

# AI-Assisted Conversational Interviewing: Effects on Data Quality and User Experience

Soubhik Barari, Jarret Angbazo, Natalie Wang, Leah M. Christian, Elizabeth Dean, Zoe Slowinski, Brandon Sepulvado

NORC at the University of Chicago

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## Abstract

Standardized surveys scale efficiently but sacrifice depth, while conversational interviews improve response quality at the cost of scalability and consistency. This study bridges the gap between these methods by introducing a framework for AI-assisted conversational interviewing. To evaluate this framework, we conducted a web survey experiment where 1,800 participants were randomly assigned to text-based conversational AI agents, or “textbots,” to dynamically probe respondents for elaboration and interactively code open-ended responses. We assessed textbot performance in terms of coding accuracy, response quality, and respondent experience. Our findings reveal that textbots perform moderately well in live coding even without survey-specific fine-tuning, despite slightly inflated false positive errors due to respondent acquiescence bias. Open-ended responses were more detailed and informative, but this came at a slight cost to respondent experience. Our findings highlight the feasibility of using AI methods to enhance open-ended data collection in web surveys.

## 1. Introduction

A core tension in survey methodology lies between scalability and adaptability. Standardized, self-administered surveys solve long-standing issues of response incomparability by minimizing interviewer effects and enforcing consistent question wording (Feldman et al., 1951; Fellegi, 1964). However, their rigidity—especially in open-ended questions—limits opportunities for clarification, elaboration, and respondent engagement (Fowler & Mangione, 1990; Schober & Conrad, 1997; Tourangeau et al., 2000).

Conversational interviewing addresses many of these challenges by enabling dynamic clarification, probing, and even real-time validation of researcher interpretations (Schober & Conrad, 1997; West et al., 2018; Hubbard et al., 2020), but its dependence on trained interviewers limits scalability and introduces new sources of bias. Moreover, integrating conversational or interactive elements into self-administered web surveys has historically been challenging.

In this article, we evaluate the usage of generative artificial intelligence (AI) to bridge these divides in web survey methodology. In particular, we assess whether large language models (LLMs), with their ability to process and generate human-like text (Bail, 2024), can be integrated into web surveys as AI assistants—referred to hereafter as *textbots*—to enable scalable, self-administered conversational interviewing. We use the term ‘textbot’ to emphasize that this approach leverages text-based inputs and outputs, distinguishing it from traditional conversational interviewing (typically facilitated through audio) and AI methods that aim to create a human-like presence (e.g., avatars, personas).

Like any new data collection technology, textbots introduce potential for error, necessitating systematic evaluation of their impact on data quality and an understanding of their effectiveness across question types. To this end, this article focuses on three key research questions:

1. Can textbots accurately live code open-ended survey responses?
2. Can textbots increase the quality of open-ended survey responses through probing?
3. Do textbots impact the overall respondent experience?

To answer these questions, we present the findings of a survey experiment conducted on a conversational AI platform. We evaluate a set of AI-assisted conversational interviewing techniques and their effects on data quality (i.e., the quality of open-ended responses as well as the codes derived from them) and the respondent experience.

## 2. Background

### 2.1. Open-Ended Survey Questions

Open-ended survey questions enable respondents to answer in their own words rather than using pre-defined response categories (Schuman & Presser, 1979; Tourangeau et al., 2000). Responses from open-ended questions can serve as a qualitative supplement or be statistically analyzed in text-as-data (Grimmer et al., 2022). The open-ended format eliminates satisficing behaviors induced by closed-ended questions, where the selection, order, and presentation of response categories can influence the respondent's choice, potentially diverting them away from the 'correct' answer (Krosnick & Alwin, 1987). Moreover, open-ended questions can be used to elicit both subjective opinions and factual information: respondents can elaborate on their opinions (e.g., social attitudes) more thoughtfully as well as specify information (e.g., occupation) that may otherwise be burdensome to identify in a long list of choices (Krosnick, 2017). These benefits are especially pronounced for web surveys (Fricker et al., 2005; Smyth et al., 2009).

Open-ended questions have their challenges too. They are more cognitively demanding, requiring more time to formulate and input a response, particularly on mobile devices (Antoun et al., 2017; Couper et al., 2017). Moreover, compared to short close-ended questions, open-ended questions may be more, rather than less burdensome exacerbating respondent satisficing or nonresponse (Krosnick, 1999). Some drawbacks of the open-ended question are specific to self-administered surveys. Without an interviewer to clarify question wording, respondents may provide incoherent or irrelevant answers or avoid answering altogether (Conrad & Schober, 2000; Conrad et al., 2005). Similarly, interviewers cannot clarify responses from respondents to ensure accurate interpretation. For quantitative comparison, open-ended responses must be reduced to low-dimensional forms, such as topics (Grimmer et al., 2022). Self-administered formats require this structuring ex-poste without the respondent's verification, which may introduce processing errors (Groves, 2005). Mitigating such errors imposes a burden on researchers to train reliable human coders or develop algorithms, a challenge exacerbated by low-quality responses (McMann et al., 2022). This creates a quality 'doom loop' that could be avoided through interactive clarification between researchers and respondents.

## 2.2. Conversational Interviewing

Many of the aforementioned issues with open-ended questions arise out of their usage in *standardized interviewing* (SI). While standardized interviewing practices solves the problem of response incomparability due to interviewer effects (Feldman et al., 1951) and question variation (Fellegi, 1964), the rigidity of scripted surveys introduces other threats to construct validity (Fowler & Mangione, 1990). By now, a substantial body of research demonstrates how *conversational interviewing* (CI), also known as *flexible interviewing* (FI), can effectively mitigate such threats.

For instance, Schober & Conrad (1997) demonstrate that allowing both respondents and interviewers to initiate follow-up questions or ‘probes’ reduces comprehension errors and fosters a more consistent understanding of survey questions. Similarly, Suchman & Jordan (1990) and Conrad & Schober (2005) show that conversational techniques enable respondents to elaborate on their answers, improving the accuracy of coding responses into pre-specified categories while also eliciting more detailed and relevant data. Further, West et al. (2018) find that conversational interviewing enhances response quality for income-related questions and other topics without compromising construct validity or introducing significant interviewer effects. More recently, Hubbard et al. (2020) demonstrate that conversational interviewing techniques can be effectively deployed by a variety of professional interviewers. While interviewers with a stronger sensitivity to respondents’ comprehension are more efficient, the technique significantly improves response quality for both opinion and informational questions.

In addition to enabling clarification and elaboration, conversational interviewing creates an opportunity for real-time respondent validation (also called ‘member checking’ in qualitative research practices), where researchers confirm their interpretations or categorizations with respondents (Schober & Conrad, 1997; Birt et al., 2016). This process amplifies the participant’s voice by directly involving them in constructing the researcher’s understanding of responses (Mason, 1997). Unlike traditional methods that defer such validation until after the study concludes, conversational interviewing allows for some real-time interaction between interviewers and respondents to verify and correct answers. For instance, the interviewer may first summarize a respondent’s answers after the conclusion of a module or, if a live codebook is being used for a particular question, explicitly state their intended coding, and then request confirmation or feedback from the respondent.

Conversational interviewing is, of course, not without its own drawbacks. The reliance on trained human interviewers may impose substantial costs on researchers (Groves, 2005) and induce effects such as socially desirable responding. Studies suggest that field interviewers, when asked to ‘live code’ information from respondents, are prone to errors like mistyping and mishearing (Olson & Smyth, 2015; West & Blom, 2017). Moreover, integrating conversational or interactive elements into self-administered web surveys has historically been challenging. Conrad et al. (2003) proposed early interactive adaptations into web surveys using hyperlinks and inaction triggers, but these lacked the adaptability and personalization of live interviewing. Similarly, interactive feedback in web forms can improve response accuracy, as demonstrated in Conrad et al. (2005), but it requires a clearly defined concept of accuracy as well as static pre-programmed rules to enforce accuracy (e.g., hours entered into daily timesheet must sum to 24). Research incorporating avatars (or virtual agents) and audio recordings into web surveys also fell short,

often disrupting the interview flow, increasing completion time, or failing to enhance the respondent experience (Conrad & Schober, 2007; Tourangeau et al., 2003).

### 2.3. Large Language Models

Conversational interviewing administered by humans, which is tailored to each respondent, is difficult to scale in large-scale web surveys, while previously studied interactive features in web surveys are scalable but lack personalization. Recent methodological and applied social science research suggests that *conversational AI* (or, more specifically, AI-assisted conversational interviewing) based on large language models (LLMs) can bridge this gap by providing scalable, personalized, and interactive survey experiences (Bail, 2024).

LLMs, such as GPT-4, are advanced generative AI systems trained on vast amounts of text data to generate and process language, enabling them to simulate human-like conversation, synthesize information, and perform reasoning. In the context of conversational interviewing, an especially attractive feature of large language models is that their behavior can be programmed through a mix of instructional prompts and training examples of ideal behavior – known as *few-shot learning* (Brown et al., 2020) – analogous to how a human interviewer may be trained (Billiet & Loosveldt, 1988). As such, they hold potential to assist or replace human interviewers.

Some promising methodological results and applications of AI-assisted conversational interviewing have already emerged. Xiao et al. (2020) show that the usage of an LLM-based chatbot in the market research context can enhance participant engagement through personalized probing and social acknowledgment. Similarly, on a small-scale convenience sample of students, Wuttke et al., (2024) evaluate the impacts of an LLM-based conversational agent on response quality relative to a human interviewer. The study found that respondents rated chatbot interviews as comparable in quality to human interviews, with the added advantage of greater efficiency and scalability. In the realm of survey experiments, Velez & Liu (2024) demonstrate that large language models can further tailor experimental prompts to individual's particular policy preferences.

Still, several areas for theoretical development and empirical evaluation remain underdeveloped in this emerging literature, which motivates the present study. First, a clear typology of the capabilities of conversational AI and their alignment with the features developed in the conversational interviewing literature remains underdeveloped. While much of the integration of conversational AI into surveys has focused on tasks like probing, LLMs possess a broader range of capabilities. This includes ‘live coding’ information (e.g., identifying subjective well-being from open-ended responses), tailoring questions or branching respondents based on previous open-ended responses (e.g., adapting question wording to reflect subjective well-being), and simplifying difficult or complex tasks (e.g., reducing the categories for lengthy close-ended questions using information from prior open-ends). Moreover, there has been limited evaluation of each of the individual capabilities that facilitate the impact of LLMs on data quality. Finally, survey methodologists lack a systematic understanding of conversational AI’s effectiveness across different question types, such as factual versus opinion questions.

### 3. Methodology

#### 3.1. Conversational Interviewing Methods

Drawing from the conversational interviewing and qualitative research literature (see Suchman & Jordan (1990)), we introduce two techniques that conversational AI may use in a text-based chat interface for open-ended questions: active coding and active probing.

*Active coding* refers to a textbot’s ability to detect concepts within open-ended answers in real time, as a field interviewer might (West & Blom, 2017) without the risks of human error (Olson & Smyth, 2015). This functionality draws on machine learning techniques such as text classification, sentiment analysis, and topic modelling (Puri & Catanzaro, 2019). Unlike post-hoc automated coding methods using supervised learning or language models (He & Schonlau, 2022; Gweon & Schonlau, 2024), active coding occurs during data collection, enabling immediate usage for survey branching respondent validation. To facilitate active coding, a standard codebook can be provided to the textbot with examples (few-shot learning), with only definitions (zero-shot learning), or omitted entirely to prompt on-the-fly category discovery (unsupervised learning).

*Active probing* refers to a textbot’s ability to generate follow-up questions based on a respondent’s answer to a seed question, mirroring practices in human interviewing (Billiet & Loosveldt, 1988; Groves et al., 2009). In typical self-administered surveys, all probes must be hard-coded using static logic. In contrast, LLM-based textbots can be trained to decide *when* and *how* to probe based on prior responses or metadata.

In this study, we enabled three types<sup>1</sup> of AI-based probes: (1) *confirmation probes* to allow the respondent to confirm whether the textbot’s active coding aligns with the respondent’s intended meaning, (2) *elaboration probes*, to invite the respondent to provide more detail about an open-ended answer they have given, elaborate on their reasoning, or offer more specific information, and (3) *relevance probes* intended to improve the relevance or interpretability of the original response provided. A confirmation probe can be asked as a yes/no question where the textbot categorizes an answer and asks for confirmation. If multiple categories are detected or if there is uncertainty, the textbot could ask the respondent to select from a list of possible categories.

It is possible to administer “hybrid probes” that overlap between multiple categories – for instance, through multiple questions in one probe. In some cases, one type of probe may accomplish the goal of another, as it might be necessary to request elaboration to determine relevance, or vice versa. For example, to clarify whether ‘space’ refers to ‘green space’ (relevant) or ‘outer space’ (irrelevant), a probe may request both elaboration and relevance.

The next section details our experimental design to formally evaluate the AI-assisted conversational approach against the standardized approach.

#### 3.2. Study Design

In order to evaluate the impacts of AI-based coding and probing on data quality, we designed and administered a survey on a chat-based interface with experiments embedded within each of four distinct question groups. Table 1 summarizes our design, including the flow of the four question

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<sup>1</sup> See Supplemental **Error! Reference source not found.** for an example of each of these interactions.

modules and their variations in format across experimental conditions. Reference questions were drawn from major surveys as were codebooks to develop the coding frame for live coding and to inform the close-ended response categories.

**Table 1. Overview of Experimental Design**

Survey Module	Seed Question Format Across Conditions			Coding Dimensions	Reference (for question and codebook)
	Control: No Probes	Treatment 1: Confirmation Probes	Treatment 2: Elaboration or Relevance Probes		
(1) Most Important Issue	Open-Ended	Open-Ended	Open-Ended	Political issues	Gallup Tracking Poll
(2) Economic Conditions	(i) Close-Ended (Sentiment)	(i) Open-Ended (Sentiment)	Open-Ended	(i) Sentiment (Pos/Neg)	Pew American Trends Panel
	(ii) Open-Ended (Reason for sentiment)	(ii) Open-Ended (Reason for Sentiment)		(ii) Reason for Sentiment	
(3) Preferred News Source	Close-Ended	Open-Ended	Open-Ended	News Source Outlets	NORC AmeriSpeak Profile Survey
Demographics	Close-Ended (Age, Gender, Education, Employment)			N/A	N/A
(4) Main Occupation (Among Employed)	Close-Ended	Open-Ended	Open-Ended	Occupation Codes	BLS Standard Occupational Classification
Respondent Experience	Close-Ended (Quality, Ease, Satisfaction, Frustration)			N/A	N/A

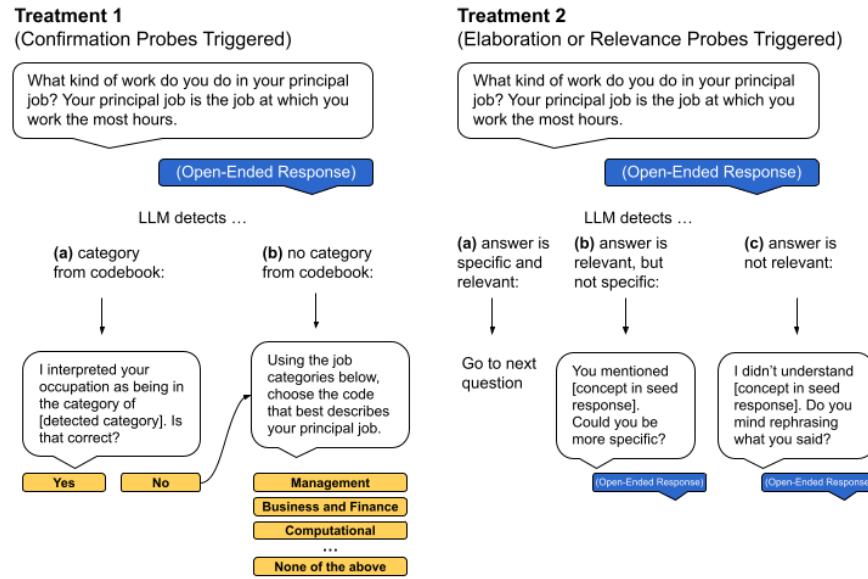
Each of the within-survey experiments included 1-2 open-ended questions on commonly surveyed topics: (1) most important national issue, (2) economic evaluation, (3) news sources, and (4) occupation. A complete questionnaire can be found in Appendix Table A1.

This design, though complex, allowed us to better generalize conversational AI's effects on data quality across different contexts. First, the formats of the control condition question reflect different real-world survey practices: short ordinal lists (economic sentiment), long nominal lists (23 standardized occupational codes), choices with varying granularity (news sources which may include apps or outlets), and open-ended questions requiring ex-post coding (national issue). Second, the four experiments spanned factual responses (news source, occupation) and subjective opinions (national issues, economic evaluation). Third, conceptual categories varied, covering topics (national issues), sentiment (economic sentiment), proper nouns (news source), and classifications (occupation), highlighting the diverse challenges for textbot coding.

The baseline control question in each experiment was standardized to all respondents with no active probing or active coding, while the two treatment versions each administered a specific type of probe based on the initial (seed) question and response. In Treatment 1, the textbot could only deploy confirmation probes while in Treatment 2, the textbot was configured to deploy only elaboration or relevance probes.<sup>2</sup> Figure 1 illustrates how the large language model was configured in order to perform the different probes, incorporating content from the seed question and response.

<sup>2</sup> Ideally, our experiment would unbundle relevance and elaboration probing into two separate conditions, but we combined them into a single treatment due to statistical power concerns and limitations in the user interface with our selected conversational AI platform.

**Figure 1. Probing Mechanism in Treatment Conditions**



In the second treatment condition, confirmation probes were configured to activate upon the coding of a category for the particular concept of interest (e.g., issue) explicitly sourced from a reference question and/or codebook (e.g., major issue categories identified in the national Gallup tracking poll).<sup>3</sup> Noting in earlier literature that too many probes may increase overall nonresponse (Behr et al., 2012), guardrails were placed in the chat interface such that the textbot could administer at most one probe per each seed question in any treatment condition.<sup>4</sup>

Finally, to explore heterogeneity in response quality effects, we collected demographic information and asked about the survey experience through a series of Likert-scale questions at the end of the survey. Details and results for heterogeneous treatment effects are given in Appendix Section A4.

### 3.3. Conversational AI

We fielded our experiment on the conversational AI platform Inca, with an interface nearly identical to that depicted in Figure 1. The particular textbots in our experiment were fine-tuned from the GPT-3 foundational model (Brown et al., 2020) proprietary database of market research surveys conducted by the platform vendor (Seltzer et al., 2023).

For each question, responses (probes) from the textbot language model were generated via an internal (proprietary) instructional prompt delivered to the underlying LLM which contained the seed question and response, additional conversational attributes generated by an intermediate model, as well as any information we provided for each question such as a codebook (Seltzer et al., 2023). Importantly, though we provided the name of each coding category in our question-level prompts to the textbot, we did not further provide examples of responses belonging to each

<sup>3</sup> If multiple categories were coded, the textbot sampled one for confirmation probing. Examining the textbot metadata, we found that in most responses for most questions, only one category was coded.

<sup>4</sup> Due to platform limitations, indicators for the type of probe administered were not available. Hence, after data collection concluded, coders re-classified the type of each probe in Treatment 2.

category – a form of *zero-shot learning* (Kojima et al., 2022) – for the purposes of a conservative ‘off-the-shelf’ measure of performance.

### 3.4. Fielding

Respondents in our study ( $n = 1,800$ ) were recruited into the Inca platform from a proprietary non-probability panel developed by Prodege, an online market research company, and quota-sampled to match marginal gender, age, and education totals of the U.S. adult population according to the 2020 American Community Survey (ACS). Participants accessed our conversational AI platform and, after providing consent (including acknowledgment of potential interaction with an AI agent), were randomly assigned to one of three experimental conditions.

The survey was fielded on July 15<sup>th</sup>, 2024 and concluded on July 17<sup>th</sup>, 2024. Fielding concluded when 601 complete interviews (chats) were collected across each condition, resulting in 1,803 complete interviews, 195 partial interviews (attrition during the survey), and a total of  $n = 1,998$  interviews altogether. 65% of complete interviews were conducted on a smartphone device, 32% were completed on a Desktop device, and the remaining 3% were completed on other devices such as tablets. Details on the composition of respondents as well as summary statistics of each outcome measure can be found in the Appendix.

### 3.5. Outcomes

**Coding Performance.** We first evaluate the confirmation probing (in Treatment 2) in terms of *accuracy* with respect to the respondent’s own confirmation of the coded category – codings met with a “no” response or undetected categories requiring a categorical confirmation were considered inaccurate. Additionally, we measured *precision* or the degree of false positive error (categories detected but not confirmed) and *recall* or the degree of false negative error (categories not detected but later confirmed by respondents).

Additionally, we compared the textbot’s active coding to a team of three human coders’ labels created after data collection, according to the same codebook, on a sample of 100 responses for each question. Discrepancies could occur, for instance, due to acquiescence bias (Krosnick, 1999), where respondents are biased towards confirmation even if the coded category is not accurate.

**Response Quality.** We measure response quality in each open-ended response across our experiments based on both qualitative human assessments of response quality and quantitative measures of textual information. Qualitative indicators of response quality were defined and assessed by a team of three human coders. First, the team of coders inductively constructed definitions of ‘response quality’ using independent samples of 100 open-ended responses divided evenly across treatment conditions from each question group. Definitions were refined until agreement could be reached on the exact meaning of each and whether they could be reliably identified. The final criteria, similar to those developed in closely related studies (Xiao et al., 2020; Wuttke et al., 2024), are as follows:

- *Relevance.* Respondent provides a response that answers the question (e.g., stays on topic, does not refer to other questions).
- *Specificity.* Respondent provides specificity in their answer (e.g., providing examples or proper nouns, if applicable, rather than referring to abstract concepts).

- *Explanation*. Respondent provides explanations, motivations, or reasons for their response (only applicable for opinion questions, i.e. ‘Most Important Issue’ and ‘Economic Conditions’).
- *Completeness*. Respondent provides a response that fully answers the question and does not omit any part of the question, if there are multiple parts.
- *Comprehensibility*. Respondent provides a response largely free of major spelling, grammatical, or other syntactic errors that deter human understanding of the response.
- *Concision*. Respondent does not provide duplicate or redundant information.

These criteria formed a codebook that was then applied to a larger sample of open-ended responses from each question-level experiment among both Control and Treatment 1 respondents. Crucially, the coders applied these criteria to the combined text of the seed/probe responses in Treatment 1 and were blind to the treatment status of each respondent that they coded. A second round of coders repeated the process on 100 pre-probing responses in Treatment 1. This allowed us to compare response quality before and after probing and to assess whether the textbot targeted low-quality responses or probed indiscriminately.

As a supplement to these human-coded criterion, we created quantitative measures of response quality were in order to capture the total informational content conveyed in each response. First, we measured the *lexical diversity* operationalized as the number of unique words in each response as a ratio of the total number of words. A higher score indicates a more diverse vocabulary which may signal that the respondent used a wide range of words, potentially providing more detailed and varied information. Second, we measured the *Shannon entropy* of responses, defined as the uncertainty or unpredictability of word occurrences within each response. This metric is calculated as:

$$H(x) = - \sum_{i=1}^n p(x_i) \log(p(x_i)),$$

where  $n$  is the number of unique words in the given response text represented by  $x$  and  $p(x_i)$  denotes the probability of the  $i$ th word  $x_i$  appearing in the response (operationalized as the number of occurrences over the total word count in the response). Greater Shannon entropy estimates mean that the response contains a wider range of words with more even distributions, implying a richer and more informative response. Conversely, lower entropy estimates indicate a less varied use of words and uneven values of  $p(x_i)$ , suggesting that the response may be more repetitive or less informative.

We also measured the *Kullback-Leibler (KL) divergence*, which quantifies how the word distribution in a respondent’s response diverges from the overall word distribution across all responses. This is operationalized as

$$KL(x) = - \sum_{i=1}^n \log \frac{p(x_i)}{q(x_i)},$$

where  $q(x_i)$  denotes the probability of word  $x_i$  appearing in any respondent’s response for that particular question (operationalized as the total count of that word in the sample over the total

word count for that question across all respondents). In contrast to Shannon entropy which provides a conservative absolute measure of informativeness, a greater KL divergence means the respondent's word usage is more unique relative to other responses in the overall sample. A lower KL divergence suggests that the response closely follows the typical word distribution, which might indicate less uniqueness or specificity in the information provided.

**Respondent Experience.** We measured the quality of respondents' survey experience both behaviorally and attitudinally.

Our behavioral measure of experience was attrition (or, interchangeably, dropout) during or after each question-level experiment. Attrition is considered a strong barometer of user experience. If a respondent drops out, it suggests that their experience was poor enough to deter them from continuing the survey (Groves et al., 2009). The advantage of this measure is that it allows us to isolate the effect of each question on respondent experience. However, it is important to note that question order may also affect dropout rates, as earlier questions could more strongly influence a respondent's decision to leave the survey. Due to limitations of the platform, we could not measure completion time for individual questions, though we were able to observe the total duration of each interview. While response times can be interpreted a proxy for respondent inattention and other sources of measurement error, in practice, it can be difficult to disentangle from natural variations in survey-taking speed not related to engagement (Yan & Olson, 2013). In our context, response times are a function of both respondent's time spent answering and the textbot's latency in generating probes. Nonetheless, we provide a summary of survey timing in Appendix Table A3 and Table A4.

Attitudinal reports of respondent experience were measured using a series of 5-point Likert scale questions at the end of the survey along different dimensions: *Quality*, *Ease*, *Frustration*, and *Satisfaction* (full question wording in Appendix). Though these attitudinal measures provide granular evaluations of the respondent's experience, there are limitations. Since they are self-reported at the end of the survey, they may be biased upwards, as respondents who had a lower evaluation of the survey experience may have already dropped out. Additionally, responses to these questions at the end of the survey may be subject to satisficing, where respondents provide satisfactory rather than optimal answers due to fatigue. Despite these limitations, consideration of both behavioral and attitudinal measures allows for a more robust understanding of how respondents experience a survey (Groves et al., 2009).

### 3.6. Analysis

All analyses were conducted using the R programming language. We estimated treatment effects on the aforementioned outcomes using OLS regression models, both without and with control covariates obtained from Prodege about our panelists—work status (except for analyses related to the occupation question), gender, household income, educational attainment, and device type. Estimates are presented with confidence intervals adjusted for multiple comparisons using the BHq correction (Benjamini & Hochberg, 1995), with the family set at the level of each figure.<sup>5</sup>

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<sup>5</sup> For the purposes of interpretability, we present estimates produced by linear regression even when outcomes are binary (e.g., response quality indicators), per the recommendations of Gomila (2021). All such results are substantively similar when replicated using average predictive comparisons estimated from logistic regression.

## 4. Results

### 4.1. Active Coding and Confirmation Probing

We begin by examining the results related to confirmation probing in Treatment 1. Table 2 and Table 3 evaluate active coding in two ways: according to the respondent's own confirmation and according to independent human coders' aggregated coding of each relevant concept.

**Table 2. Coding Performance (Respondent Confirmation) in Confirmation Probing Condition (Treatment 1)**

Performance Metric	Most Imp. Issue	Econ. Cond. (Sentiment)	Econ. Cond. (Reason)	Pref. News	Main Occu.
<b>Accuracy</b> (% responses where respondent agreed with coded category / non-coding)					
	73.5%	96.2%	80.9%	66.1%	84.8%
<b>Precision</b> (% codings with response 'yes' in confirmation probe)					
	95.9%	96.2%	96.2%	93.0%	91.8%
<b>Recall</b> (% confirmed category incidences that were coded)					
	73.6%	92.2%	80.7%	61.2%	85.1%

With the exception of news sources, where accuracy and recall both fell below 70%, the textbots performed better than random guesses (>70% correct) without additional training, based on respondents' confirmations. The textbot's recall for the preferred news source question was low, reflecting a greater need for respondents to manually confirm a category that was missed by the textbot (path (b) under Treatment 2 in Figure 1). Nevertheless, the textbot's initial selection of response categories in Treatment 2 correlates strongly with those directly selected by Control respondents in close-ended questions (Figure A9).

Respondents tend to agree more often with the textbot's coding than do independent human coders. For instance, 81% of respondents confirm that the textbot's characterization of their economic sentiment reasons is correct, while only 72% of the human codings align with the textbot's coding. What accounts for this discrepancy? As shown in Table 3 (second row), the precision of coder assessments is, on average, 20% lower than that of respondents' confirmations (second row in Table 2). In other words, respondents tend to favor the "yes" choice in a confirmation probe, a sign of acquiescence bias and a common issue in surveys.

**Table 3. Coding Performance (Human Coder Agreement) in Confirmation Probing Condition (Treatment 1)**

Performance Metric	Most Imp. Issue	Econ. Cond. (Sentiment)	Econ. Cond. (Reason)	Pref. News	Main Occu.
<b>Accuracy</b>					
(% responses where majority human coding matched coded category / non-coding)	73.1%	90.9%	72.0%	71.0%	82.6%
<b>Precision</b>					
(% coding where majority human coding agreed with category)	79.7%	90.9%	66.7%	60.9%	77.9%
<b>Recall</b>					
(% human-coded category incidences that were coded)	72.0%	90.9%	69.6%	56.0%	76.8%

Supplementary analyses (Appendix Figure A7) provide further evidence of acquiescence bias: while overall category rates are positively correlated between coders and respondents ( $\rho = 0.48\text{--}0.87$ ), “None of the above” is a consistent outlier, with respondents selecting it under 5% of the time despite coders applying it 10–40% of the time.

What are the consequences of using active coding and confirmation probing relative to simply asking close-ended questions? In supplementary analyses (Figure A8 – Figure A12) comparisons of response categories in other conditions to how they’re either confirmed by respondents or coded by coders in Treatment 2 reveal strong correlations in category incidence ( $\rho = 0.75\text{--}0.88$  across questions). This suggests that the usage of confirmation probing may not necessarily induce severe construct validity errors as sometimes occurs through probing (Kuha et al., 2018). Moreover, when respondents do not confirm the textbot’s suggested response, they often select a thematically similar category (e.g., ‘Inflation’ rather than ‘Employment/Jobs’), suggesting the textbot is unlikely to grossly misrepresent a respondent’s intended meaning (Appendix Figure A13).

Finally, coding performance remained consistent across device types, with economic tone and occupation showing the highest levels of accuracy (see Table A5). However, desktop users tended to affirm the textbot’s coding more frequently for economic reasons. It is important to note that these differences do not necessarily indicate greater acquiescence bias on one device type versus another. The original content of the responses—and consequently the textbot’s coding accuracy—may differ between devices, which could also influence respondents’ confirmation behavior. Moreover, survey fatigue, and correspondingly the willingness to acquiesce particularly on later questions, may operate differently across device type.

## 4.2. Elaboration and Relevance Probing

Before presenting the effects of probing on response quality, we first examine patterns of when probes were and were not triggered in Treatment 2. As Table 4 shows, for only a tiny minority (1-4%) of seed responses to each question were probes not administered. Moreover, the vast majority of probes (up to 98% for the occupation question) could be strictly characterized as elaboration probes, rather than relevance probes. This should be entirely expected, since the baseline relevance of seed responses nearly hits the ceiling, almost 100% for the most important

issue and economic conditions questions (baselines by condition shown in Appendix Figure A3), whereas explanation and specificity tends to be present slightly less often.

Frequent triggering of elaboration probes suggests that the textbot may be perceptive of the specific quality ‘needs’ in the respondent’s seed response, tailoring the type of probe to the dimension of quality in deficit. A comparison of response quality between seed responses and post-probe responses in Appendix Figure A14 shows this is true for some questions – with the most important issue question, for instance, the average seed response that does receive a probe is one of lower quality across the six criteria than the average seed response that induced a probe. This pattern, however, does not extend to the news question where no-probe seed responses have significantly lower completeness and relevance than probed seed responses, though this can only be garnered from 6 seed responses who did not receive a probe.

Finally, as we noted, our coders discovered that there were instances where the textbot delivered “hybrid probes” with elements of both elaboration and relevance, particularly for the news question (15 such instances).

**Table 4. Rates of Probes Triggered in Treatment 2 (Elaboration/Relevance Probing)**

Probe Triggered	% (n) of Seed Responses Where Probe Was Triggered			
	Most Imp. Issue	Econ. Cond.	Pref. News	Main Occu.
<b>Elaboration Probe</b>	94% (622)	85% (538)	68% (414)	98% (361)
<b>Relevance Probe</b>	2% (13)	11% (69)	29% (175)	1% (5)
<b>Hybrid Probe</b>	0% (1)	1% (6)	2% (15)	0% (0)
<b>No Probe</b>	4% (24)	3% (17)	1% (6)	0% (1)
<b>Probe Error</b>	0% (0)	0% (0)	0% (2)	0% (0)

*Note:* Counts exclude respondents who dropped out prior to question being asked (and thus were given no opportunity for a probe). Examples of specific probes can be found in Appendix Table A6.

### 4.3. Probing Effects on Response Quality

Next, we turn to the effects of elaboration/relevance probing on the overall quality of open-ended responses (combining the seed and post-probe response) for each question.

Figure 2 shows that there is, on average, a substantial increase in rates of specificity and explanation criteria of the most important issue and economic evaluation reasoning open-ended responses when respondents are exposed to probing. Probing introduces the risk of redundancy between the seed and post-probe response, but concision does not, on average, decrease when probes are delivered in Treatment 2. Between the Control and Treatment 2 conditions, no other response quality criteria experienced a difference in either direction. The results from Figure 2 are consistent with results from a pre-post design – comparing coded rates of response quality in the seed response to the post-probe response within individual (Appendix Figure A15).

**Figure 2. Effects of Elaboration/Relevance Probing (Treatment 2 vs. Control) on Human-Coded Quality Criteria**

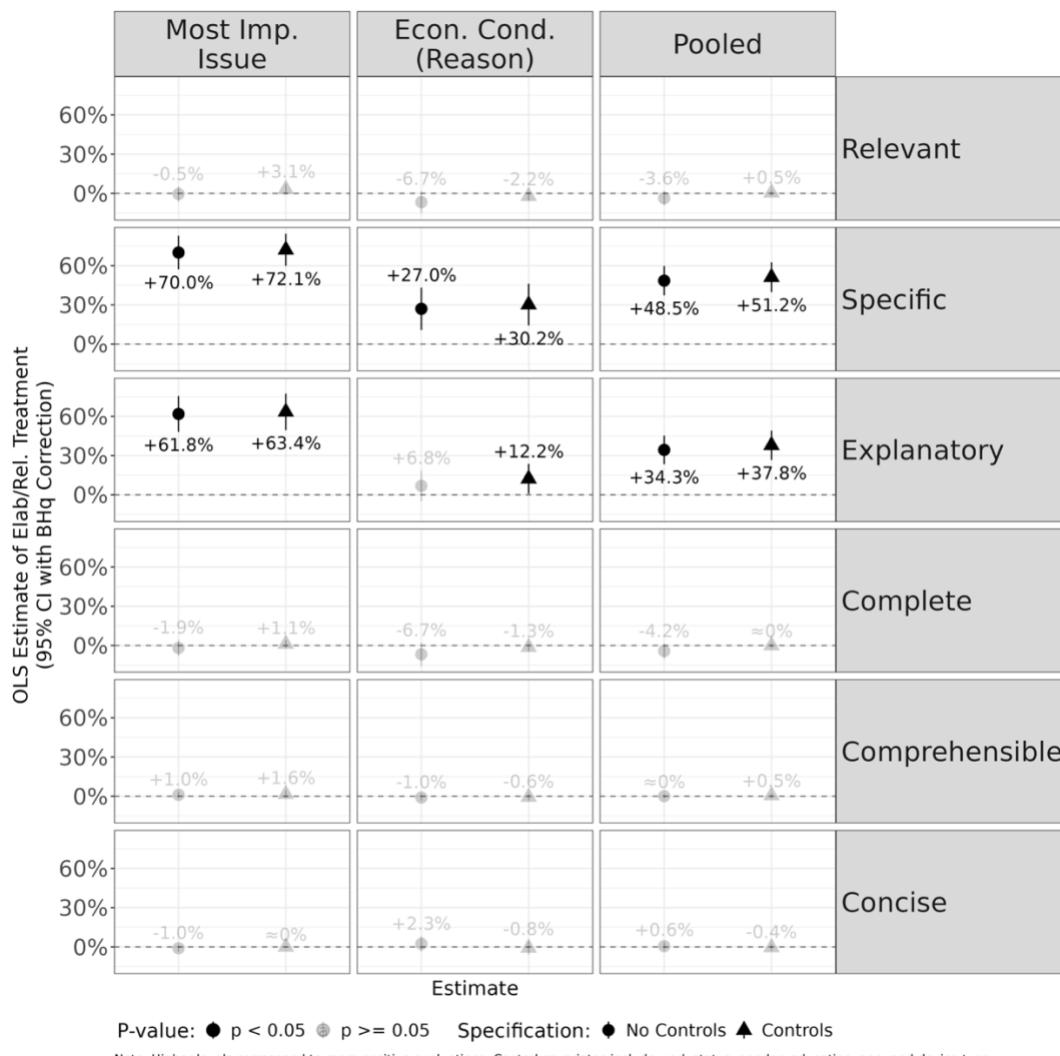
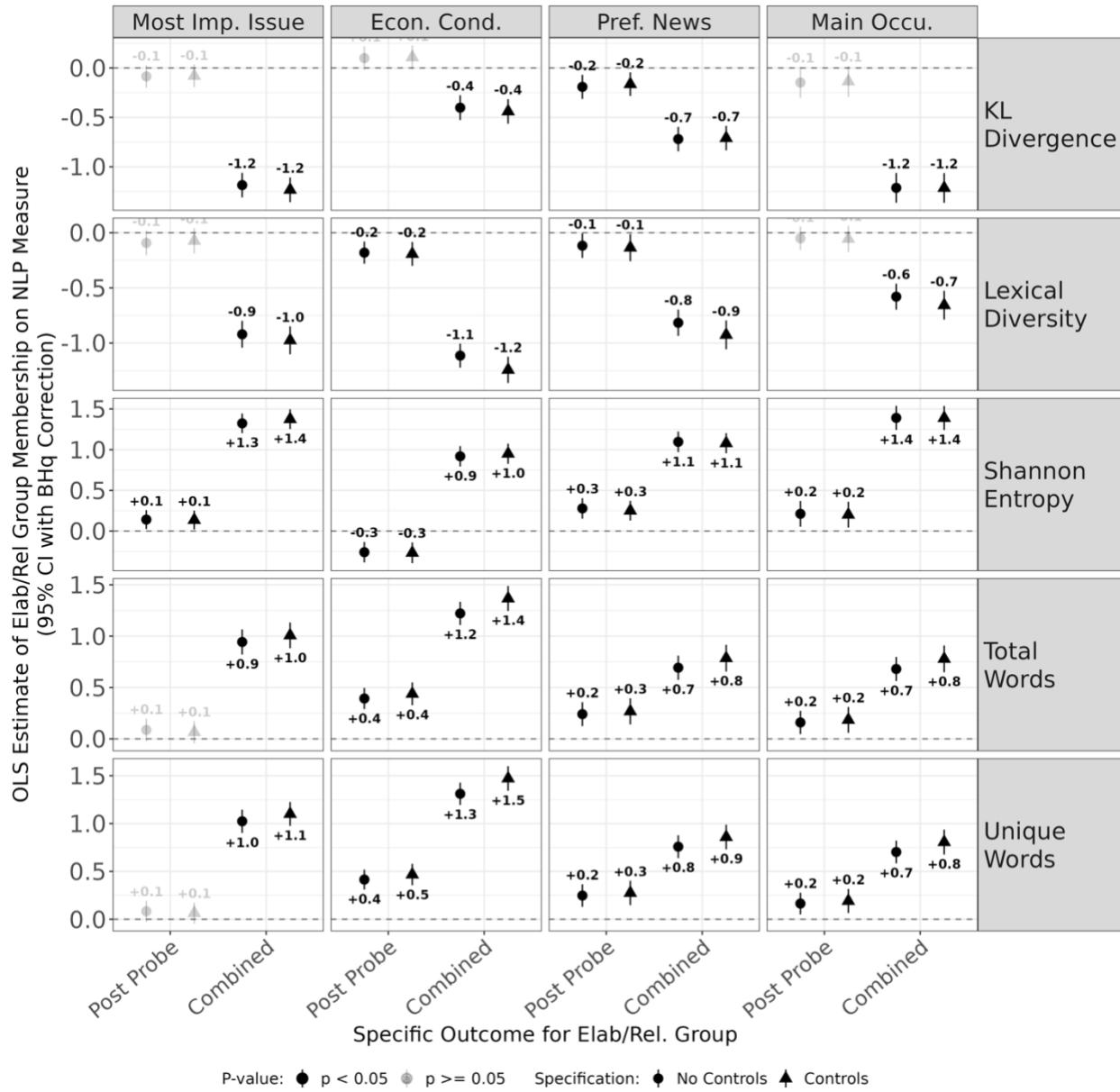


Figure 3 presents the impacts of receiving probes in Treatment 2 on information content, operationalizing the outcome to be either the post-probe or combined seed/post-probe response, with seed responses in the Control condition as the baseline. It is trivial that both total and unique words increased with probing when the outcome is the combined response, though the mean word count in the post-probe response was higher than the mean word count in the seed response. While probing increased the Shannon Entropy in the subsequent response, it did not increase (and sometimes decreased) the KL divergence, meaning that new words in the post-probe response did not significantly deviate from the overall distribution of words, or ‘contribute new information’ to the sample. Lexical diversity also did not experience an effect, suggesting that new concepts may not have been systematically introduced post-probe that were not referenced in the first response. Subgroup-level estimates of treatments effects exhibit nearly no variation across these measures.

**Figure 3. Effects of Elaboration/Relevance Probing (Treatment 2 vs. Control) on Informational Measures**

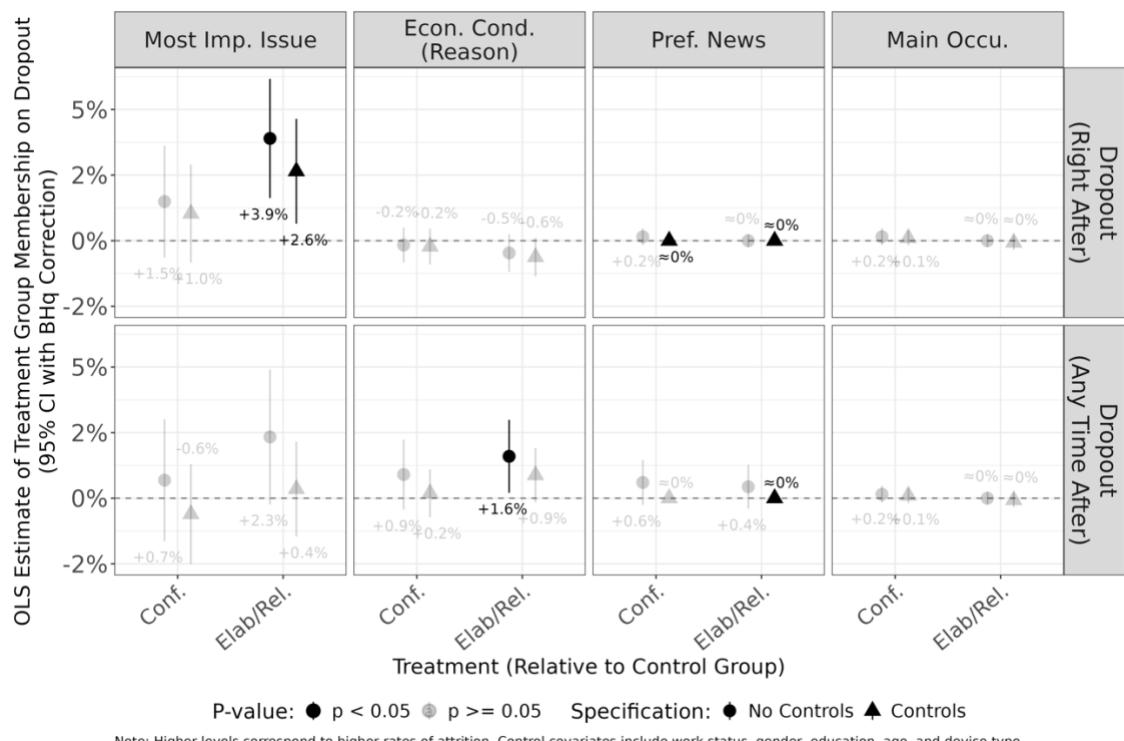


#### 4.4. Probing Effects on User Experience

Completion patterns suggest probing does impact respondent experience (Appendix Table A2): dropouts were approximately twice as high in Treatment 1 (Confirmation Probing) compared to the Control Condition ( $n = 88$  vs.  $n = 43$ ). Similarly, interview duration was longer for both treatment conditions, particularly in Treatment 2 (Elaboration or Relevance Probing) where the average chat lasted twice as long (6 min.) as in the Control Condition (3 min.) (Appendix Table A3 and Table A4).

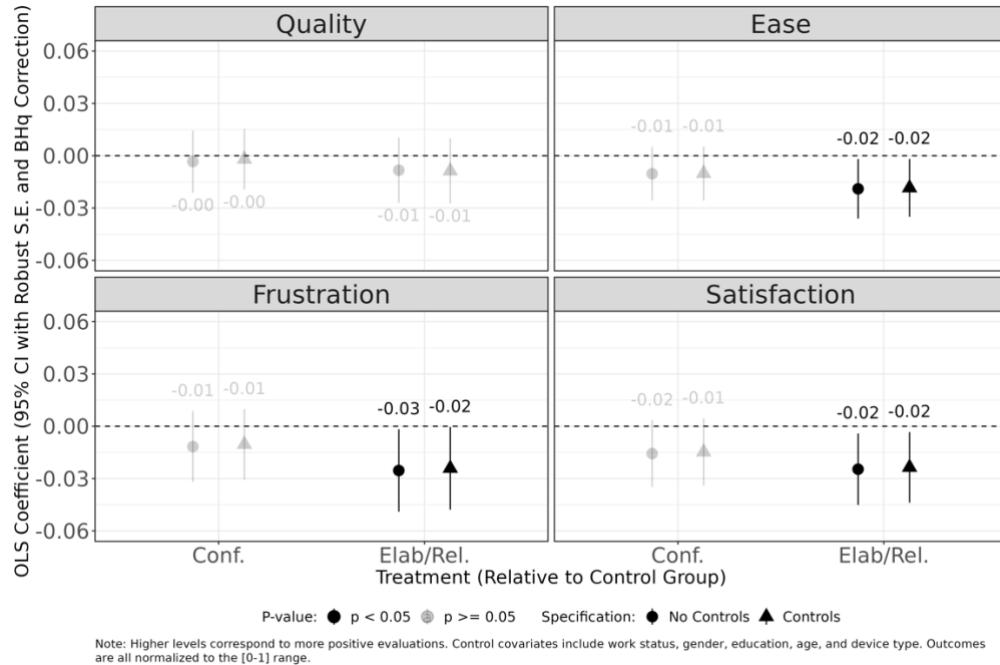
Figure 4 provides a comparison of attrition (operationalized either as respondent drop-out immediately after or any time after exposure to a question) across questions in both Treatment 1 and Treatment 2 relative to rates in the Control condition. Confirmation probing does not appear to increase attrition propensity any time during the survey, while elaboration or relevance probing only increases the likelihood to drop out by 2-3% for the first question. That subsequent probes do not induce further attrition suggests that either respondents habituate to the probing design or that the first question probes weeds out respondents who cannot habituate, or both (Behr et al., 2014). We did not detect any heterogeneity in attrition effects across any subgroup for any question or treatment condition. Despite the greater attrition rates induced by elaboration/relevance probing, coded response categories between Treatment 1 and Treatment 2 remain highly correlated across questions (Appendix Figure A10).

**Figure 4. Effects of Probing (Treatment 1 or 2) on Respondent Attrition**



Lastly, we present how exposure to either treatment bundle of probes shapes the overall self-reported survey experience. As Figure 5 shows, we find statistically significant but substantively small negative effects (in all cases, a movement of less than 0.05 on a normalized 0-1 scale) of receiving the full dosage of elaboration/relevance probing (Treatment 2) on ease, frustration, and satisfaction. Relative to the Control interview, the full sequence of confirmation probes introduced in Treatment 1 has no effect on any self-reported dimensions of respondents' experience. These results are almost certainly biased in a positive direction: respondents who 'survive' to evaluate the survey experience are likely to have a less negative experience than respondents who did not complete the interview.

**Figure 5. Effects of Probing (Treatment 1 or 2) on Self-Reported User Experience**



On user experience, we do observe differences in treatment effects by demographic group. In particular, when exposed to elaboration/relevance probing, mobile respondents tend to report lower ease of use and frustration, while desktop respondents only rate lower frustration. Older respondents (aged 60+) are the only age group to significantly rate lower ease of use as are respondents with a Bachelor's degree. While such subgroup-level negative effects are statistically significant, as with sample-wide effects, they remain small in overall magnitude.

## 5. Discussion

Altogether, our findings present a mixed picture: AI-assisted conversational interviewing via textbots can elicit more specific, detailed, and informative open-ended responses—though not consistently across all measures or subgroups. Notably, without any training on our specific survey, the textbot was generally able to identify when elaboration was needed. While the first probe in the elaboration/relevance condition led to slightly higher dropout than the standardized condition, those who remained reported only slightly less favorable experiences, even after receiving multiple probes by the end of the survey. Moreover, dropout rates were significantly lower than in previous evaluations of open-ended probing (Behr et al., 2012; Holland & Christian, 2009; Neuert & Lenzner, 2021). Confirmation probing, in particular, had little impact on attrition or respondent experience and introduced minimal shifts in response category distributions. Nevertheless, coding via textbot exhibited variable accuracy by question type and inflated the false positive rate in coding error, likely due to acquiescence bias.

It is perhaps unsurprising that confirmation probes have fewer negative impacts than other probes, as prior research indicates that close-ended (e.g., confirm vs. don't confirm) probes impose a lower cognitive burden than do open-ended probes (Neuert et al., 2023). One practical recommendation that arises from our results is to administer open-ended probes sparingly,

particularly for mobile users who are more sensitive to the user experience both in our study and previous research (De Bruijne & Wijnant, 2014). The effectiveness of probing did not appear to differ significantly between factual and opinion-based questions, though our evaluation is limited since only opinion-based questions included open-ended control responses for comparison. The textbot achieved high accuracy in coding binary economic sentiment and occupation, but struggled more with news sources—likely due to variability in naming conventions and acronym ambiguity—though still performed better than chance, with a 74% confirmation rate among desktop users. These errors could inform future model fine-tuning.

Despite promising results, researchers should apply large language models in survey research with caution. LLMs remain “black boxes,” prone to hallucination—that is, misinterpreting instructions or confidently producing incorrect or misleading outputs (Ji et al., 2023). While our conversational textbots were not tasked with generating factual information, hallucinations in this context might involve ignoring or misapplying preprogrammed prompts used to guide probing behavior. Additionally, just as complex or ambiguous survey questions can burden respondents, lengthy or vague answers may tax the textbot, increasing response time and potentially reducing the quality of follow-up probes. Future studies should explore these limitations further by comparing models, adjusting system parameters (e.g., temperature, tone), and testing different LLM configurations—from smaller, faster models optimized for latency to more reasoning-intensive agents. These trade-offs will shape how well conversational agents perform in real-world data collection. In short, textbots seem at present to exhibit too varied performance to support rigorous statistical conclusions, yet this study indicates clear promise and concrete paths toward the realization of this promise.

Improvements to the conversational interface itself might address problems of attrition, response bias, and poor user experience. Introducing ‘skip’ buttons into the chat interface could, for instance, convert attrition into non-response, providing a question-by-question lever for respondents to alleviate cognitive burden without exiting the survey. The acquiescence bias associated with ‘yes/no’ confirmation probes might be mitigated by displaying the textbot’s coded category as the default or suggested choice in a categorical, rather than binary, confirmation probe. Researchers could also approach the process of live-coding using an entirely different mixed-format approach, where close-ended options are paired with an “other, specify” input, followed by confirmation probing only on “other specify” responses.

Finally, future studies might consider other AI-assisted interviewing techniques such as the dynamic generation of motivational statements or respondent feedback, both shown to increase respondent engagement in conventional probing (Dillman et al., 2008; Oudejans & Christian, 2010). Expanding beyond ‘textbots’ to audio-based conversational agents could be fruitful, given the differing information (Gavras et al., 2022) as well as rich context found in oral responses (Höhne et al., 2024) relative to written responses. Future work should carefully balance these benefits against potential costs in respondent experience.

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## References

- Antoun, C., Couper, M. P., & Conrad, F. G. (2017). Effects of Mobile versus PC Web on Survey Response Quality: A Crossover Experiment in a Probability Web Panel. *Public Opinion Quarterly*, 81(S1), 280–306. <https://doi.org/10.1093/poq/nfw088>
- Bail, C. A. (2024). Can Generative AI improve social science? *Proceedings of the National Academy of Sciences*, 121(21), e2314021121. <https://doi.org/10.1073/pnas.2314021121>
- Behr, D., Bandilla, W., Kaczmirek, L., & Braun, M. (2014). Cognitive probes in web surveys: On the effect of different text box size and probing exposure on response quality. *Social Science Computer Review*, 32(4), 524–533. <https://doi.org/10.1177/0894439313485203>
- Behr, D., Kaczmirek, L., Bandilla, W., & Braun, M. (2012). Asking Probing Questions in Web Surveys: Which Factors have an Impact on the Quality of Responses? *Social Science Computer Review*, 30(4), 487–498. <https://doi.org/10.1177/0894439311435305>
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1), 289–300.
- Billiet, J., & Loosveldt, G. (1988). Improvement of the Quality of Responses to Factual Survey Questions by Interviewer Training. *The Public Opinion Quarterly*, 52(2), 190–211.
- Birt, L., Scott, S., Cavers, D., Campbell, C., & Walter, F. (2016). Member Checking: A Tool to Enhance Trustworthiness or Merely a Nod to Validation? *Qualitative Health Research*, 26(13), 1802–1811. <https://doi.org/10.1177/1049732316654870>
- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020). *Language Models are Few-Shot Learners*. arXiv. <https://doi.org/10.48550/arXiv.2005.14165>
- Conrad, F. G., Couper, M. P., Tourangeau, R., & Galesic, M. (2005). Interactive Feedback Can Improve the Quality of Responses in Web Surveys. *Proceedings of the ASA Section on Survey Research Methods*.
- Conrad, F. G., & Schober, M. F. (2000). Clarifying Question Meaning in a Household Telephone Survey. *Public Opinion Quarterly*, 64(1), 1–28. <https://doi.org/10.1086/316757>
- Couper, M. P., Antoun, C., & Mavletova, A. (2017). Mobile Web Surveys. In *Total Survey Error in Practice* (pp. 133–154). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781119041702.ch7>
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2008). Internet, mail, and mixed-mode surveys: The tailored design method. In *Internet, mail, and mixed-mode surveys: The tailored*

- design method* (pp. xii, 499). Wiley. <https://www.proquest.com/docview/1095630275?pq-origsite=summon&sourcetype=Books>
- Feldman, J. J., Hyman, H., & Hart, C. W. (1951). A Field Study of Interviewer Effects on the Quality of Survey Data. *Public Opinion Quarterly*, 15(4), 734. <https://doi.org/10.1086/266357>
- Fellegi, I. P. (1964). Response Variance and its Estimation. *Journal of the American Statistical Association*. <https://www.tandfonline.com/doi/abs/10.1080/01621459.1964.10480747>
- Fowler, F., & Mangione, T. (1990). *Standardized Survey Interviewing*. SAGE Publications, Inc. <https://doi.org/10.4135/9781412985925>
- Fricker, S., Galesic, M., Tourangeau, R., & Yan, T. (2005). An Experimental Comparison of Web and Telephone Surveys. *The Public Opinion Quarterly*, 69(3), 370–392.
- Gavras, K., Höhne, J. K., Blom, A. G., & Schoen, H. (2022). Innovating the Collection of Open-Ended Answers: The Linguistic and Content Characteristics of Written and Oral Answers to Political Attitude Questions. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 185(3), 872–890. <https://doi.org/10.1111/rssa.12807>
- Gomila, R. (2021). Logistic or linear? Estimating causal effects of experimental treatments on binary outcomes using regression analysis. *Journal of Experimental Psychology: General*, 150(4), 700–709. <https://doi.org/10.1037/xge0000920>
- Grimmer, J., Roberts, M. E., & Stewart, B. M. (2022). *Text as Data: A New Framework for Machine Learning and the Social Sciences*. Princeton University Press.
- Groves, R. M. (2005). *Survey Errors and Survey Costs*. John Wiley & Sons.
- Groves, R. M., Jr, F. J. F., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2009). *Survey Methodology*. John Wiley & Sons.
- Gweon, H., & Schonlau, M. (2024). Automated Classification for Open-Ended Questions with BERT. *Journal of Survey Statistics and Methodology*, 12(2), 493–504. <https://doi.org/10.1093/jssam/smad015>
- He, Z., & Schonlau, M. (2022). A Model-Assisted Approach for Finding Coding Errors in Manual Coding of Open-Ended Questions. *Journal of Survey Statistics and Methodology*, 10(2), 365–376. <https://doi.org/10.1093/jssam/smab022>
- Höhne, J. K., Kern, C., Gavras, K., & Schlosser, S. (2024). The sound of respondents: Predicting respondents' level of interest in questions with voice data in smartphone surveys. *Quality & Quantity*, 58(3), 2907–2927.
- Holland, J. L., & Christian, L. M. (2009). The Influence of Topic Interest and Interactive Probing on Responses to Open-Ended Questions in Web Surveys. *Social Science Computer Review*, 27(2), 196–212. <https://doi.org/10.1177/0894439308327481>
- Hubbard, F. A., Conrad, F. G., & Antoun, C. (2020). The Benefits of Conversational Interviewing Are Independent of Who Asks the Questions or the Types of Questions They Ask. *Survey Research Methods*, 14(5), Article 5. <https://doi.org/10.18148/srm/2020.v14i5.7617>

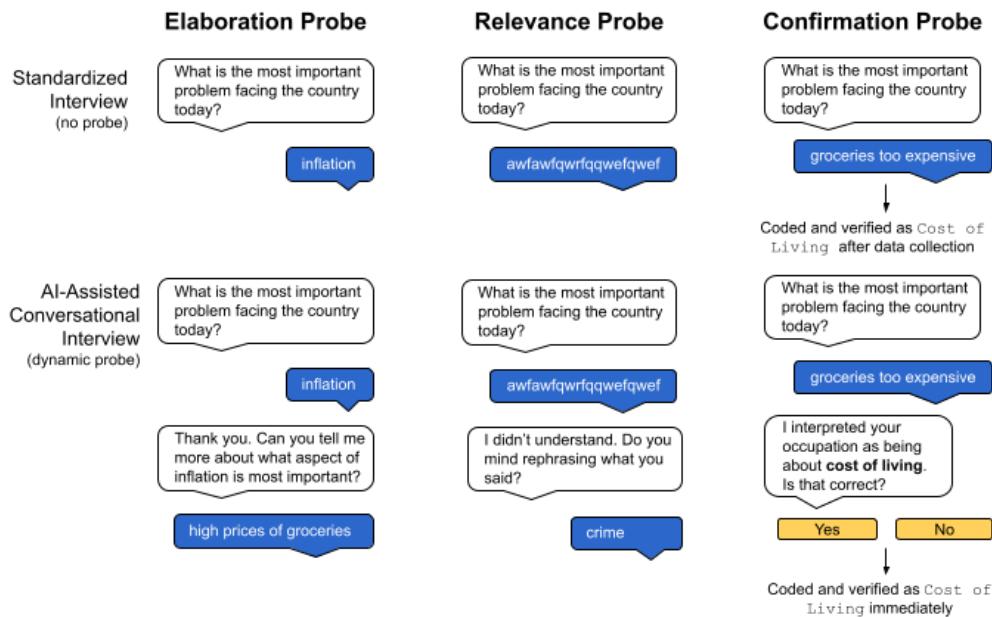
- Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., & Fung, P. (2023). Survey of Hallucination in Natural Language Generation. *ACM Comput. Surv.*, 55(12), 248:1-248:38. <https://doi.org/10.1145/3571730>
- Kojima, T., Gu, S. (Shane), Reid, M., Matsuo, Y., & Iwasawa, Y. (2022). Large Language Models are Zero-Shot Reasoners. *Advances in Neural Information Processing Systems*, 35, 22199–22213.
- Krosnick, J. A. (1999). Survey Research. *Annual Review of Psychology*, 50(Volume 50, 1999), 537–567. <https://doi.org/10.1146/annurev.psych.50.1.537>
- Krosnick, J. A. (2017). Questionnaire Design. In *The Palgrave Handbook of Survey Research* (pp. 439–455). Palgrave Macmillan. [https://link.springer.com/chapter/10.1007/978-3-319-54395-6\\_53](https://link.springer.com/chapter/10.1007/978-3-319-54395-6_53)
- Krosnick, J. A., & Alwin, D. F. (1987). An Evaluation of A Cognitive Theory of Response-Order Effects in Survey Measurement. *Public Opinion Quarterly*, 51(2), 201–219. <https://doi.org/10.1086/269029>
- Kuha, J., Butt, S., Katsikatsou, M., & Skinner, C. J. (2018). The Effect of Probing “Don’t Know” Responses on Measurement Quality and Nonresponse in Surveys. *Journal of the American Statistical Association*, 113(521), 26–40.
- Mason, J. (1997). *Qualitative Researching*. SAGE Publications, 2455 Teller Road, Thousand Oaks, CA 91320; phone: 805-499-0721; fax: 805-499-0871; e-mail: info@sagepub.
- McMann, K., Pemstein, D., Seim, B., Teorell, J., & Lindberg, S. (2022). Assessing Data Quality: An Approach and An Application. *Political Analysis*, 30(3), 426–449. <https://doi.org/10.1017/pan.2021.27>
- Montgomery, J. M., Nyhan, B., & Torres, M. (2018). How Conditioning on Posttreatment Variables Can Ruin Your Experiment and What to Do about It. *American Journal of Political Science*, 62(3), 760–775.
- Neuert, C. E., & Lenzner, T. (2021). Effects of the Number of Open-Ended Probing Questions on Response Quality in Cognitive Online Pretests. *Social Science Computer Review*, 39(3), 456–468. <https://doi.org/10.1177/0894439319866397>
- Neuert, C. E., Meitinger, K., & Behr, D. (2023). Open-ended versus Closed Probes: Assessing Different Formats of Web Probing. *Sociological Methods & Research*, 52(4), 1981–2015. <https://doi.org/10.1177/00491241211031271>
- Olson, K., & Smyth, J. D. (2015). The Effect of CATI Questions, Respondents, and Interviewers on Response Time. *Journal of Survey Statistics and Methodology*, 3(3), 361–396. <https://doi.org/10.1093/jssam/smv021>
- Oudejans, M., & Christian, L. M. (2010). Using Interactive Features to Motivate and Probe Responses to Open-Ended Questions. In *Social and Behavioral Research and the Internet*. Routledge.
- Puri, R., & Catanzaro, B. (2019, December 10). *Zero-shot Text Classification With Generative Language Models*. 3rd Workshop on Meta-Learning at NeurIPS 2019. <http://arxiv.org/abs/1912.10165>

- Schober, M. F., & Conrad, F. G. (1997). Does Conversational Interviewing Reduce Survey Measurement Error? *Public Opinion Quarterly*, 61(4), 576–602.  
<https://doi.org/10.1086/297818>
- Schuman, H., & Presser, S. (1979). The Open and Closed Question. *American Sociological Review*, 44(5), 692–712. <https://doi.org/10.2307/2094521>
- Seltzer, J., Pan, J., Cheng, K., Sun, Y., Kolagati, S., Lin, J., & Zong, S. (2023). *SmartProbe: A Virtual Moderator for Market Research Surveys* (No. arXiv:2305.08271). arXiv. <https://doi.org/10.48550/arXiv.2305.08271>
- Smyth, J. D., Dillman, D. A., Christian, L. M., & McBride, M. (2009). Open-Ended Questions in Web Surveys: Can Increasing the Size of Answer Boxes and Providing Extra Verbal Instructions Improve Response Quality? *Public Opinion Quarterly*, 73(2), 325–337. <https://doi.org/10.1093/poq/nfp029>
- Suchman, L., & Jordan, B. (1990). Interactional Troubles in Face-to-Face Survey Interviews. *Journal of the American Statistical Association*, 85(409). <https://www.tandfonline.com/doi/abs/10.1080/01621459.1990.10475331>
- Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). *The Psychology of Survey Response*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511819322>
- Velez, Y. R., & Liu, P. (2024). Confronting Core Issues: A Critical Assessment of Attitude Polarization Using Tailored Experiments. *American Political Science Review*, 1–18. <https://doi.org/10.1017/S0003055424000819>
- West, B. T., & Blom, A. G. (2017). Explaining Interviewer Effects: A Research Synthesis. *Journal of Survey Statistics and Methodology*, 5(2), 175–211.
- West, B. T., Conrad, F. G., Kreuter, F., & Mittereder, F. (2018). Can Conversational Interviewing Improve Survey Response Quality Without Increasing Interviewer Effects? *Journal of the Royal Statistical Society Series A: Statistics in Society*, 181(1), 181–203. <https://doi.org/10.1111/rssa.12255>
- Wuttke, A., Aßenmacher, M., Klamm, C., Lang, M. M., Würschinger, Q., & Kreuter, F. (2024). *AI Conversational Interviewing: Transforming Surveys with LLMs as Adaptive Interviewers* (No. arXiv:2410.01824). arXiv. <https://doi.org/10.48550/arXiv.2410.01824>
- Xiao, Z., Zhou, M. X., Liao, Q. V., Mark, G., Chi, C., Chen, W., & Yang, H. (2020). Tell Me About Yourself: Using an AI-Powered Chatbot to Conduct Conversational Surveys with Open-ended Questions. *ACM Transactions on Computer-Human Interaction*, 27(3), 15:1–15:37. <https://doi.org/10.1145/3381804>
- Yan, T., & Olson, K. (2013). Analyzing Paradata to Investigate Measurement Error. In *Improving Surveys with Paradata* (pp. 73–95). John Wiley & Sons, Ltd. <https://doi.org/10.1002/9781118596869.ch4>

# Appendix

## A1. Additional Experiment Details

**Figure A1. Examples of AI-Assisted Conversational Interviewing**



**Table A1. Full Questionnaire**

Question Group #	Seed Question / Probe	Control (No Probes)	Treatment 2 (Elaboration/Relevance Probes)	Treatment 1 (Confirmation Probes)
<b>Q0</b>	Consent Screener			
<b>Q1</b>	Most Important Issue	What do you think is the most important problem facing this country today? _____ (open-ended)		
	Elaboration/relevance probe	(If triggered) Could you be more specific?		
	Confirmation probe (binary)			(For sampled category detected in Q1) I interpreted your answer as generally being about _____. Is that correct?
	Confirmation probe (categorical)	(if Q1 probe 2 = no OR Q1 probe 1 category not detected) Which of the following topics did you mention in your answer to the previous question? 1 Economy 2 Cost of Living 3 Federal Budget 4 Jobs 5 Wages 6 Taxes 7 Economic Inequality 8 Corporate Power 9 International Trade 10 Immigration 11 Poverty 12 Elections and Democracy		

Question Group #	Seed Question / Probe	Control (No Probes)	Treatment 2 (Elaboration/Relevance Probes)	Treatment 1 (Confirmation Probes)
				13 Crime 14 Foreign Policy 15 Abortion 16 Race Relations and Racism 17 Climate Change 18 Education 19 Guns/Gun control 20 LGBTQ Issues
Q2	Economic Conditions	How would you rate economic conditions in this country today? 1 Very Good 2 Good 3 Neither Good Nor Bad 4 Bad 5 Very Bad	How would you rate the economic conditions in this country today? _____ (open-ended)	
	Confirmation probe (tone)			(If negative detected in Q2 & not positive detected in Q2) Just to confirm, are you saying that economic conditions are more negative than positive? (If positive detected in Q2 & not negative detected in Q2) Just to confirm, are you saying that economic conditions are more positive than negative?
Q3	Economic Conditions (Reasons)	What are the main reasons for your rating of economic conditions in this country?		What are the main reasons for your rating of economic conditions in this country?
	Elaboration/relevance probe		(If triggered) Could you be more specific?	
	Confirmation probe (binary)			(for each category detected in Q3) Just to confirm, I interpreted one of your reasons as being about _____. Is that correct?
	Confirmation probe (categorical)			(if Q3 probe 2 = no OR Q3 probe 1 category not detected) Which of the following reasons matches your answer to the previous question? 1 Employment/Jobs 2 Layoffs 3 Inflation 4 Wages 5 Stock Market 6 Economic Growth 7 Government Spending 8 Gas Prices 9 Democratic / Biden Administration Policies 10 Interest Rates 11 Illegal immigration 12 Wealth inequality 13 Corporations or Corporate greed 14 Poverty or homelessness 15 Taxes 16 Politicians
Q4	Preferred News Source	What is your main source of news about politics and government? 1 Fox News or FoxNews.com 2 Local TV 3 CNN or CNN.com 4 Facebook 5 NBC 6 ABC or ABCNews.com 7 NPR 8 The New York Times	What is your main source of news? _____ (open-ended)	

Question Group #	Seed Question / Probe	Control (No Probes)	Treatment 2 (Elaboration/Relevance Probes)	Treatment 1 (Confirmation Probes)
		9 Local radio 10 CBS or CBSNews.com 11 MSNBC 12 The Washington Post 13 Another newspaper 14 Newsmax, OANN, Daily Wire or Daily Caller 15 Another TV network 16 Other		
	Elaboration/specificity probe		(If triggered) Could you be more specific?	
	Confirmation probe (binary)			(if Q4 category detected) I interpreted your answer as _____. Is that correct?
	Confirmation probe (categorical)			(if Q4 probe 2 = no OR Q4 category not detected) Do any of the following news sources match your previous answer? 1 Fox News or FoxNews.com 2 Local TV 3 CNN or CNN.com 4 Facebook 5 NBC 6 ABC or ABCNews.com 7 NPR 8 The New York Times 9 Local radio 10 CBS or CBSNews.com 11 MSNBC 12 The Washington Post 13 Another newspaper 14 Newsmax, OANN, Daily Wire or Daily Caller 15 Another TV network 16 None of the above match my answer
	Demographic Instructions	Thank you for answering those questions. Now I have a few questions about you...		
Q5	Age	What is your age? ____		
Q6	Gender	How would you describe your gender? 1 Male 2 Female 3 Other		
Q7	Education	What is the highest level of education you have completed? 1 Less than high school 2 High school graduate or equivalent 3 Some college/associate's degree 4 Bachelor's degree 5 Postgraduate study/professional degree		
Q8	Employment	Are you currently working?		
Q9	Main Occupation (if working)	What kind of work do you do in your principal job? Your principal job is the job at which you work the most hours. Select from the following list of job codes from the Bureau of Labor Statistics that best describes your principal job. 1 Management Occupations 2 Business and Financial Operations Occupations 3 Computer and Mathematical Occupations 4 Architecture and Engineering Occupations	What kind of work do you do in your principal job? Your principal job is the job at which you work the most hours. ____ (open-ended)	

Question Group #	Seed Question / Probe	Control (No Probes)	Treatment 2 (Elaboration/Relevance Probes)	Treatment 1 (Confirmation Probes)
		5 Life, Physical, and Social Science Occupations 6 Community and Social Service Occupations 7 Legal Occupations 8 Educational Instruction and Library Occupations 9 Arts, Design, Entertainment, Sports, and Media Occupations 10 Healthcare Practitioners and Technical Occupations 11 Healthcare Support Occupations 12 Protective Service Occupations 13 Food Preparation and Serving Related Occupations 14 Building and Grounds Cleaning and Maintenance Occupations 15 Personal Care and Service Occupations 16 Sales and Related Occupations 17 Office and Administrative Support Occupations 18 Farming, Fishing, and Forestry Occupations 19 Construction and Extraction Occupations 20 Installation, Maintenance, and Repair Occupations 21 Production Occupations 22 Transportation and Material Moving Occupations 23 Military Specific Occupations		
	Elaboration/specificity probe		(If triggered) Could you be more specific?	
	Confirmation probe (binary)			I recorded your occupation as being in the category of ____ Is that correct?
	Confirmation probe (categorical)			(if Q9 probe 2 = no OR Q9 probe 2 category not detected) Using the job category codes (used by the Bureau of Labor Statistics) below, choose the code that best describes your principal job.
	UX Instructions	Finally, please answer the following questions about your survey experience.		
Q10	Formal Tone	Overall, how formal was the tone of questions in this survey? 1 Very formal 2 Somewhat formal 3 Not very formal 4 Not formal at all		
Q11	Quality	Overall, how would you rate the quality of your responses to questions in this survey? 1 Very high quality 2 Somewhat high quality 3 Somewhat low quality 4 Very low quality		
Q12	Ease	How easy was it to complete this survey? 1 Very easy 2 Somewhat easy 3 Neither easy nor difficult 4 Somewhat difficult 5 Very difficult		
Q13	Frustration	How frustrating was this survey experience? 1 Very frustrating		

Question Group #	Seed Question / Probe	Control (No Probes)	Treatment 2 (Elaboration/Relevance Probes)	Treatment 1 (Confirmation Probes)
		2 Somewhat frustrating 3 Not very frustrating 4 Not frustrating at all		

**Table A2. Completions by Treatment Condition**

Condition	Completes	Dropouts
	Control	601
<b>Treatment 1 (Conf. Probing)</b>	601	64
<b>Treatment 2 (Elab/Rel. Probing)</b>	601	88

**Table A3. Summary Statistics of Interview Duration by Treatment Condition**

Condition	Duration of Interview (Minutes)					
	1%	25%	Median	Mean	75%	99%
<b>Control</b>	0m	1.9m	2.4m	3.1m	3.2m	14.2m
<b>Treatment 1 (Conf. Probing)</b>	0m	2.5m	3.3m	4.1m	4.7m	15.8m
<b>Treatment 2 (Elab/Rel. Probing)</b>	0m	3.1m	4.5m	5.9m	6.8m	29.3m

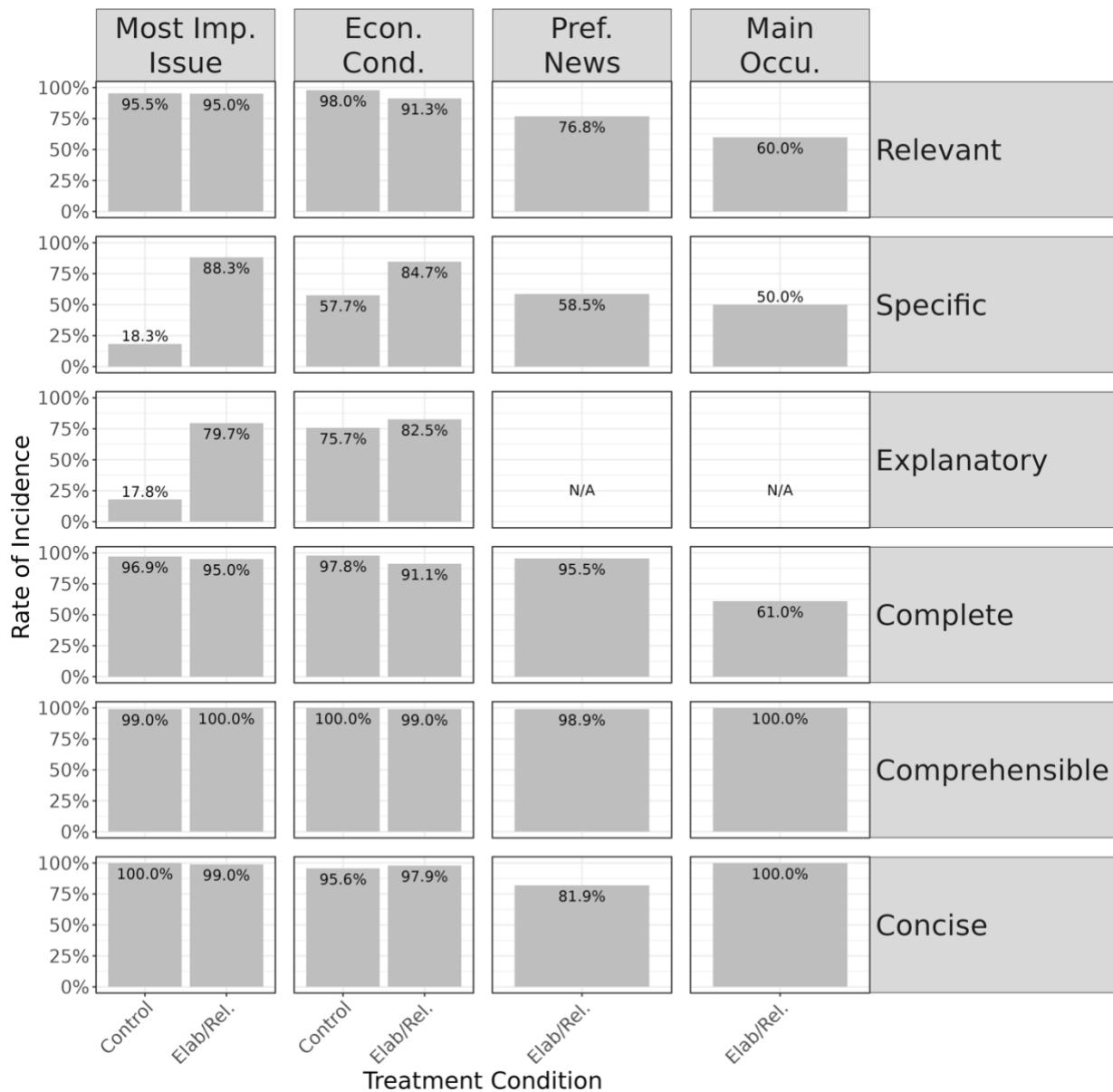
**Table A4. Summary Statistics of Completion Time by Treatment Condition**

Condition	Duration of Interview Among Non-Dropouts (Minutes)					
	1%	25%	Median	Mean	75%	99%
<b>Control</b>	1.3m	1.9m	2.5m	3.3m	3.3m	16.1m
<b>Treatment 1 (Conf. Probing)</b>	1.8m	2.7m	3.5m	4.4m	4.8m	16.2m
<b>Treatment 2 (Elab/Rel. Probing)</b>	1.9m	3.4m	4.9m	6.4m	7.1m	29.3m

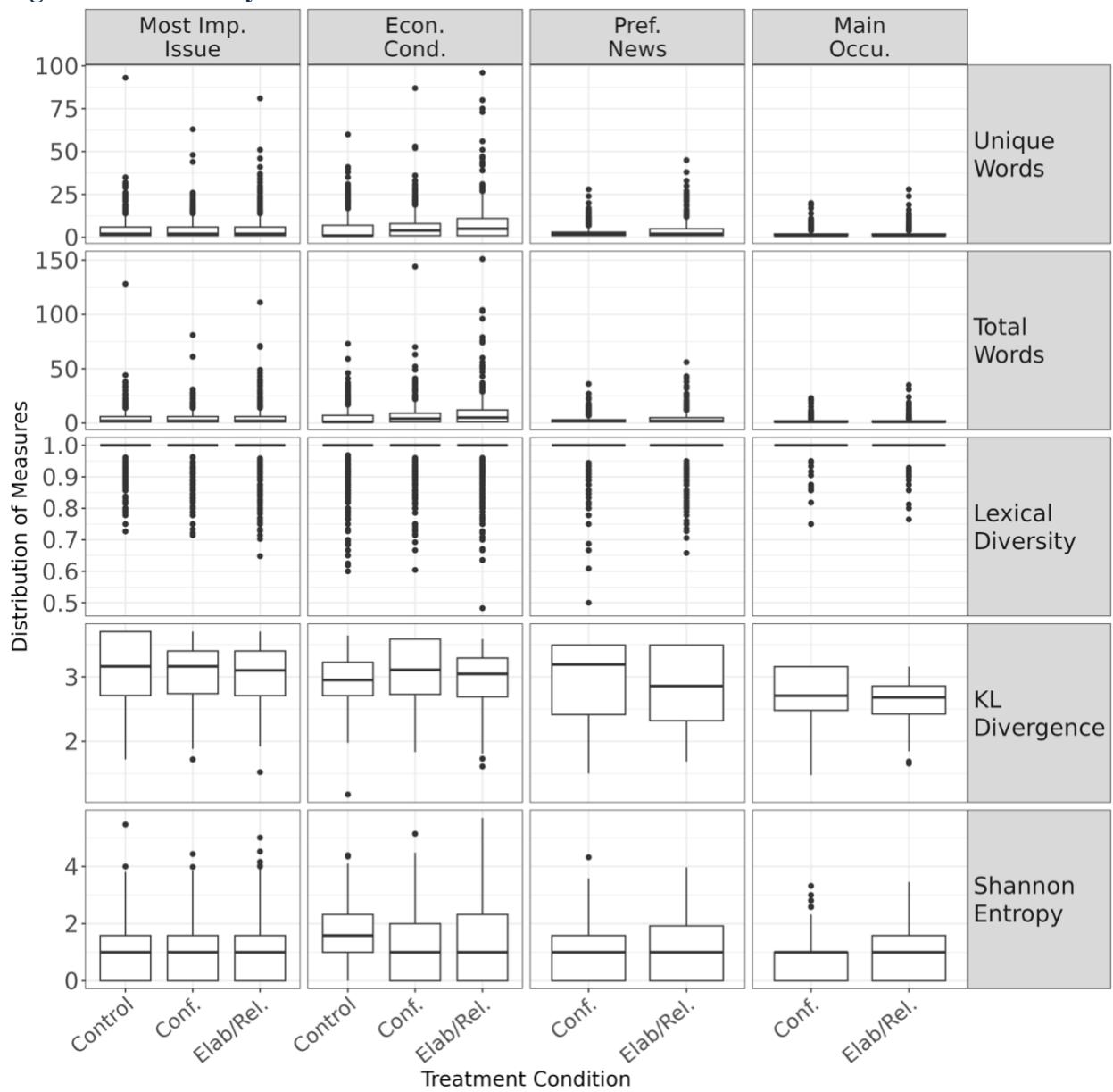
**Figure A2. Sample Composition**



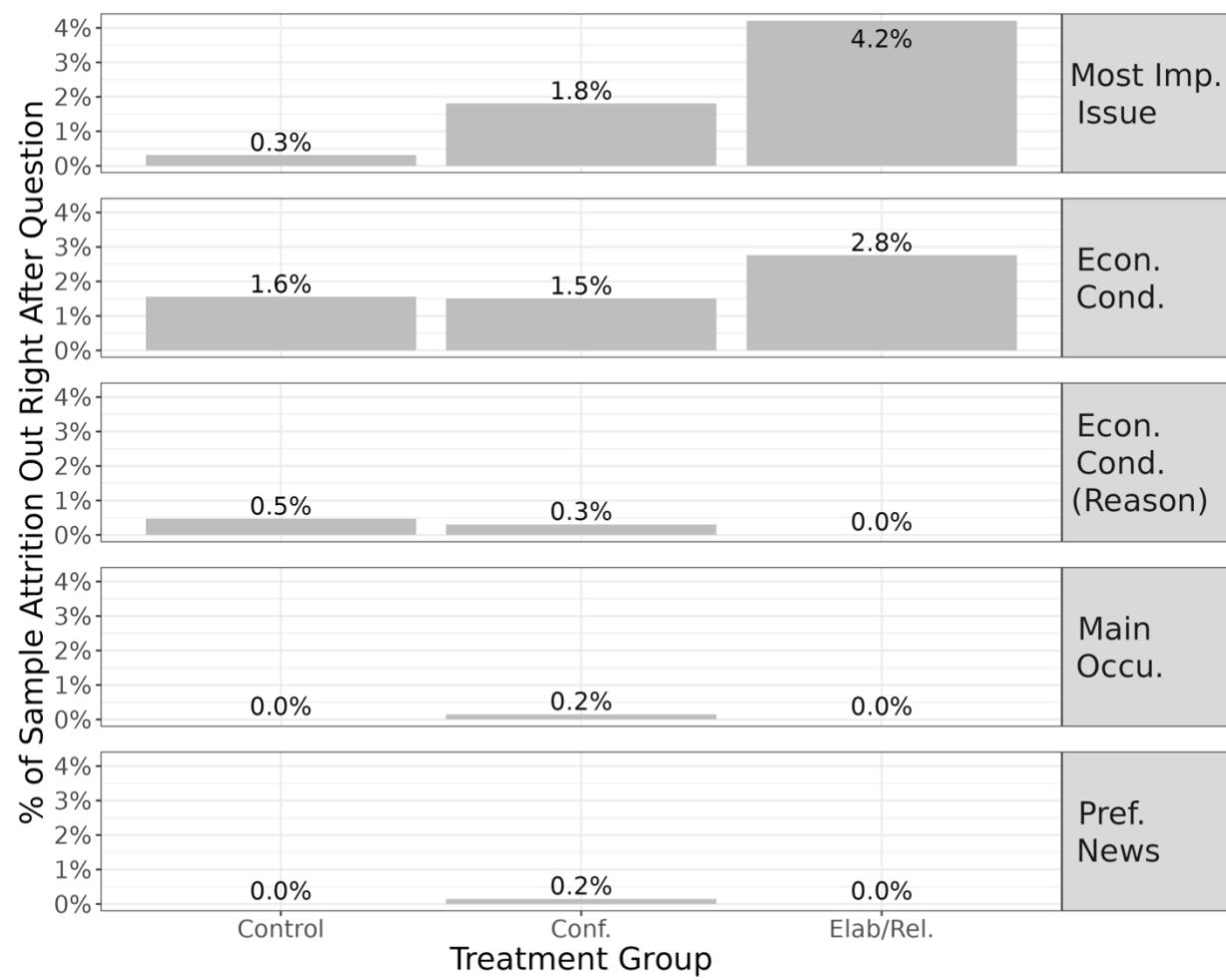
**Figure A3. Summary of Human-Coded Quality Criteria**



**Figure A4. Summary of NLP-Based Informational Measures**



**Figure A5. Summary of Respondent Attrition**

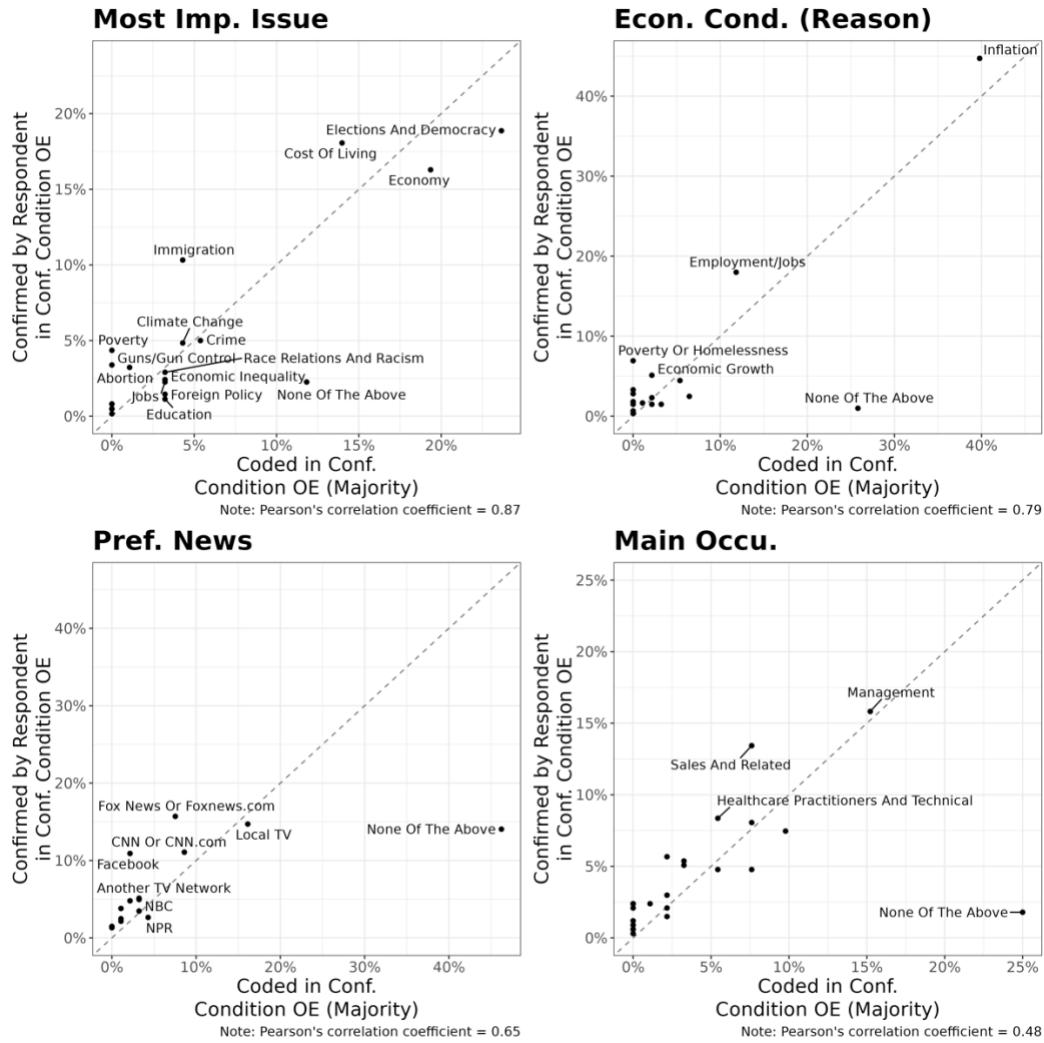


**Figure A6. Summary of Self-Reported User Experience**

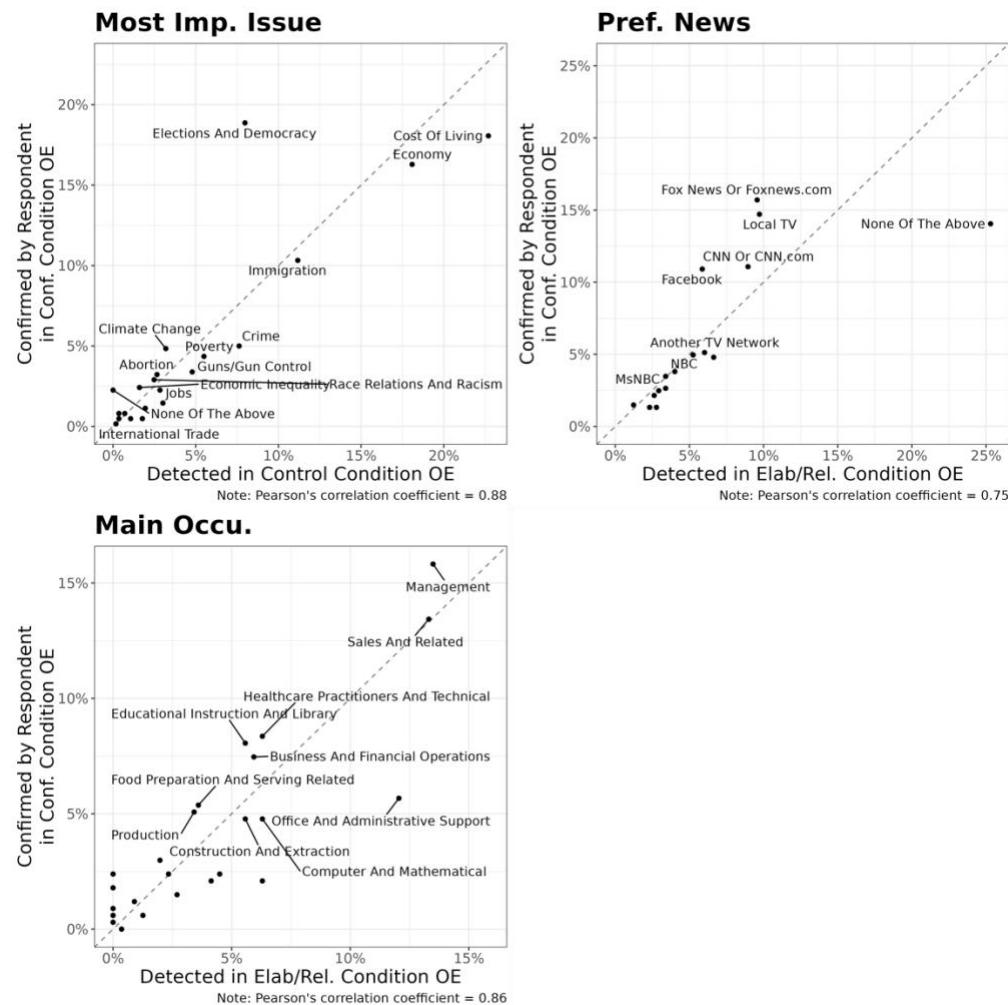


## A2. Additional Active Coding Results

**Figure A7. Evidence of Acquiescence Bias in Confirmation Probing: Comparison of Response Categories (Coded by Coders in Treatment 1 vs. Confirmed by Respondent in Treatment 1)**

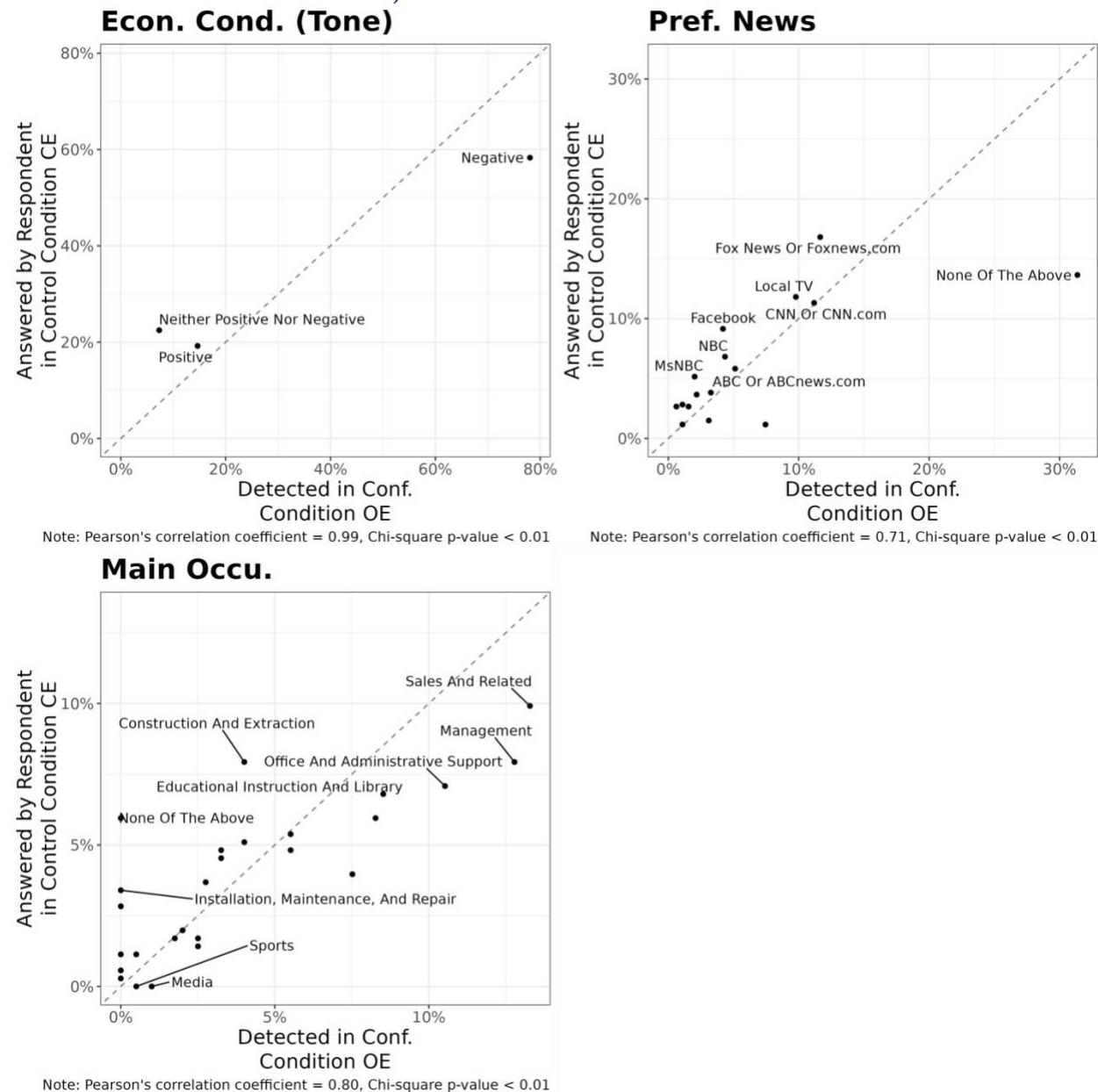


**Figure A8. Comparison of Response Categories (Confirmed in Treatment 1 vs. Coded By Coders in Other Conditions)<sup>6</sup>**

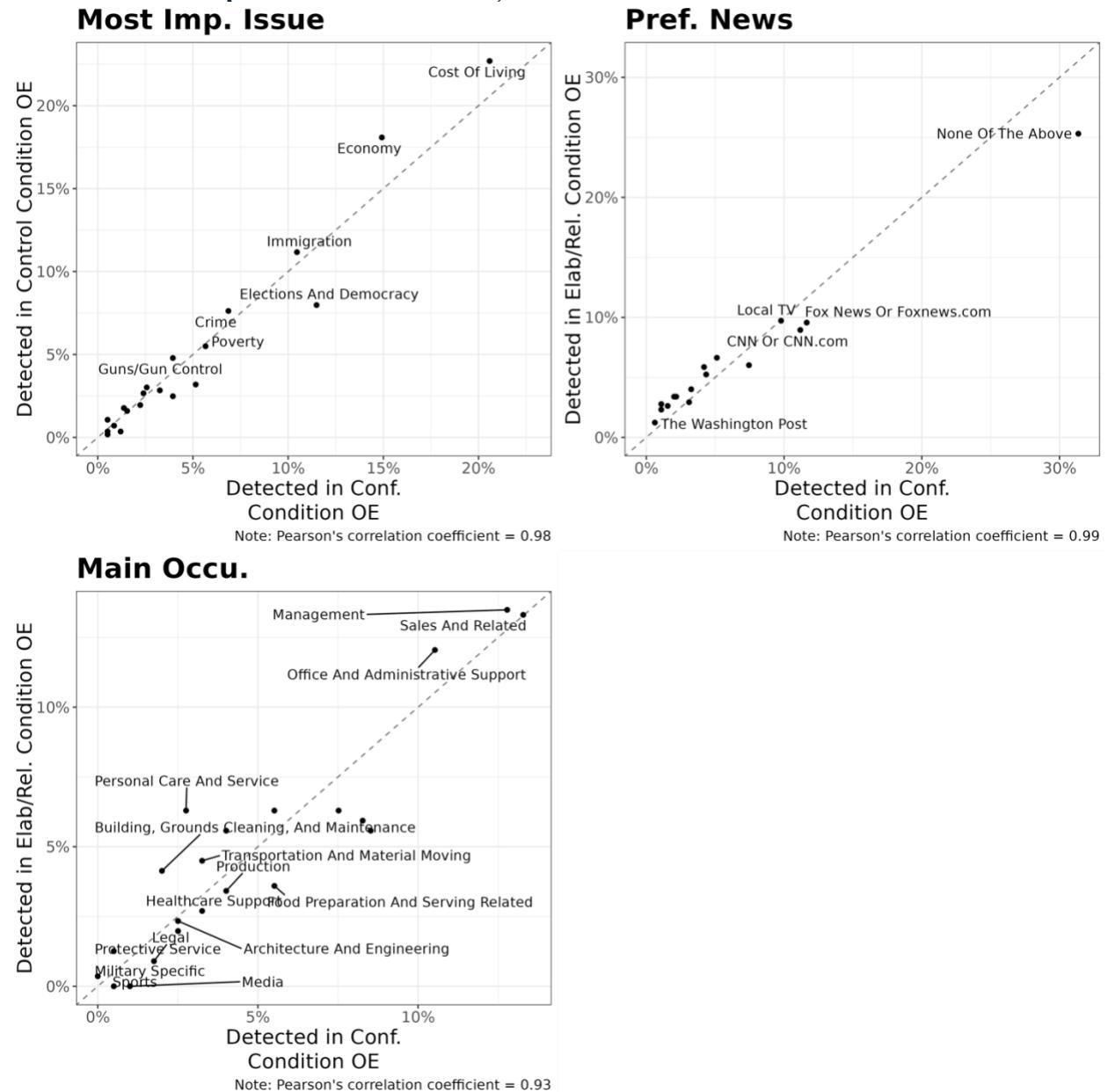


<sup>6</sup> Due to the way the economic conditions (reason) question was asked in the control condition (close-ended) versus the elaboration/relevance conditions (as a probe, rather than a standalone static question), coding of categories was not possible and is therefore omitted from Figure 4.

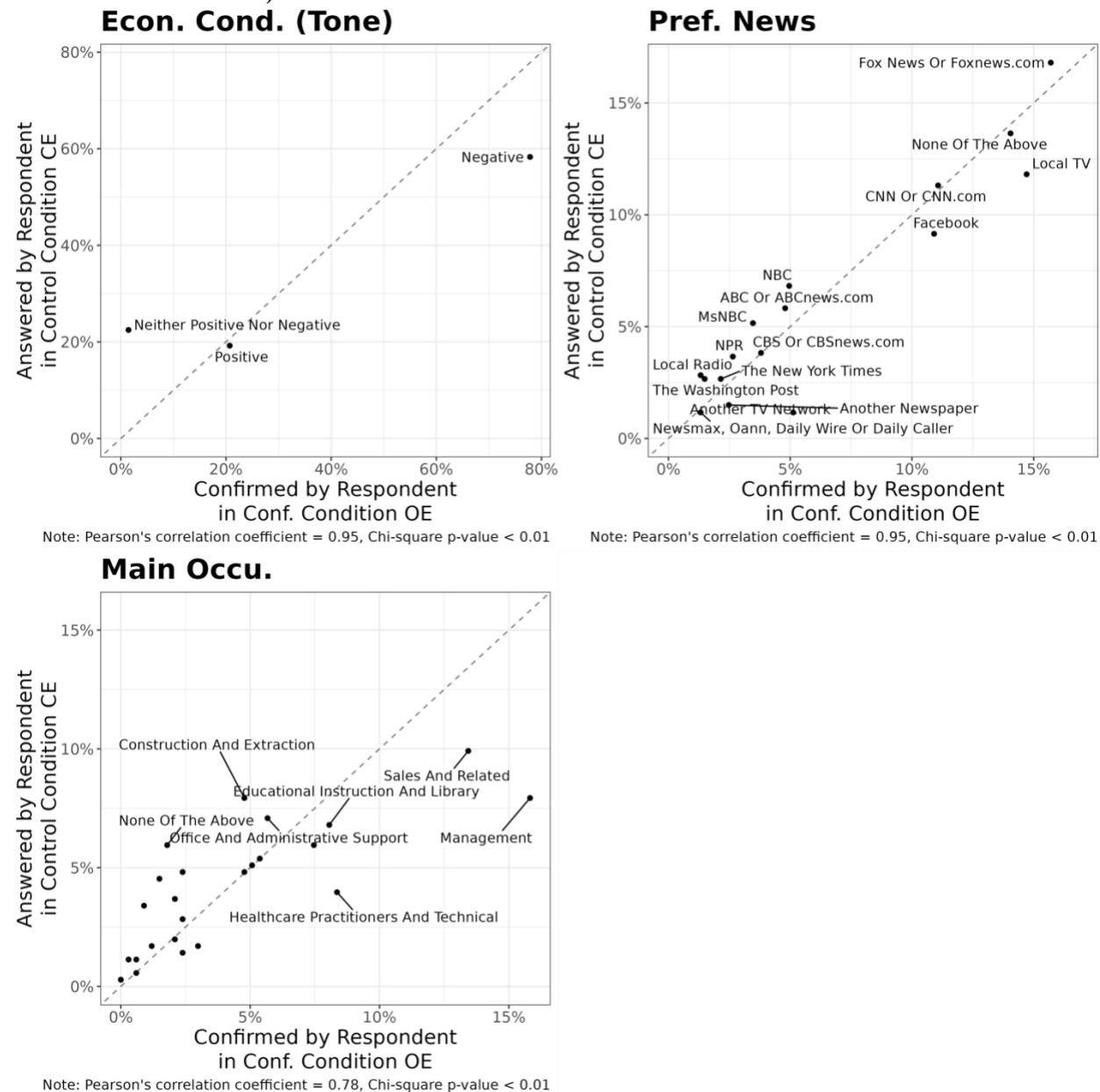
**Figure A9. Comparison of Response Categories (Live Coded by Textbot in Treatment 1 vs. Answered in Control Close-End)**



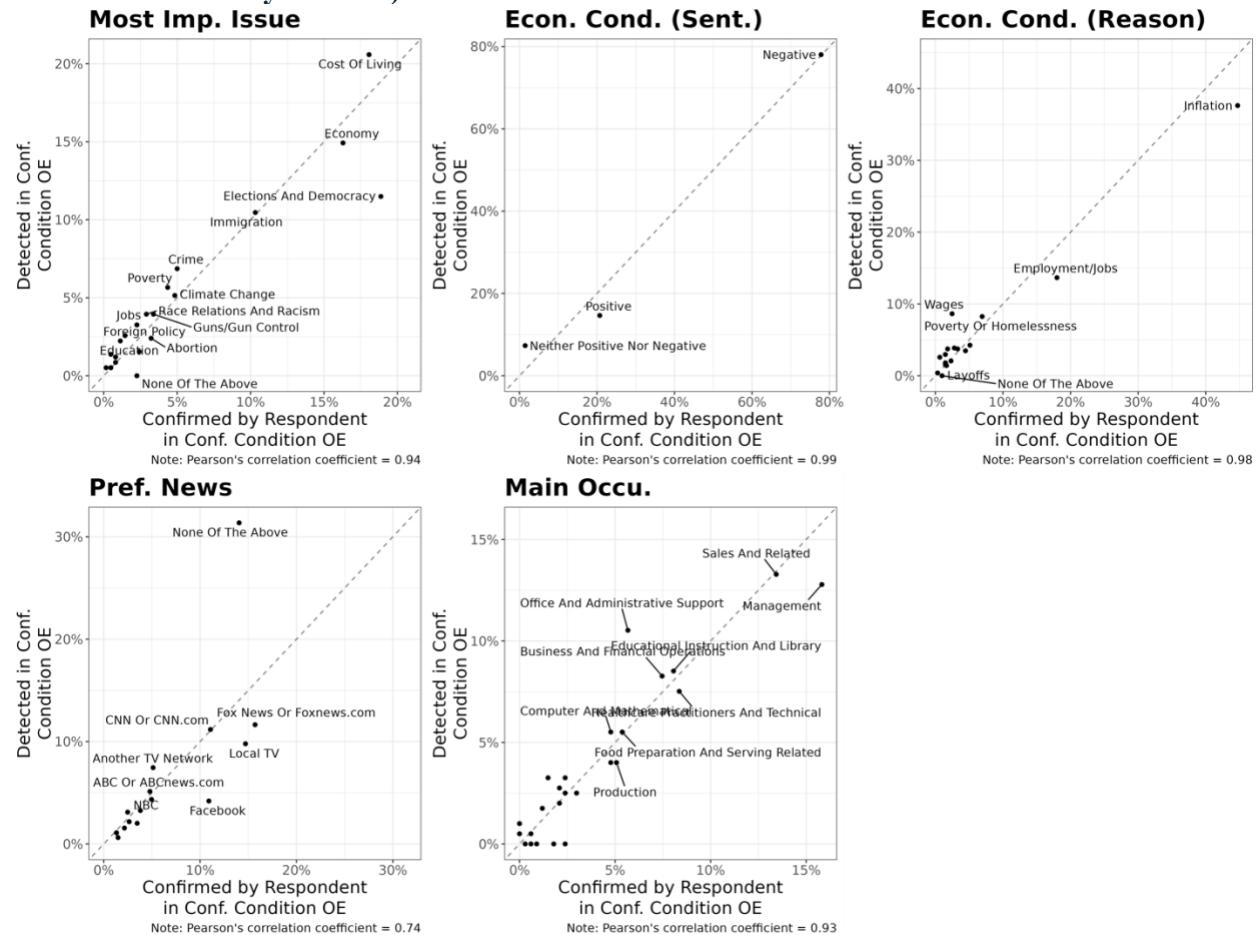
**Figure A10. Comparison of Response Categories (Live Coded by Textbot in Treatment 1 vs. Coded in Other Open-Ended Conditions)**



**Figure A11. Comparison of Response Categories (Confirmed in Treatment 1 vs. Answered in Control Close-End)**



**Figure A12. Comparison of Response Categories (Confirmed by Respondent in Treatment 1 vs. Live Coded by Textbot)**

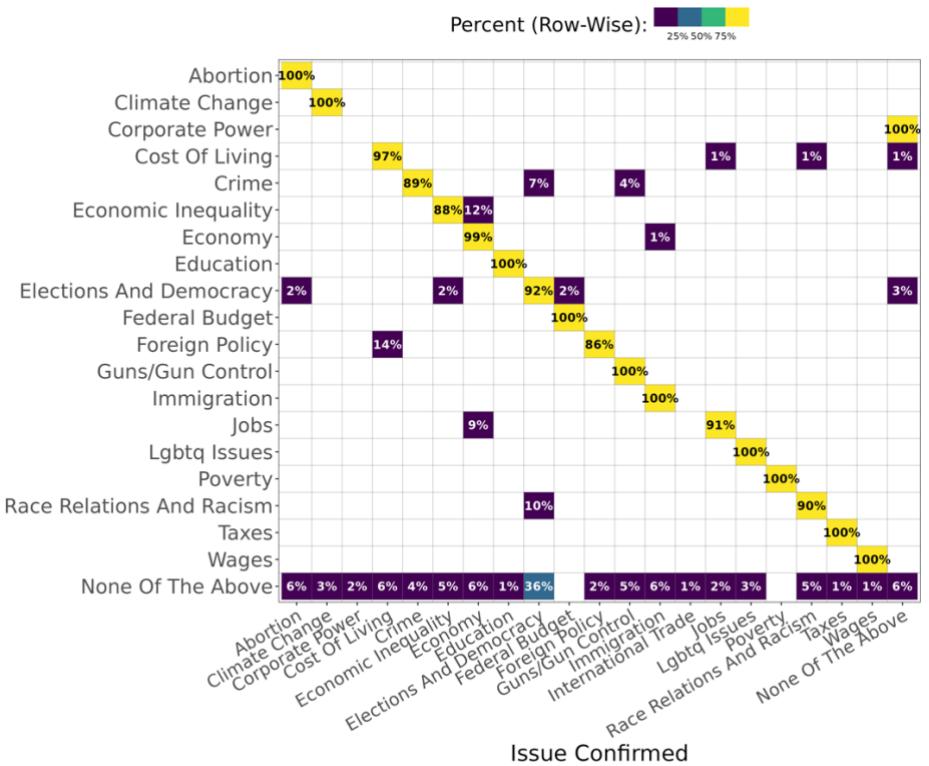


**Table A5. Respondent Confirmation (Treatment 1) by Device Type**

Device	Most Imp. Issue	Econ. Cond. (Sent.)	Econ. Cond. (Reason)	Pref. News	Main Occu.
Smartphone (n=445)	74.0%	95.9%	77.1%	62.8%	87.7%
Desktop (n=194)	73.3%	97.2%	88.8%	74.0%	76.8%
Tablet (n=24)	69.6%	95.0%	91.3%	65.2%	90.9%

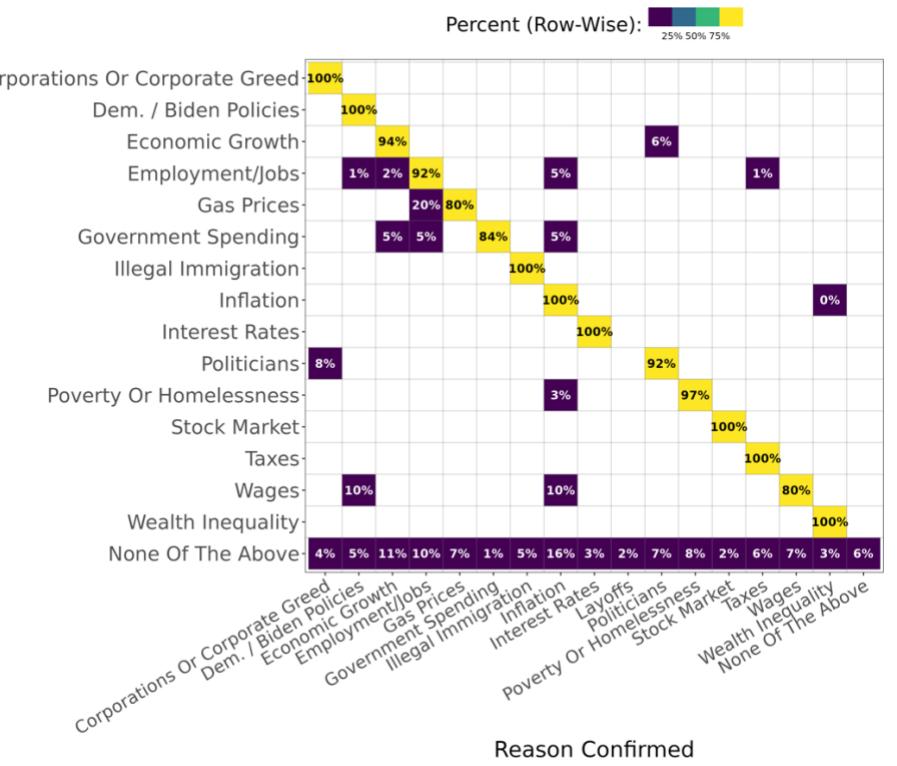
**Figure A13. Active Coding (Treatment 1) Confusion Matrices**

Issue Detected + Probed

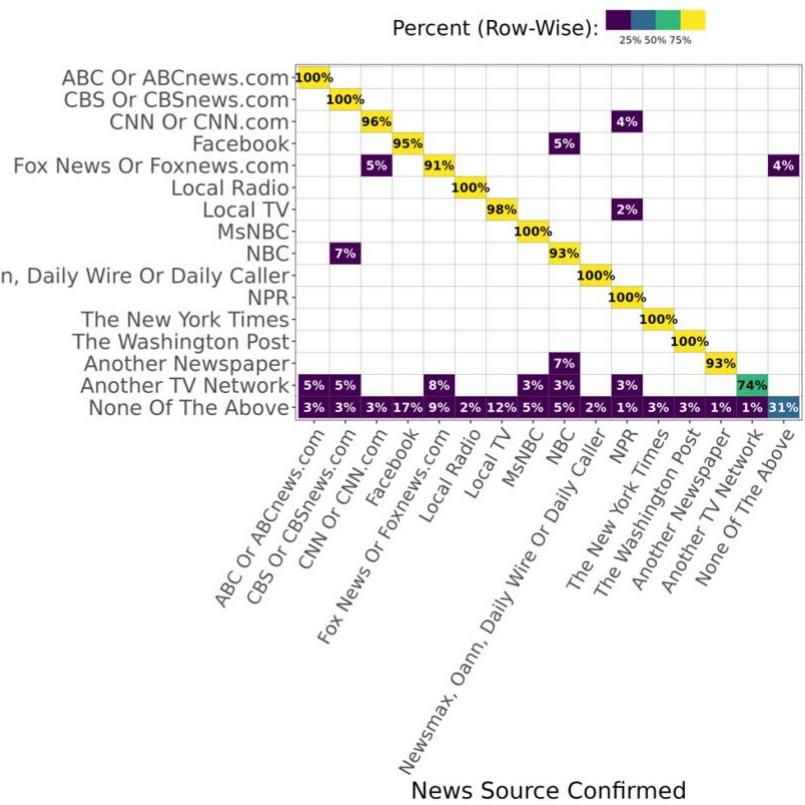


**(a) Most Important Issue**

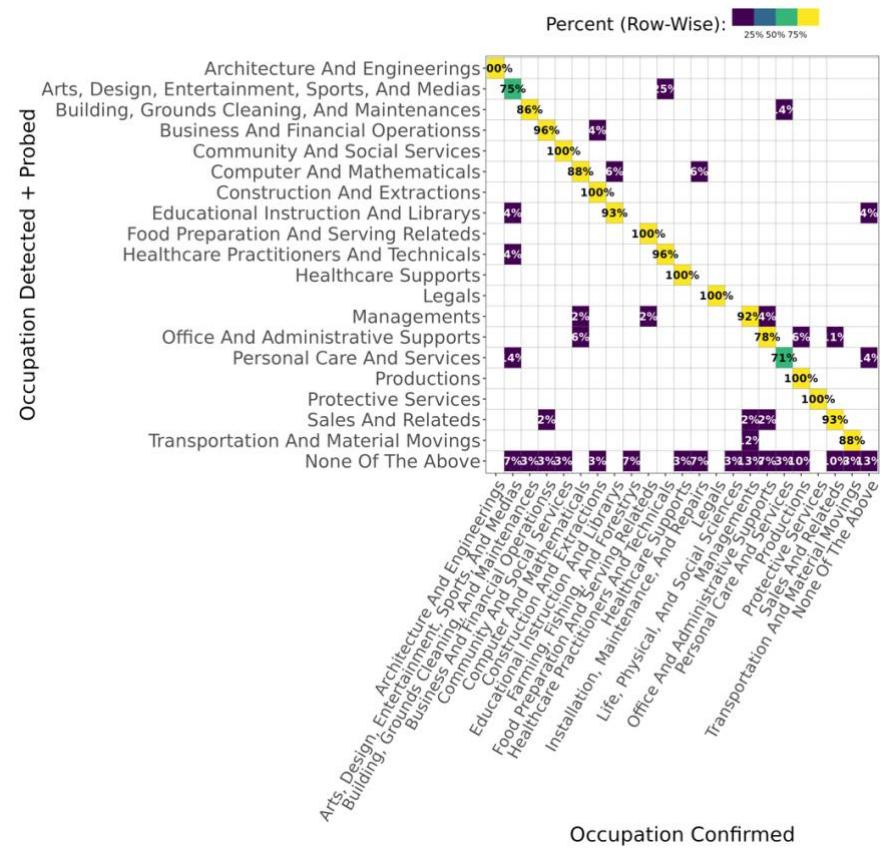
Reason Detected + Probed



**(b) Economic Conditions (Reason)**



### (c) Preferred News Source



**(d) Occupation**

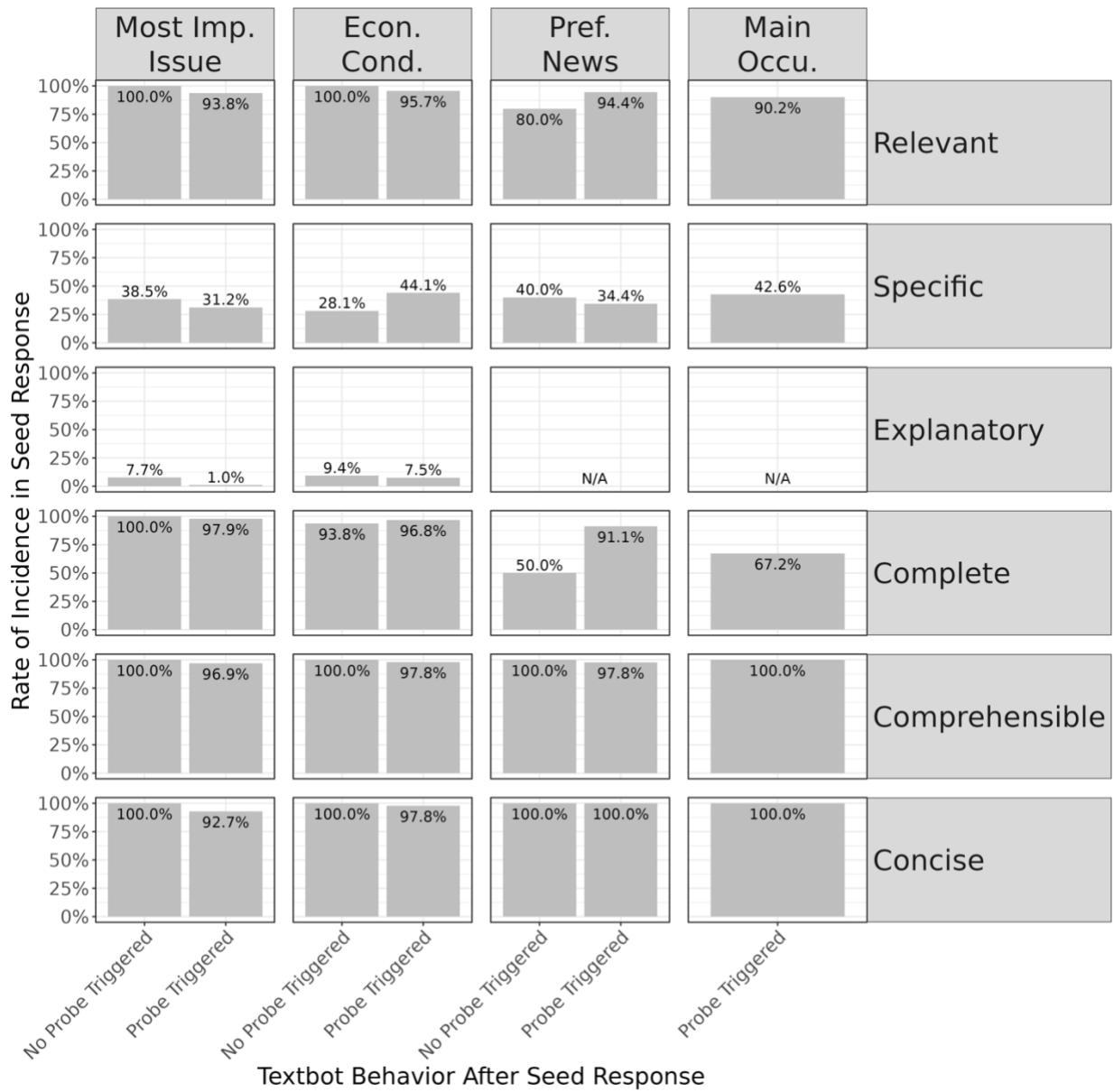
## A3. Additional Active Probing Results

Regression results in this section follow the same corrections and specifications as in the main text.

**Table A6. Examples of Elaboration/Relevance Probes**

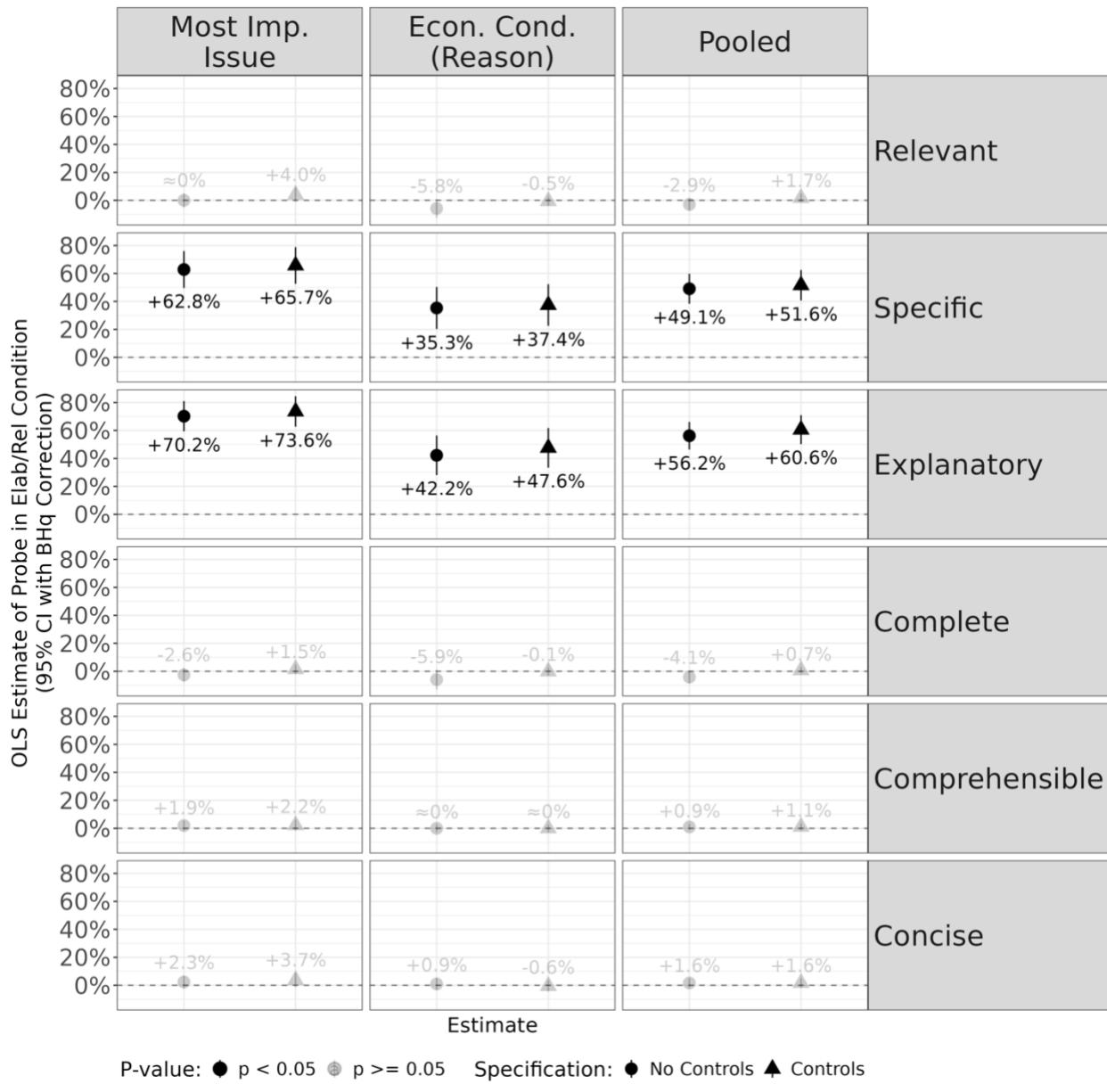
Probe Triggered	Example Question Sequence			
	Most Imp. Issue	Econ. Cond.	Pref. News	Main Occu.
<b>Elaboration Probe</b>	[Seed Response] Economy and inflation	[Seed Response] Our food bank needs more donations since more people are in need	[Seed Response] New York Times and the Washington Post.	[Seed Response] Contractor
	[Textbot Probe] Thank you for sharing your thoughts. Could you please elaborate on why you think the economy and inflation are the most important problems facing the country today?	[Textbot Probe] It sounds like you're saying that there are more people in need of assistance. Can you tell me more about how the economy is affecting people's ability to provide for themselves?	[Textbot Probe] That's interesting. Can you tell me more about why you prefer these sources over others?	[Textbot Probe] That's interesting. Could you tell me more about the type of contracting work you do?
<b>Relevance Probe</b>	[Seed Response] Democracy not what religion	[Seed Response] good	[Seed Response] Internet and my husband	[Seed Response] per week 35 hours
	[Textbot Probe] I'm sorry, I'm not sure I understand your response. Could you please elaborate on what you mean by "democracy not what religion"?	[Textbot Probe] Hmm I think I know what you mean, but could you explain a bit more?	[Textbot Probe] Thank you for sharing. Could you please clarify which specific websites or online platforms you use to consume news? And when you say your husband, do you mean he shares news articles with you or do you discuss news topics together?	[Textbot Probe] I'm sorry, but I think there might have been a misunderstanding. I was asking about the type of work you do in your principal job. Could you please provide more information about the kind of work you do?

**Figure A14. Comparison of Seed Response Quality (Treatment 2 Probe Triggered vs. No Probe Triggered)**



Note: For occupation experiment, probes were administered for every response.

**Figure A15. Effects of Elaboration/Relevance Probing (Treatment 2 Post-Probe vs. Pre-Probe) on Human-Coded Quality Criteria**

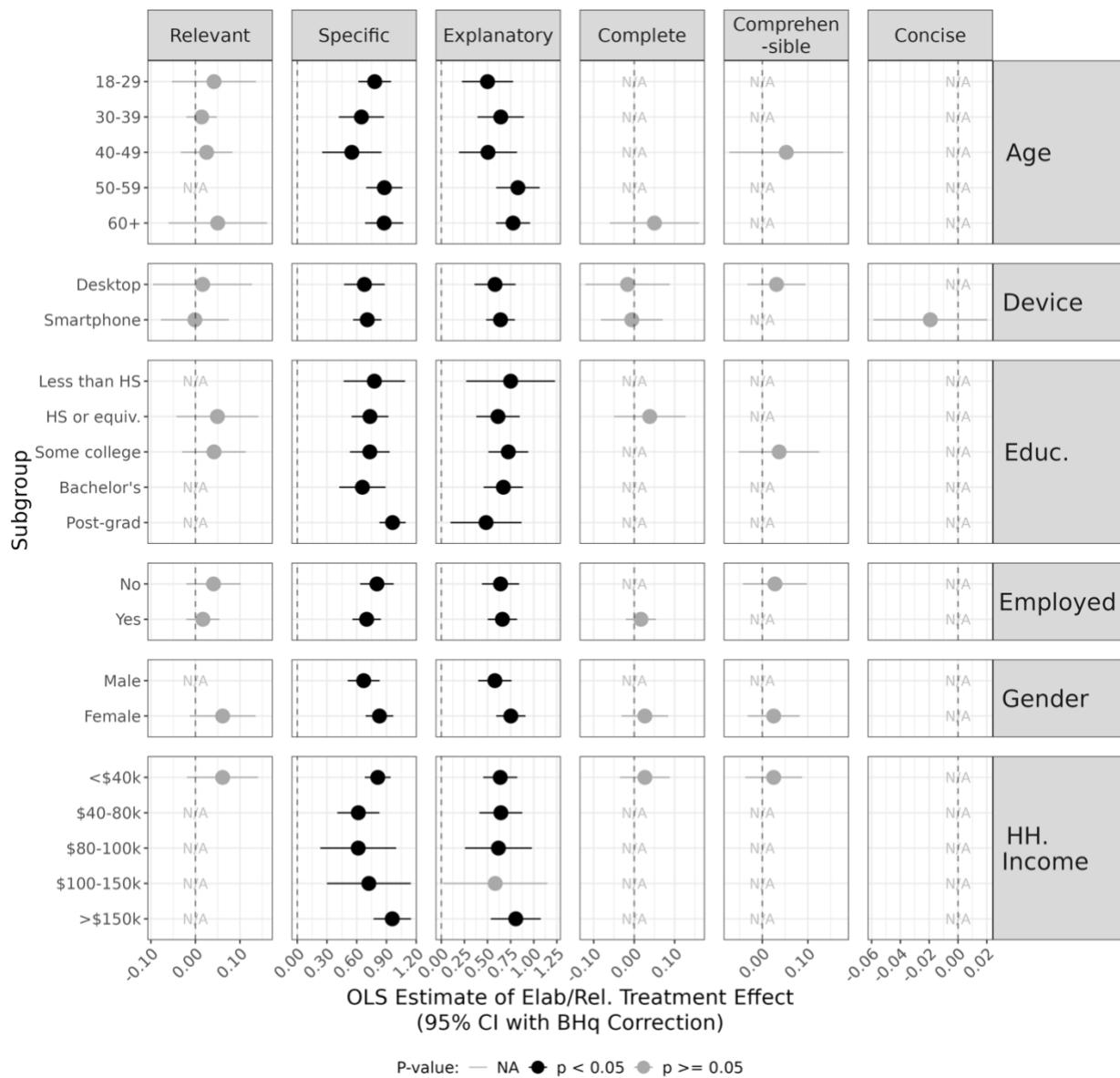


## A4. Heterogeneous Treatment Effects of Active Probing

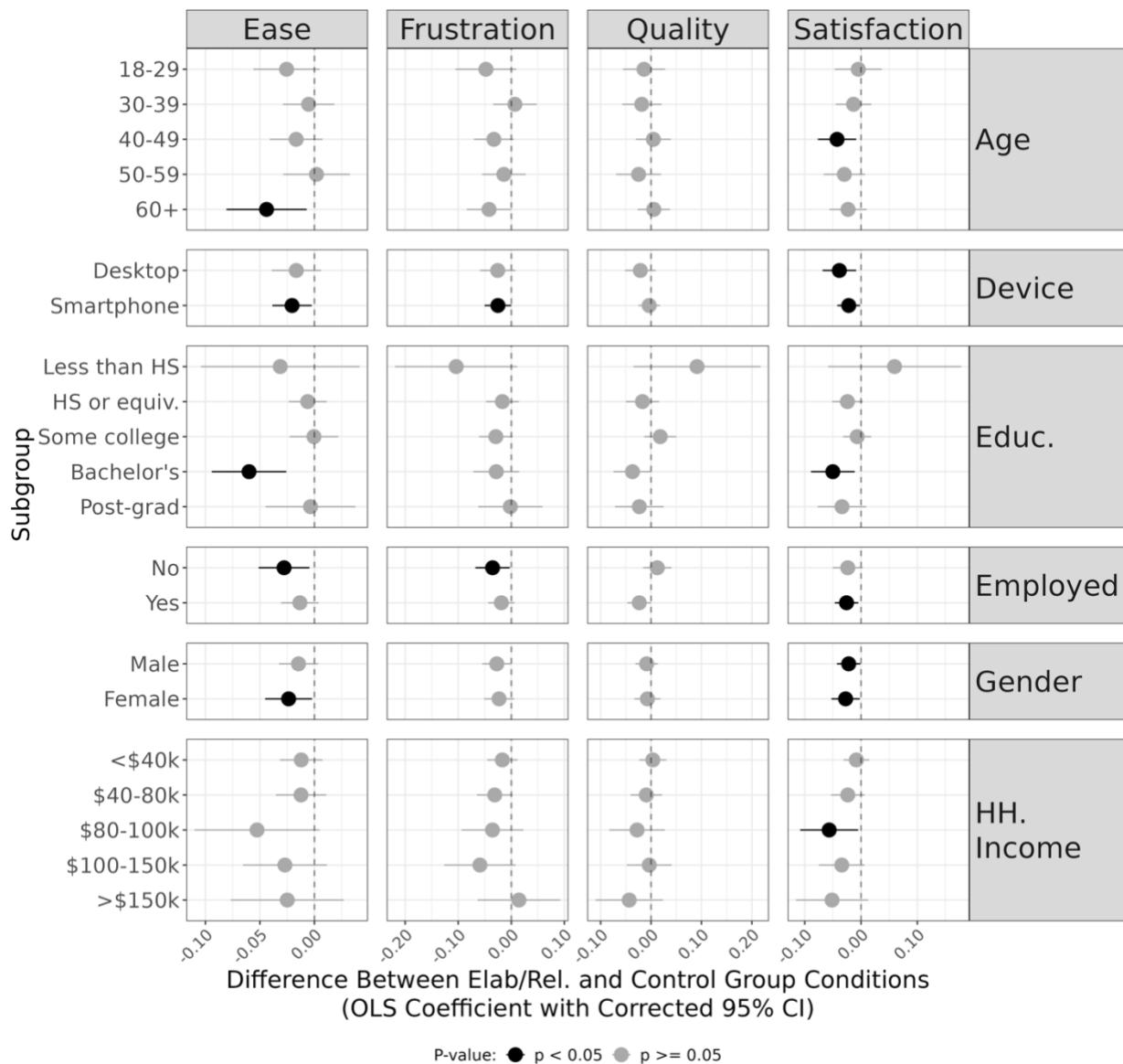
To capture heterogeneity in response quality effects, we collected demographic information and asked about the survey experience through a series of Likert-scale questions at the end of the survey. For a consistent user experience and for validation purposes, we included demographic questions in the survey, even though similar variables were available from the panel provider. Analyses requiring demographic variables (e.g., heterogeneity analyses and multivariate regression models of treatment effects) prioritized the use of panel-provided data when available. In instances where panel data were unavailable, survey-collected variables were used. Our comparison of these sources revealed only minor discrepancies, with a few exceptions. Age was exclusively captured through the survey, introducing the possibility of post-treatment bias if used as a control variable in analyses of treatment effects (Montgomery et al., 2018). We, however, find little to no differences in the regression estimates of treatment effects when including or excluding age as a covariate.

Regression results here follow the same corrections and specifications as in the main text.

**Figure A16. Heterogeneous Effects of Elaboration/Relevance Probing (Treatment 2 vs. Control) on Human-Coded Quality Criteria**



**Figure A17. Heterogeneous Effects of Elaboration/Relevance Probing (Treatment 2) on Self-Reported User Experience**



Note: Higher levels correspond to more positive evaluations. Control covariates include work status, gender, education, age, and device type. Outcomes are all normalized to the [0-1] range. Excluded subgroups in 'Other' categories and who answered by tablet due to small sample sizes.