90], we expected that those who saw their preferred participant win would report increased confidence in the 2024 election and its vote counting. In survey 1,

[4]Our survey analysis code is included in supplementary materials.

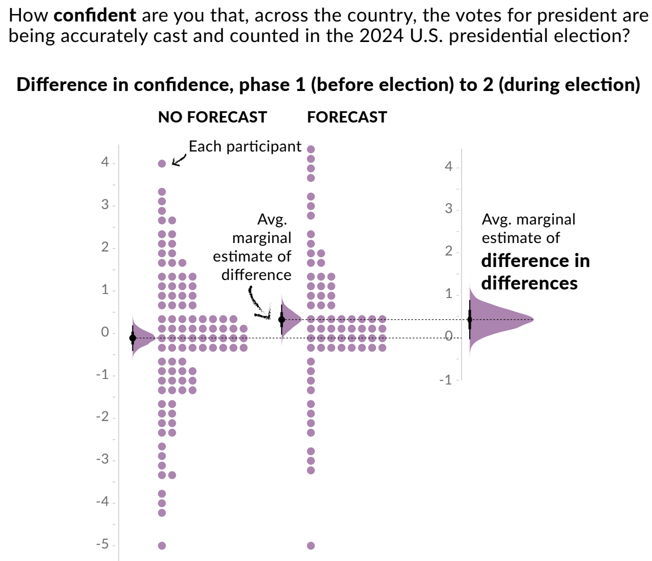

Figure 10: (Left) Change in confidence ratings between phase 2 and phase 1 surveys, grouped by whether participants saw a live forecast. (Right) Distribution of the average marginal effect of this difference-in-differences, comparing those who saw a forecast with those who did not. Densities are posterior distributions of means.

participants who lean Republican began with a **lower confidence** rating in the 2024 presidential election on average (3.9) than those who lean Democratic (5.3). Comparing the average marginal confidence estimates between phase 1 and phase 2, Republican-leaning participants *possibly* **increased in confidence** (1.04, 95% CI = [0.63, 1.45]) while Democratic-leaning participants possibly **decreased in confidence** (-0.54, 95% CI = [-0.84, -0.24]). This finding, shown in Fig. 11, is consistent with Trump's early lead in vote counts. In phase 2, before Trump was called as president, **belief in evidence of fraud in live vote counts was low** among participants, but slightly lower among Democratic-leaning (1.7) than Republican-leaning (2.6) participants. After Trump was called as president, those who lean Democratic *possibly* **increased their belief in evidence of fraud** slightly (0.24, 95% CI = [-0.09, 0.57]) while those who lean Republican possibly **decreased their belief in evidence of fraud** slightly (-0.37, 95% CI = [-0.72, 0]).

6 FINDINGS: POST-ELECTION INTERVIEWS

All 16 interviewees had seen a live forecast in their assigned condition. Interviews were transcribed using Adobe Premiere and manually corrected before the start of coding. We conducted a hybrid thematic analysis [9, 10] that followed our proposed framework for interpretation of live data (Fig. 4), by coding participants' pre-election expectations and changes in expectations. We also coded for how they perceived different design components and for components' impacts on expectations. Finally, we labeled any additional factors that contributed to interviewees' impressions of and trust in

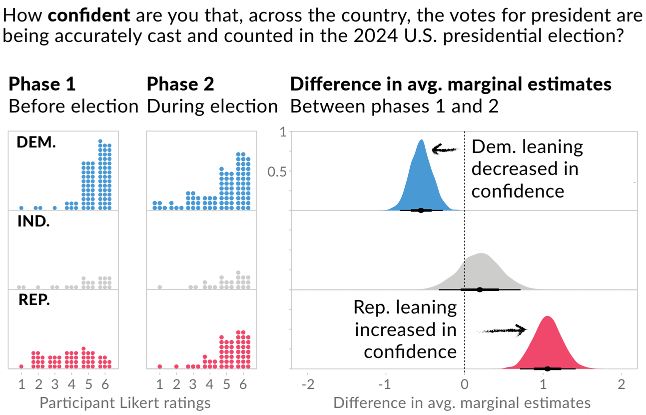

Figure 11: (Left) Participant ratings of confidence in votes, by political party lean. (Right) Distributions of the difference in average marginal estimates in confidence between survey 2 and 1.

the election, to stay open to new themes in the data. Interview coding was done by the first author and iterated on in several rounds over 8 months, by clustering codes into higher level themes and refining the themes with feedback from the other authors.

6.1 Dashboard as an anchor and alternative to media hype, supporting viewer agency

6.1.1 Dashboard as a reference point. Interviewees relied on our dashboard as an **"all-in-one place"** (C7) **reference point** (C2, 6, 7, 10–12, 14, 15), **using it to corroborate their beliefs of how the election was progressing** (C2, 6) and a way to check what has happened and what is happening (C1, 8, 10, 11, 14, 15). Almost all interviewees said that they viewed the dashboard in a personal, prioritized fashion, viewing states they had personal ties with (C1, 2, 8, 9) or states that were rumored to be particularly contentious or determinative in the election (C2, 4, 5, 7–12, 13, 15). Interviewees also reminded us of the preferred granularity and depth of a dashboard display, with many (C4, 7–10, 15) appreciating the level of detail in the county-level pie charts of vote share (and remaining vote) while some remarked not needing that level of detail (C3, 14) or wanting a birds-eye view (C6, 10).

6.1.2 Dashboard as affording agency and resisting media hype. The theme of agency in monitoring the underlying data cropped up in several interviews (C1, 2, 8, 11, 15). Our dashboard was perceived as **just showing the numbers and factual in nature** (C2, 7, 9, 11, 16)—"This is just the facts, ma'am" (C11)—a statement often coupled with a **feeling of agency interviewees had because they could monitor the dashboard whenever they wanted to**. It seemed that, in a storm of perceived media bias (C2–4, 6–12, 14), interviewees felt a clean dashboard of election results **resisted the hype of media coverage** and was a nice contrast to the usual noisy election news commentary that drew unnecessary attention and fanfare (C1, 2, 8, 11, 15). Regarding our text explanations of why vote trajectories between candidates may change, C10 and C11 spoke of them as a "little reminder", "laid [...] out very simply and very well" (C10), and as helpful for those who are not as familiar with electoral processes (C11). Interestingly, some of our interviewees (C7, 9) stated a desire for *more* explanation on our dashboard, on what types of votes are counted and when, and on how to read components on our dashboard, like the live forecasts.

But why did our dashboard strike participants as "factual" and "unbiased", when our interface had been designed with a particular objective (Sec. 3)? These perceptions may be related to the air of neutrality that is often associated with data and visualizations—our 2D design that suggests a birds-eye, all-encompassing view of the election, the use of geometric shapes and relatively minimalist design, our inclusion of The Associated Press as a data source [45]. But we also speculate that interviewees felt less whiplash as they watched the numbers populate into our dashboard. Several participants (C8, 11, 16) described current news media and its election commentary, in contrast to our dashboard, as a hype machine, as "beating a dead horse" (C8), and as not respecting audience members to be able to critically think for themselves:

> *Media is very good at making people angry and media is very good at making people happy. But media is not very good at telling the truth. Just flat out, telling out facts and letting you decide for yourself which it is. They have now assumed you're stupid and therefore they're going to tell you how to feel.*—C11

> *I don't really like the commentary as it's happening because it's sort of just talking heads. [...] It's just people talking about, you know, quickly changing situation where the thing goes up by a quarter point over here or one point over there or two points over there. And then they blather on about it for a while. You know, I would just rather and personally wake up and read a considered recap.*—C16

Could the abundant, hyped up commentary from mainstream news contribute to a feeling of disempowerment? The "bias" of news outlets felt by interviewees may be related to a feeling of passivity and powerlessness when consuming election news, lost in a sea of assertions that are quickly multiplying. There is financial and institutional pressure within news outlets to communicate real-time information and offer an interpretative lens to these updates [6, 13, 50]. But this abundance of interpretation, that would seem to appeal to the news value of *impartiality*—showing diverse and competing claims without evaluating the weight of evidence behind them [21]—was not received well by our participants. Frustrated by the lack of reliability in mainstream media and its failure to simply get the facts out, interviewees (C3, 11, 12, 16) turned to alternative sources of information on social media and streaming platforms.

6.2 Tensions in perceptions of live forecasts

6.2.1 Live forecasts as trustworthy, but hesitancy with forecasts overall. Interviewees (C2, 3, 12) stated that our **live forecasts seemed trustworthy**, and our larger pool of survey participants rated the forecasts between 4.5 to 5 on average (on a scale where 6 represented the highest level of trust and understanding). They cited reasons like the analysis for our live forecasts likely being trustworthy (C9), the forecasters having knowledge they lacked (C7), and the forecasts aligning with trends in live vote counts and with other elections coverage (C3, 11). However, interviewees (C4, 9, 10, 15, 16) discussed a **cautious approach with all forecasts** because forecasts have been wrong in the past, mentioning that polling data underlying forecasts can be biased or incorrect (C1, 9, 10, 16) (though our live forecasts did not integrate polls) and that historically, predictions are not always accurate (C12, 15, 16).

6.2.2 Live forecasts as communicating "too much" uncertainty or not offering enough new information. We hypothesized that our live forecasts of vote trajectories might prepare audiences for how vote counts might change. However, when asked directly about our live forecasts, several interviewees (C1, 4, 7, 10, 12, 16) **did not view them much or find them useful**. One reason for confusion or hesitation towards the forecasts was that they **initially communicated wide ranges of possible election outcomes** (Fig. 12), which interviewees (C7, 11) stated were unhelpful, other than reminding them that the outcome was unknown:

> *They were a little confusing, actually, because some of them were so broad right at the beginning that you could click on one and the forecast all of a sudden had one going up here and one going down there. And so they had this huge area where it could be like, well, that's not super helpful. That's like tossing a coin, you know.*—C7

It is worth noting that this participant perfectly understood the forecast (indeed, in the early stage of vote counting the primary message of the forecast *is* that the outcome is highly uncertain) but did not consider this message useful. The live forecasts were additionally considered unhelpful when **differences in predicted vote shares between candidates were visually imperceptible to viewers** (Fig. 12), again reminding viewers that the outcome is uncertain (C3).[5] Interviewees (C1, 2, 5, 15) also took live-updating forecasts with a grain of salt because they can change—why make an effort to look at the forecast and alter expectations if the forecast **may change shortly with new votes** anyway? On the contrary, we had initially assumed a forecast that changes with new information would be perceived as more useful because it reflects our most up-to-date state of knowing.

Some (C12, 16) also regarded the live forecasts as less useful later into the election, once the forecasts **confirmed a belief they were already certain about**. During the 2024 presidential election, steady wins in swing states led participants to believe by the evening of Election Day that Trump would win. There was little new information once the live forecasts began predicting Trump as the likely winner with a narrower range of uncertainty, because participants had already shifted their expectation to an almost guaranteed Trump win. We note that while interviewees previously framed confirmation as a reason to value the dashboard (Sec. 6.1), in this context they referenced confirmation to justify why they found the forecasts less useful.

[5]It is worth noting that we might have narrowed the forecast axes to focus on the 50% region, but this was complicated by the variable width of the credible intervals of trajectories. We may explore alternative designs in the future.

6.2.3 Preference for actual vote counts and outstanding vote. C4, 7, 10, and 15 also stated a **preference to look at the vote counts themselves rather than forecasts or speculation**. They felt that vote counts gave a clear enough picture of how the election was going. However, this may reflect the comparatively swift and straightforward nature of the 2024 presidential election, unlike the 2020 election, which stretched over several days and **exhibited biases in when different vote types were reported**. Given the misinterpretations of vote trends in 2020, we cannot always assume vote counts will provide a clear picture, without the inherent biases in which votes are counted and when, that fits within audiences' existing expectations.

Some (C1, 2, 4, 8, 15) **really appreciated our visual emphasis on progress of vote counting**, which is encouraging. The indication of outstanding vote by county "kind of gives you an idea of where it's headed" (C2), "helped me know what to expect coming, you know, whether I was going to expect a miracle or not" (C8), that "once it reaches a certain percentage [of votes counted], you know, pretty much know who won" (C15). C7 was able to triangulate that at the equivalent stage of vote counting in 2020, the Democratic candidate held a higher percentage of the vote, which suggested that their prospect of winning in 2024 was bleak. Furthermore, C9 said that he expected a future bump for the Democratic candidate if he saw more populous, Democratic-leaning counties at 70% votes counted.

6.2.4 Tension between perceived usefulness, uncertainty conveyed, trustworthiness. Live forecasts seem to be perceived as most useful when they provide some clear signal of certainty about who will win, ideally with a comfortable margin. This aligns with some of Yang et al.'s [89] design findings that people look for clarity and certainty in election forecasts. **But uncertainty in election outcomes, especially in contentious swing states, is still useful information**—and is necessary for those who are trying to draw premature conclusions. We also note this particular election went from highly uncertain to highly certain about the winner relatively quickly, aligning with participants' idea of a "normal" election. In a counterfactual scenario where the 2024 election spanned several days, our forecasts' emphasis on uncertainty, coupled with explanations of why, might be unsettling but also regarded as more useful.

Perceived usefulness of forecasts seems related to the amount of new, surprising information that they communicate (though this recognized value likely holds only if the forecast is correct [90]). But the criteria for surprising information in a forecast introduces a potential tension with criteria for trustworthiness: C3 and C11 justified their trust in our live forecasts on the basis that they were consistent with patterns in the ongoing vote counts and with concurrent elections coverage. **Forecasts may seem more useful when they present surprises, but more trustworthy when they align with observed results so far and other coverage**, which warrants further research to explore forecast designs in uncertain situations that are considered *both* useful (because they may predict the *unexpected*) and trustworthy.

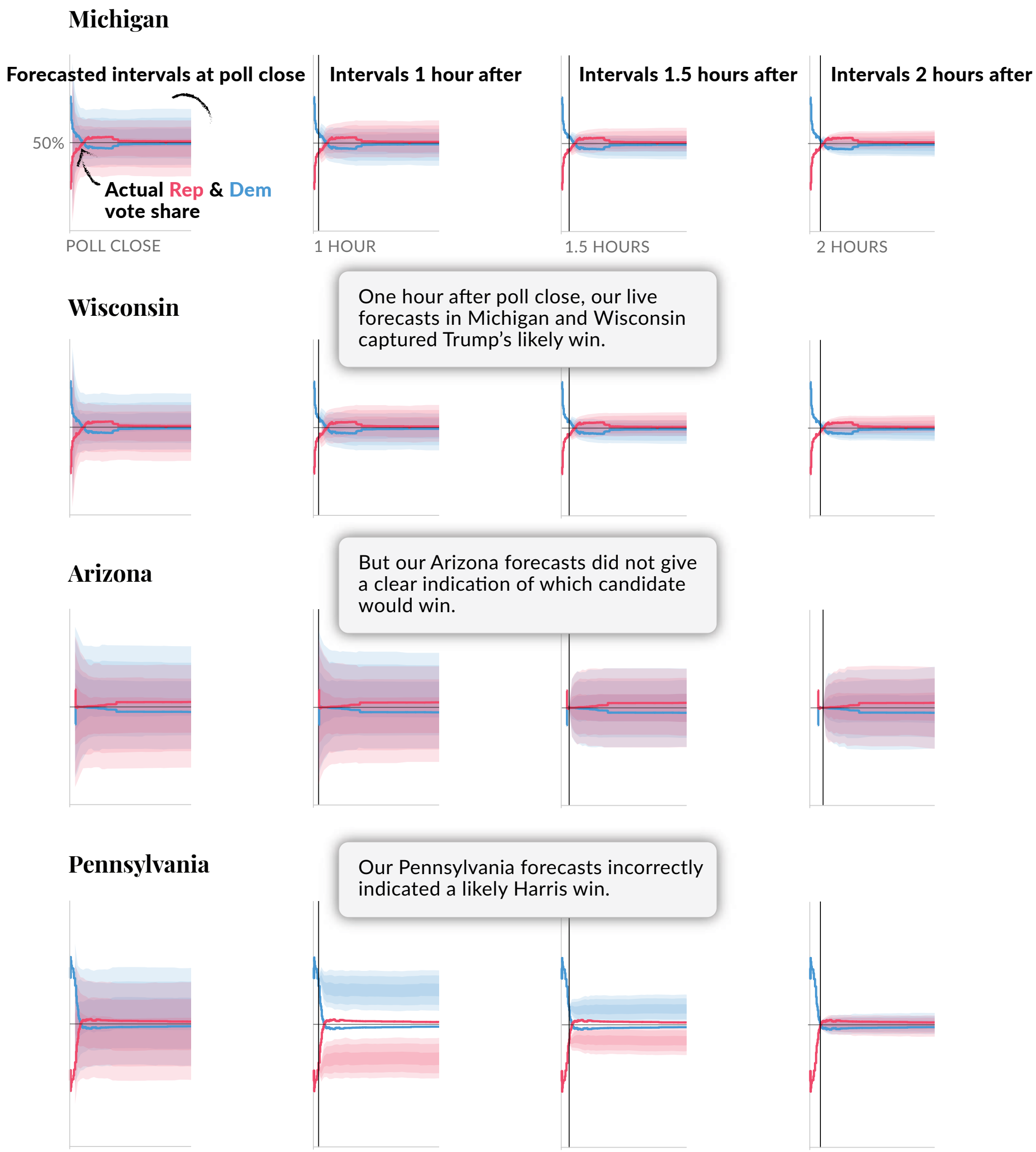

Figure 12: Live forecasts of vote share trajectories in Michigan, Wisconsin, Arizona, and Pennsylvania during the 2024 presidential election. Forecasts were also generated for the other swing states: Georgia, Nevada, and North Carolina. Only credible intervals are shown here; in the live version, participants also saw discrete draws.

6.3 Undercurrent of external information and emotions in expectations

We devote a section of our interview findings to examples of external information, anecdotes, and emotions mentioned by participants. These factors shaped audiences' prior expectations of the election depicted in our framework in Fig. 4 and support the possible impact of political partisanship in Sec. 5.3. Emotions—specifically, a deep sense of hope—can prevent an individual, like C14, from accepting how the election will pan out even when there are only a few possibilities left. We argue that information external to the visualized data should be considered and measured in studies of visualizations in contested political spaces, and discuss in Sec. 7 how to integrate external information and emotions into our design framework of viewer expectations over time.

6.3.1 Role in shaping pre-election expectations. Interviewees brought countless examples of external information—**accumulated knowledge from other sources**, **personal experiences**, **emotions**—to their interpretations of live results, apart from the data on our dashboard. External information largely **informed interviewees' pre-election expectations of the 2024 election timeline**. Namely, interviewees (C2, 3, 7–9, 12, 14, 15) expected the vote count in 2024 to be longer, displaying a recency bias brought on by the longer period of uncertainty in the 2020 presidential election. After the 2024 election was over, C2, 7, and 8 reasoned that voting and vote counting went smoother because they suspected election institutions were more streamlined and prepared this time around. Most interviewees (C6–9, 11–16) also expected the election to be a "closer" race, which perhaps translates to the expectation that they would wait longer before knowing the winner, or that Harris and Trump would each win some swing states. Additionally, external information and personal experiences served to **rationalize pre-election expectations of the presidential election winner**. C6, 13, and 14 expected that Harris would have a more favorable outcome, given that "Kamala's campaign seemed to be doing virtually everything right" (C6), the "despicable" things that Trump had done in office, and the conversations they were having with those around them (C14).

6.3.2 Role in rationalizing or rejecting the ultimate election outcome. Some (C1, 5, 6, 8, 13, 14, 16) began the election with a deep sense of hope that Kamala Harris would win the 2024 presidential election. After Trump's win, C1, 9, 13, and 16 reasoned that perhaps America was not ready to vote for a female president of color, and that there were several stay-at-home-voters who could not bring themselves to vote for a woman but who also did not want to vote for Trump. Additionally, there was a sense that Republicans made more use of the mail-in ballot and early voting in 2024 (C4, 6, 11), and thus mail-in ballots did not lean as Democratic as they had in 2020 (C9). C14, hopeful of a Harris win, resisted accepting a guaranteed Trump win during the election even when Trump was in the lead with a majority of votes counted.

6.3.3 Role in shaping beliefs of election fraud. Impressions around the **occurrence of election fraud relied heavily on external information and anecdotes**, including participants' own knowledge of how certain types of votes are cast and counted (C4) and fraudulent incidents they had heard of (C2, C3). C3 made frequent reference to state-specific issues and lawsuits around vote counting, citing several instances of alleged malfeasance from the 2020 election, e.g., election observers being kicked out and water pipe breaks (that have since been debunked as attempts to steal the election). C12 and C16 also referenced the counting of dead people's ballots in 2020. But other interviewees denied mass election fraud for several reasons: there are many measures in place to stop fraud and instances in which those measures were invoked (C4–8, 10, 16), that past lawsuits brought on by Republicans did not find evidence of voter fraud, nor did Trump's own investigators (C4, 9), that personal experiences working as a poll worker showed them the security of elections (C5, 9), among other reasons.

7 DESIGN IMPLICATIONS

7.1 Designing for live data ↔ designing for agency

Participants' resistance to mainstream news commentary in our interview findings (Sec. 6.1) relates to the concept of *information receptivity* ("a transient state of willingness or openness to receive information") defined by He et al. [33]. Most of our interviewees would fall under He et al.'s "Data Cautious" and "Data Enthusiastic" characterizations—individuals who are enthusiastic about looking at live vote counts and seek out interpretations from trusted sources that "contained implied, rather than direct, references to data". Encouragingly, our participants felt that our dashboard design, which built upon existing live elections dashboards by data journalists, provided them with a feeling of autonomy.

However, we wonder if audience agency is at odds with many journalists' desires to increase people's receptivity to frequent live updates, no matter the significance. It is unclear if this should remain a journalistic priority in the age of information overload and a growing trend of news avoidance [71, 85], but it is hard to imagine mainstream news outlets advising audiences to ignore their breaking news coverage (given attention and profit incentives).

Furthermore, is it possible for data journalists to provide interpretations of live data in an "implied" way? Can an interpretation of live data that influences or corrects expectations ever feel devoid of an agenda? We are not sure. Even our dashboard design, which was perceived as "just the facts", had a specific objective and design goals (Sec. 3).

Still, journalists might consider being more mindful of the pace at which new insights are presented through their live elections coverage and the degree of certainty conveyed. One strategy is to perhaps follow the design approach anchored in uncertainty and partiality that we took—to state from the start that each snapshot of results is a partial, incomplete view and that there is *uncertainty* even in the information we show (related to **DG1:** *communicating that vote counts are partial*)—rather than follow each update in vote totals with analysis and assertive speculation. Another option is for news outlets to publish decidedly opinionated dashboards with live interpretations of results from a particular perspective, but to clearly state their agenda and values guiding coverage (given that value alignment seems to be essential for information receptivity [33]). A dashboard cannot realistically service every user need, so it will be up to data journalists to assign particular roles to the interface and make that explicit. What would a live elections dashboard look like that acknowledges every piece of it—the "raw" vote counts, the added text, the live forecasts—constitutes interpretation? That all data is a "lens, not a mirror" [1], mired in complex human practices that adheres to certain values?

7.2 Designing to show possibilities and shape expectations

Though our live forecasts were successful in communicating uncertainty, and did show that Trump would likely win in some states (related to **DG2:** *showing how counts may change over time*), our participants did not perceive the forecasts to be useful for several reasons: they were regarded as communicating "too much" uncertainty, offered little surprising information, and were less preferred to the actual vote counts. The perceived lack of usefulness in predictive elements of journalism was also encountered by Witzenberger and Diakopoulos [87]. Our live forecasts, however, were still judged as trustworthy, in part because they aligned with ongoing vote trends. This alignment supported appreciation of the dashboard as a confirmatory reference point but simultaneously diminished the forecasts' perceived usefulness. The comparative straightforwardness of the 2024 election, along with the speed at which the winner became clear, likely played a role in how useful a forecast *could* be. In a longer election, particularly one where certain types of votes (e.g., mail-in ballots) skewed politically and were counted on different timescales, raw vote counts and forecasts would diverge more saliently and we would have been able to investigate this tension more thoroughly.

Given that some interviewees (C7, 9) wanted even more explanation specifying the intent of the forecasts, one approach is to caption forecasts as we want readers to view them. We might specify that forecasts are not purely for the purposes of suggesting clear, certain outcomes, that showing uncertainty is still a form of clarity, that raw vote counts have systematic biases in when they are reported, and that there are reasons for uncertainty about the election outcome in contentious swing states (related to **DG1:** *communicating that vote counts are partial* + **DG3:** *explaining how processes of vote counting may create visual trends in the data*). The format of election forecasts might also matter—perhaps people expect more certainty when seeing forecasts through a visualization. We speculate that viewers expect a clearer answer if they take the cognitive effort to understand a visualized forecast, versus if they read a simple textual statement like "We do not know enough right now to narrow down possibilities of election outcomes." In future studies, it is worth experimenting with varying formats of forecasts, going from text to more expressive visualizations at different levels of uncertainty (wider to narrower ranges of possibilities) in election outcomes, and observing how viewers receive them and understand the role of uncertainty [87]. Though live forecasts were not perceived as highly useful in this particular election, they might still be useful in future elections with longer waiting times.

7.3 Incorporating external information and emotions into our design framework

Our participant findings highlighted the degree to which expectations are shaped by a backdrop of external information, personal experiences, and emotions (Sec. 6.3), which may act as "perceptual screens" (theoretical filters that distort how political partisans view the world even when confronted with the same set of facts [23]). Battle & Ottley [8] conceptualize "insights" as the linking of knowledge inferred from the data with external contextual knowledge *outside of the data*. Examples of external information we noted in our interview findings include live elections coverage from other outlets and participants' pre-existing beliefs and anecdotes about election fraud, which are interwoven with one's broader information ecosystem and political affiliations.[6] Ultimately, *alignment* with existing beliefs and with other coverage played an important role in whether participants trusted the overall election results and our live forecasts.

How might data journalists and visualization researchers make use of our design framework (Fig. 4), incorporating these myriad external factors from the beginning of the dashboard design process? Designers of live elections dashboards could lay out ahead of time the many diverse expectations viewers have heading into an election, e.g., a strong belief in a Democratic win, a strong belief in a Republican win, or a strong belief in a toss-up scenario. They could then outline how those expectations might change at different points of the vote counting process in response to historically "pivotal" events—e.g., has there been a flip in the leading candidate, or has a larger batch of votes come in from a more populous urban area? If politicians begin casting doubt on some aspect of the electoral process, dashboards should be prepared to supply additional context when that procedural element surfaces in the data, requiring that such information be available in real time as votes are reported. Crucial to this outline is listing out the ways emotion may influence or distort shifts in expectations (C14, for example, resisted shifting expectations to a Trump win because she wanted Harris to win). More research is needed to develop this framework of evolving expectations and to more precisely model the evolution of viewers' subjective probabilities as they watch live dashboards of vote counting.

7.4 Considering the real-world setting of an interface

The persistent theme of agency and participants viewing information on their own terms, the particular idiosyncrasies of the 2024 presidential election, and the reality of participants bringing in their external knowledge and emotions all speak to the argument that dashboards cannot be understood outside of a real-world context. In this study, we prioritized realism—in the live elections dashboard we created, and in conducting the study during a real election. Though it was difficult, the benefit of running a study during an actual election is that the estimated effects we observe are more believable (though noisy and challenging to interpret), versus a lab study in which estimates of effects are precise (but less believable and reflective of the real world).

Researchers who choose to pursue this type of "realistic" study should be aware that it will require building trust with people outside your research team who can provide you with guidance, that your research team will need to weigh the concerns and requests of these individuals as seriously as your own research agenda, and that there is an inherently unexpected nature to these studies requiring flexibility. We had several contingency plans—versions of what our study could look like even without a custom dashboard—in the months leading up to the election. During the study, we had the option to change when our surveys were administered, and could alert and help participants troubleshoot when unexpected issues occurred. For a roughly twenty-four hour period around Election Day, we effectively transformed our research lab into a newsroom, recruiting labmates as volunteers to track live results and coordinate participant surveys. This kind of work is messy and resource-intensive, and its outcomes are far from certain.

8 LIMITATIONS

Because our participants lean slightly more liberal and educated, having been recruited off Prolific, we note that our findings may not be completely reflective of the broader U.S. population. The applicability of our findings may also be confined to the U.S. elections domain, though they are likely still relevant for contextualizing and visualizing other controversial, public-facing datasets tracked in real time, e.g., COVID-19 case counts. Our findings may also

[6] This aligns with political science research finding that people whose preferred candidate wins an election tend to report increased trust in that election [36], and that Democrats and Republicans may consider different factors to determine the trustworthiness of an election [72].

differ in future elections with different dynamics, requiring more studies. Additionally, we note that our dashboard unexpectedly faced some intermittent outages until 10:30 PM CST, after one state (North Carolina) was projected for Trump but before his eventual presidential win around 4:30 AM—still leaving a sizable window for participants to observe vote counting. We recognize that these outages probably contributed to confusion among our participants early on, which we addressed by directly messaging them, and impacted our participant retention rate (Sec. 4). To account for this, we only considered surveys administered to participants while the dashboard was working in our survey analysis.

9 CONCLUSION

Live displays of vote counting serve as examples of public-facing progressive visualization that must communicate evolving information in a politically charged context. We designed and deploying a dashboard during the 2024 U.S. presidential election with the design objective of fostering understanding of the progressive nature of vote counts and more realistic expectations of the vote counting timeline, examining how our design choices shaped confidence and perceptions of fraud. While our surveys suggested small effects of the live forecasts, post-election interviews showed that participants primarily valued the dashboard as a factual reference point that gave them a sense of agency. Our live forecasts successfully communicated uncertainty in early results, but were perceived as less useful in this particular election—raising questions about how to design forecasts that can convey uncertainty while remaining useful and trustworthy. We suggest future designs for public-facing progressive visualizations and forecasts that prioritize viewer agency over hyped up speculation, are explicit about partiality and uncertainty in live data, and that clarify intent of forecasts and experiment with different forecast formats. We also contribute an amended framework of viewer engagement with live data that considers external information and emotions to guide future design work. Our study demonstrates how live, real-world deployments can reveal both the possibilities and limitations of dashboards in helping the public interpret contested, dynamic information.

Acknowledgments

We would like to extend a thank you to our reviewers for their thoughtful feedback, our friends and colleagues (Abhraneel Sarma, Ayse Hunt, Maryam Hedayati, Melissa Chen) for helping us run our experiment during a chaotic election night, the many journalists, designers, and elections analysts who provided us with their time and guidance, and The Associated Press.

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