

Correlates of Item Nonresponse to Open-Ended Web Probes

Zachary Smith^{1,2,3}, Kristen Cibelli Hibben^{1,2,3}, Benjamin Rogers^{2,3}, Valerie Ryan^{1,2,3}, Paul Scanlon^{1,2,3}, and Travis Hoppe³

¹Collaborating Center for Questionnaire Design and Evaluation Research

²Division of Research and Methodology

³National Center for Health Statistics

Federal Committee on Statistical Methodology Research and Policy Conference

Washington, DC

October 25-27, 2022

The findings and conclusions in this presentation are those of the authors and do not necessarily represent the official position of the National Center for Health Statistics, Centers for Disease Control and Prevention.

Outline

- Item nonresponse in open-ends: the problem
- A semiautomated model for detecting item nonresponse
- Web probes evaluated and model validity
- Subgroup variation in model-coded nonresponse
- Implications for question evaluation

Item nonresponse in open-ends: the problem



Value and challenges of working with open-text data

- Wide range of methodological uses (Singer & Couper, 2017)
- Because responses are unconstrained, particularly useful when little is known about a topic (Neuert et al., 2021, Scanlon, 2019; 2020)
- However:
 - More burdensome to respondents
 - Prone to nonresponse or inadequate, non-codable responses
 - Coding and analysis is time- and labor-intensive for researchers

A semiautomated model for detecting item nonresponse



Building a model to detect nonresponse

- Prior work:
 - Categorizing item nonresponse (Behr et al., 2012; Meitinger et al., 2021)
 - Detecting item nonresponse via rule-based approach (Kaczmirek et al. (2017); available on GitHub)
 - Leveraging advances in data science to build a more accurate detector
 - Trained a natural language processing (NLP) model
 - Refined with human coding (active learning)
-
- EvalAnswer: <https://git.gesis.org/surveymethods/evalanswer>
 - Bidirectional Transformer for Language Understanding (BERT): <https://arxiv.org/abs/1810.04805>
 - Simple Contrastive Sentence Embedding (SimCSE): <https://arxiv.org/abs/2104.08821>

Taxonomy of responses

- The model assigns a score (0-1) for the extent to which a response falls into each of the item non-response categories
 - **Complete non-response:** Blank text box
 - **Gibberish** or nonsensical: “dfgjh”
 - **Don’t knows:** “I don’t know”; DK; idk
 - **Refusals:** “no comment”; “Because”; “none”
 - **Other, high-risk:** non-useful response, non-codable
 - **Valid:** useful response, codable
- Several rounds of arbitration and refined training produced latest model version

Web probes evaluated and model validity



Data source

- NCHS's Research and Development Survey (RANDS) During COVID-19
<https://www.cdc.gov/nchs/rands/index.htm>
 - Three-round web/phone survey
 - Focused on health, impacts of pandemic, behaviors
- Conducted using NORC at the University of Chicago's Amerispeak®, a probability-based panel representative of the US adult, English-speaking, non-institutionalized household population
- Round 3 fielded May-June 2021: 5,458 Completes
 - 7,852 NORC's AmeriSpeak probability-based sample = 11.8% weighted cumulative response rate / 69.5% completion rate

Web probes evaluated

- Vaccine hesitancy:
 - Please list the reasons you say you [are / are not] hesitant about vaccines in general.
- Social distancing:
 - When you were answering about social distancing in the previous questions, what were you thinking about?
- Religion:
 - Currently, how important is religion in your daily life? (Very, somewhat, not important)
 - Why do you say that?

Model validity

- Manually evaluated all coded soft nonresponses and 1,000 randomly sampled coded valids to determine model sensitivity and specificity
- Overall:
 - Sensitivity: 83.6%
 - Specificity: 86.5%
- Hesitancy:
 - Sensitivity: 77.7%
 - Specificity: 89.7%
- Distancing:
 - Sensitivity: 81.9%
 - Specificity: 95.6%
- Religion:
 - Sensitivity: 90.1%
 - Specificity: 70.9%

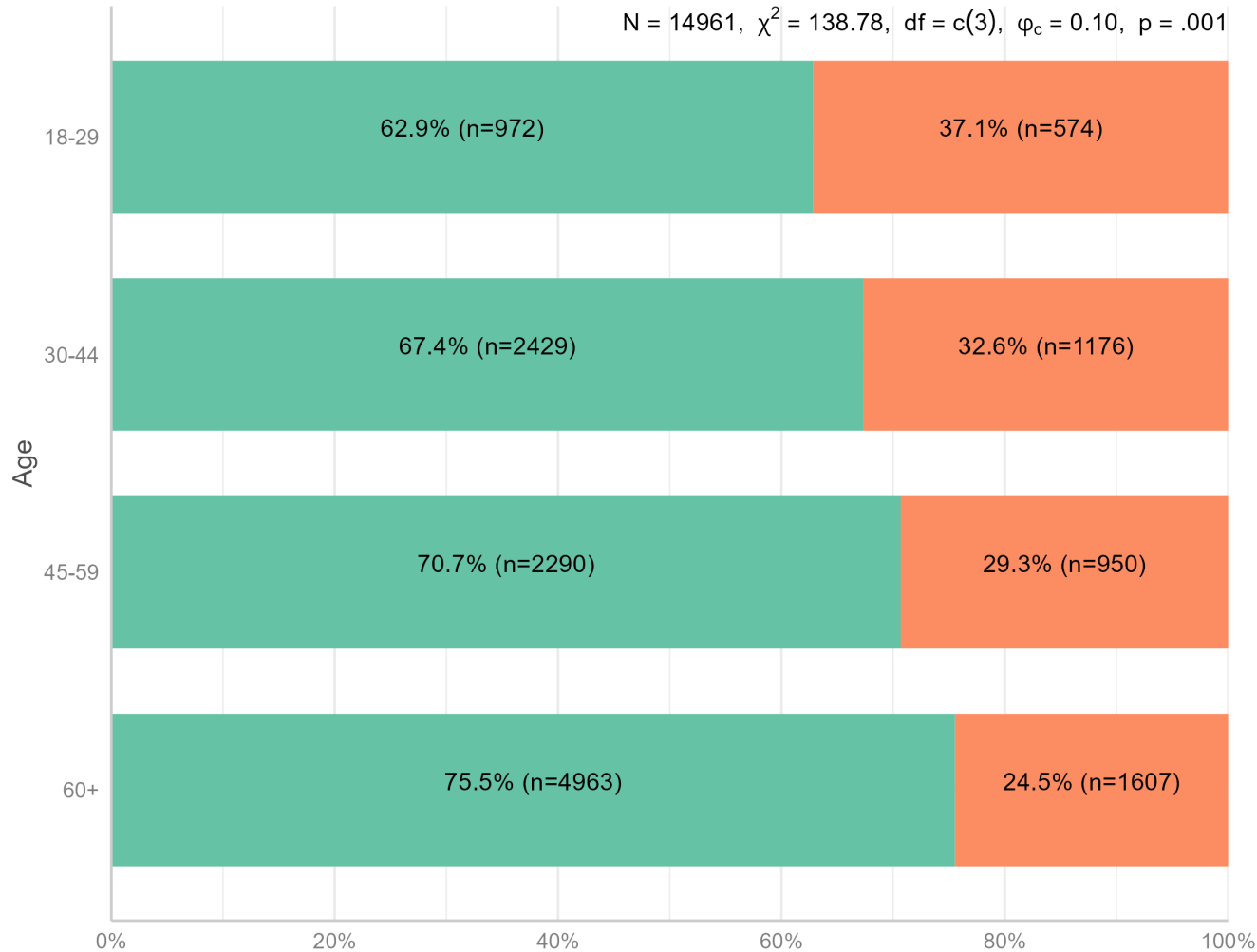
Subgroup variation in model-coded nonresponse



Subgroup variation: age

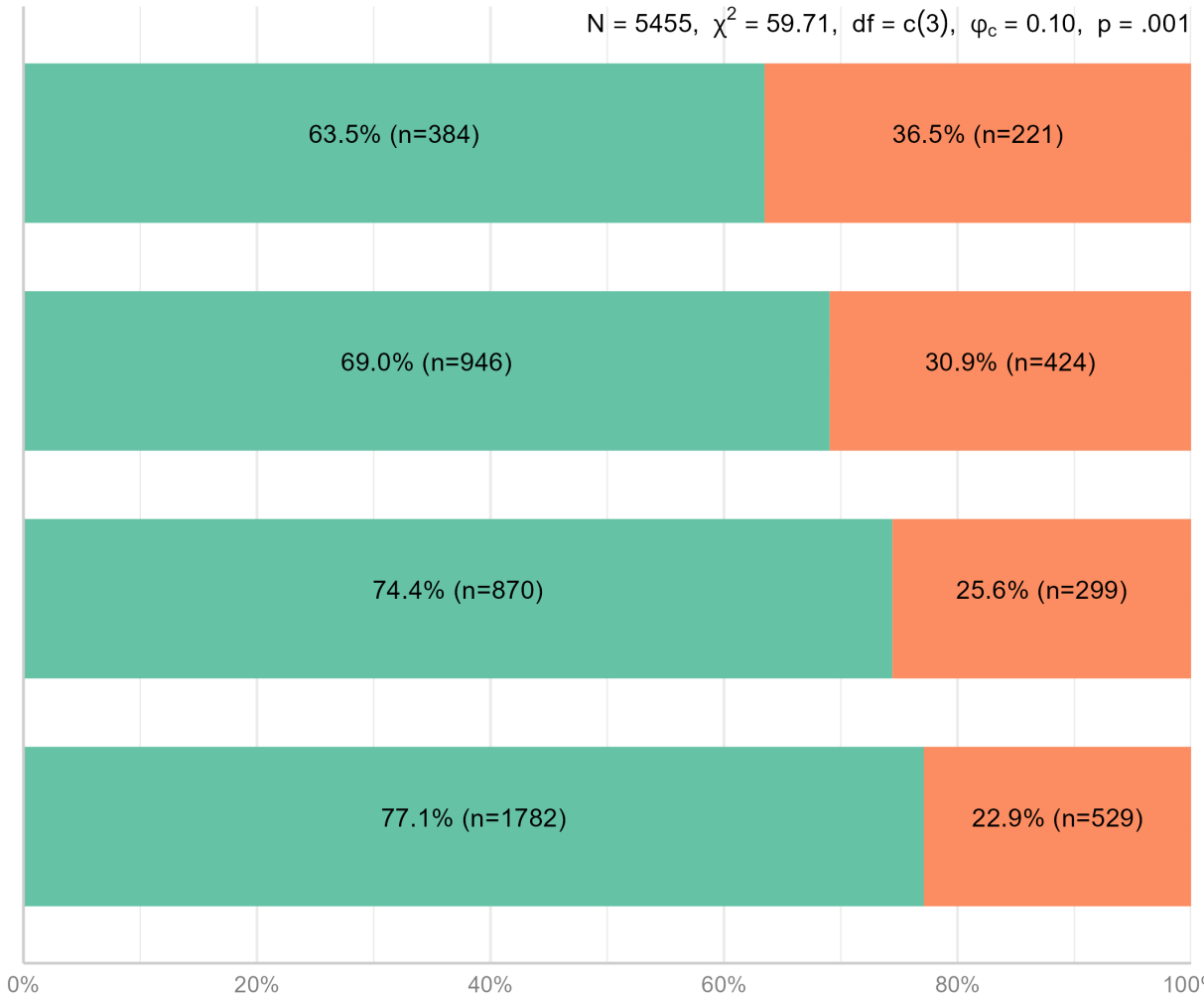
Item Nonresponse and Age, All Probes

N = 14961, $\chi^2 = 138.78$, df = c(3), $\phi_c = 0.10$, p = .001



Item Nonresponse and Age, Social Distancing

N = 5455, $\chi^2 = 59.71$, df = c(3), $\phi_c = 0.10$, p = .001

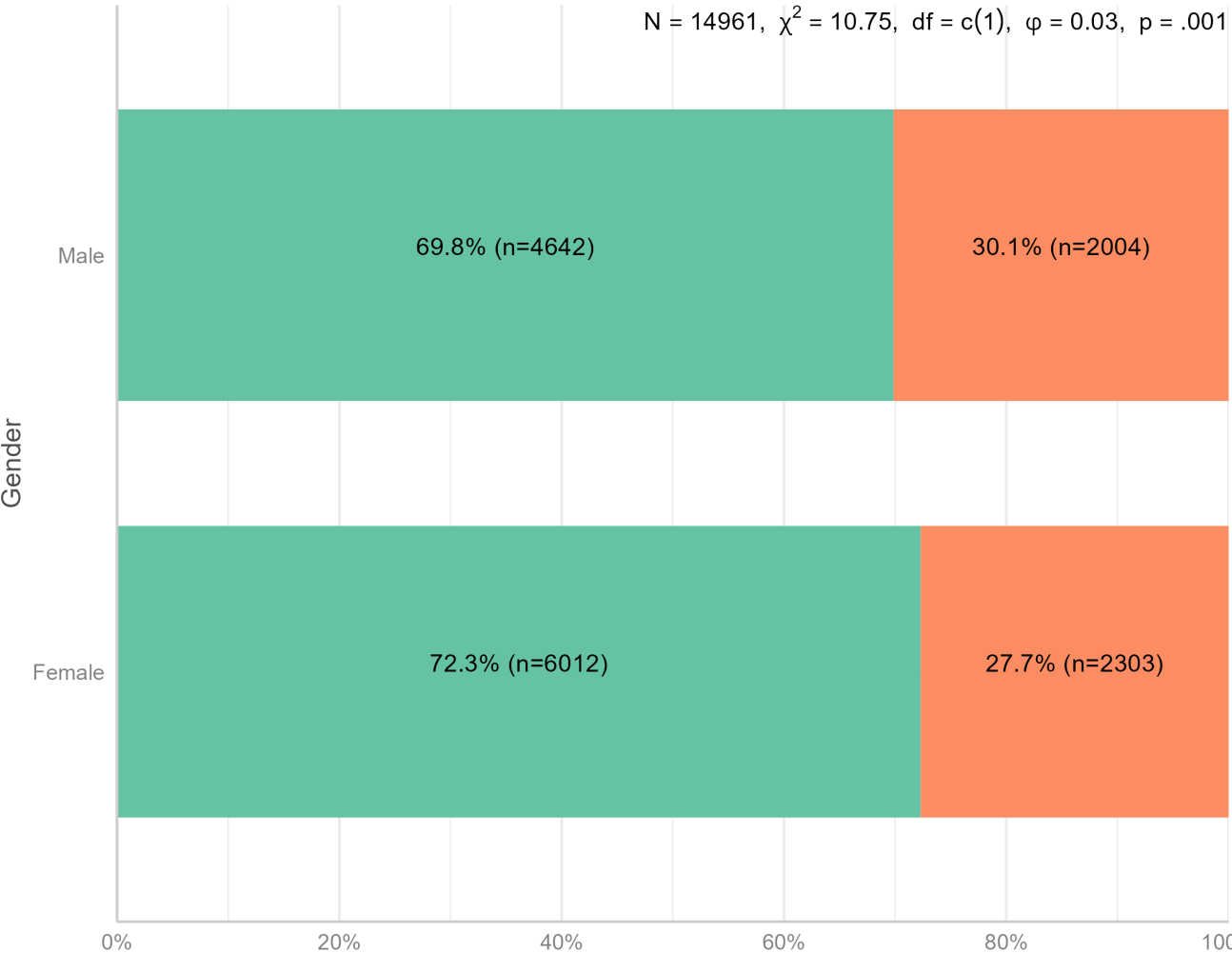


Response Type Coded Valid Coded Nonresponse

Subgroup variation: gender

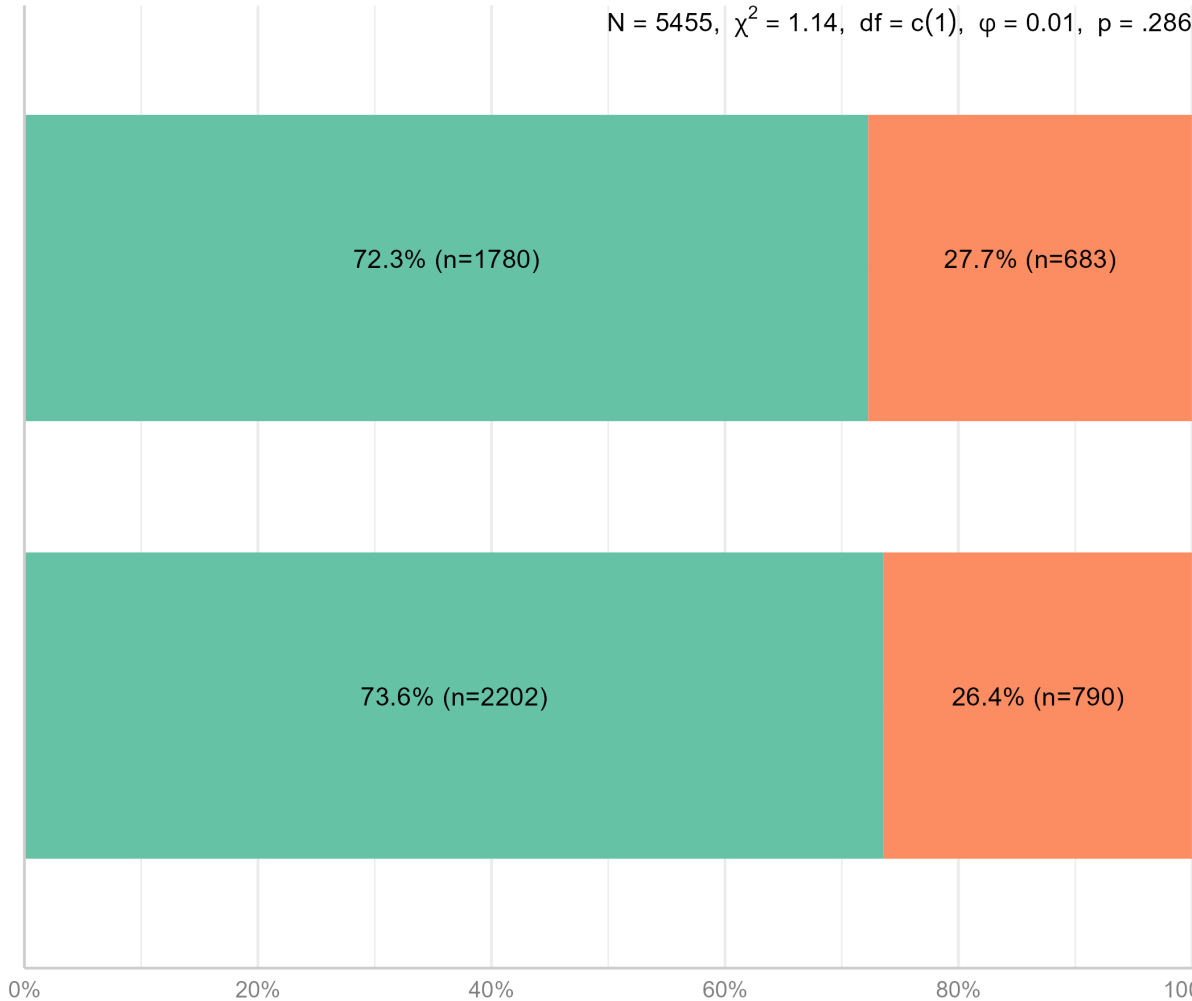
Item Nonresponse and Gender, All Probes

N = 14961, $\chi^2 = 10.75$, df = c(1), $\phi = 0.03$, p = .001



Item Nonresponse and Gender, Social Distancing

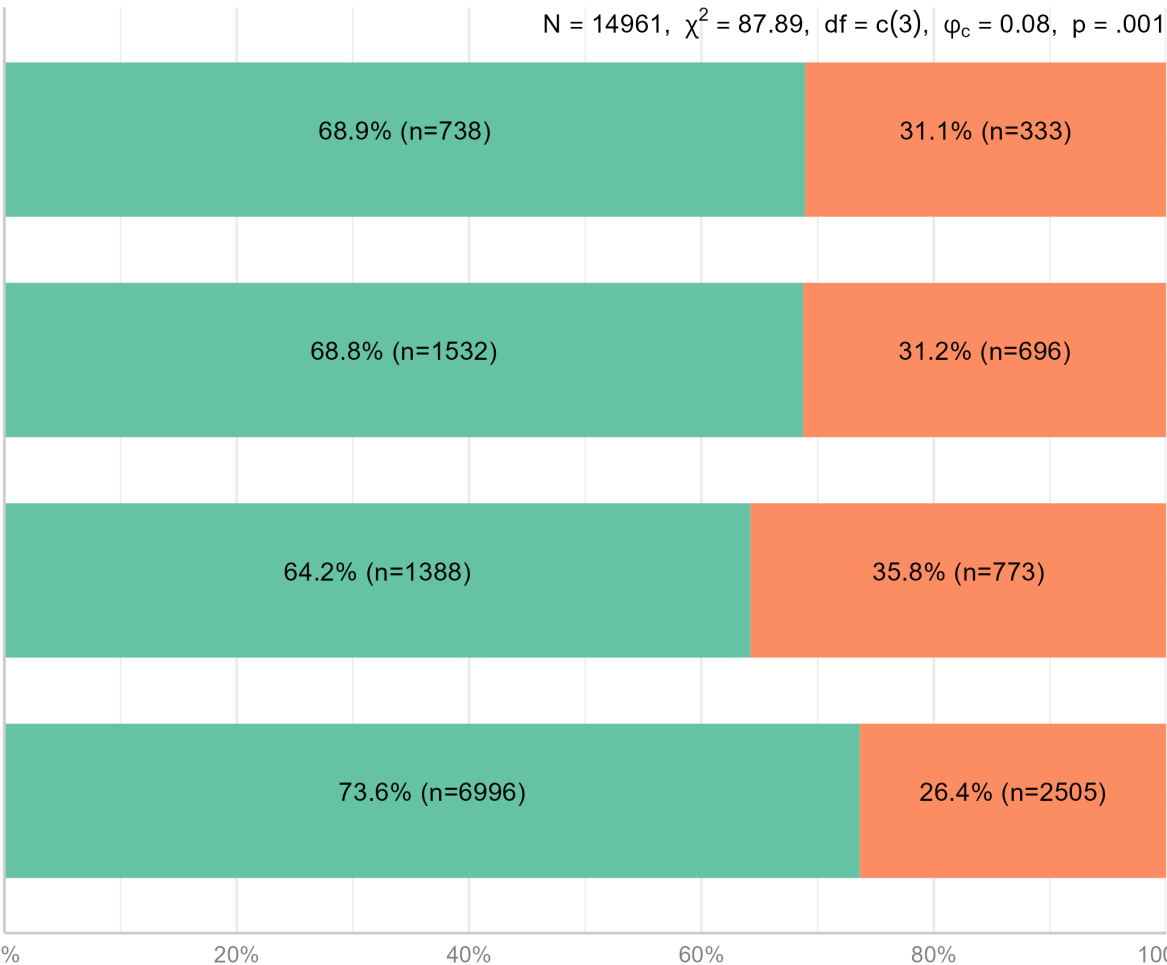
N = 5455, $\chi^2 = 1.14$, df = c(1), $\phi = 0.01$, p = .286



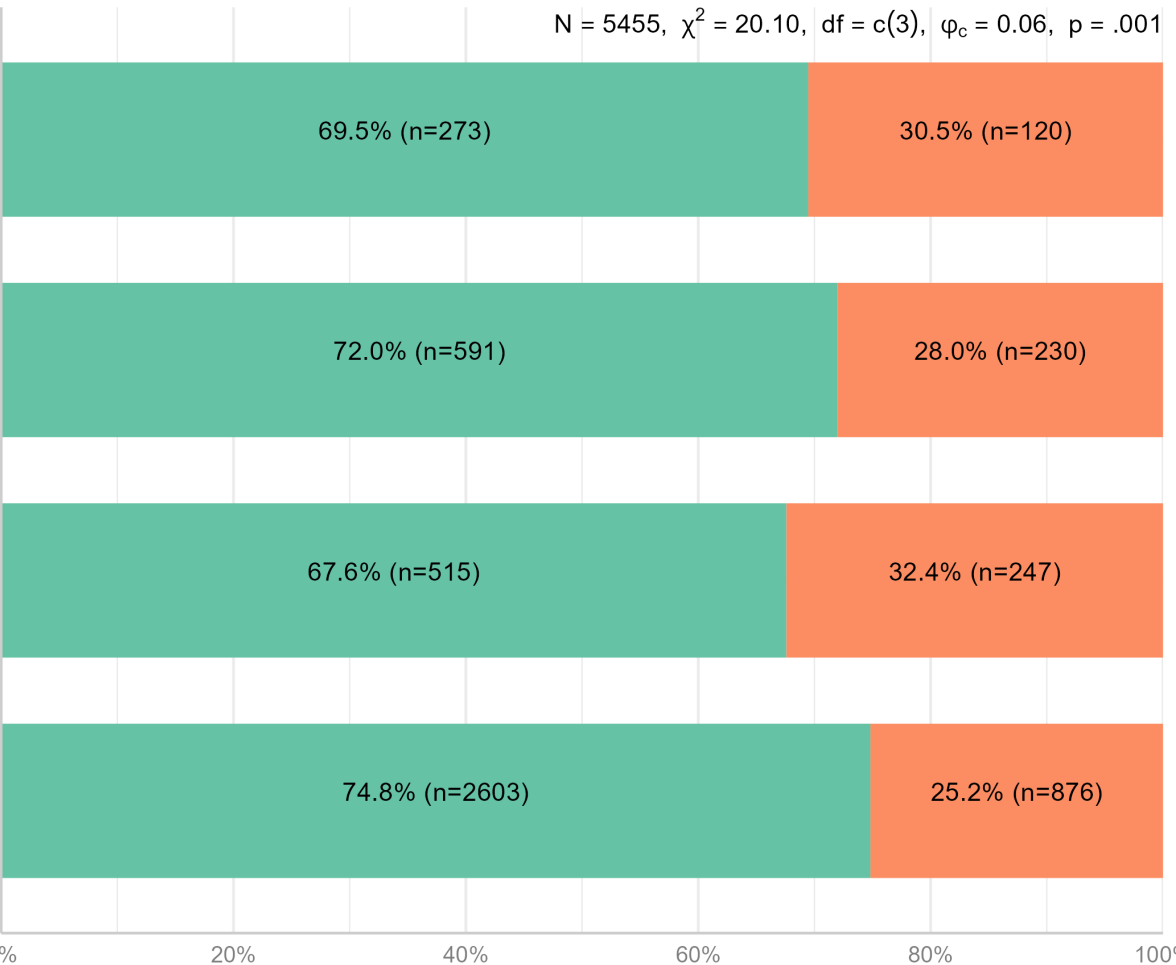
Response Type Coded Valid Coded Nonresponse

Subgroup variation: race/ethnicity

Item Nonresponse and Race/Ethnicity, All Probes



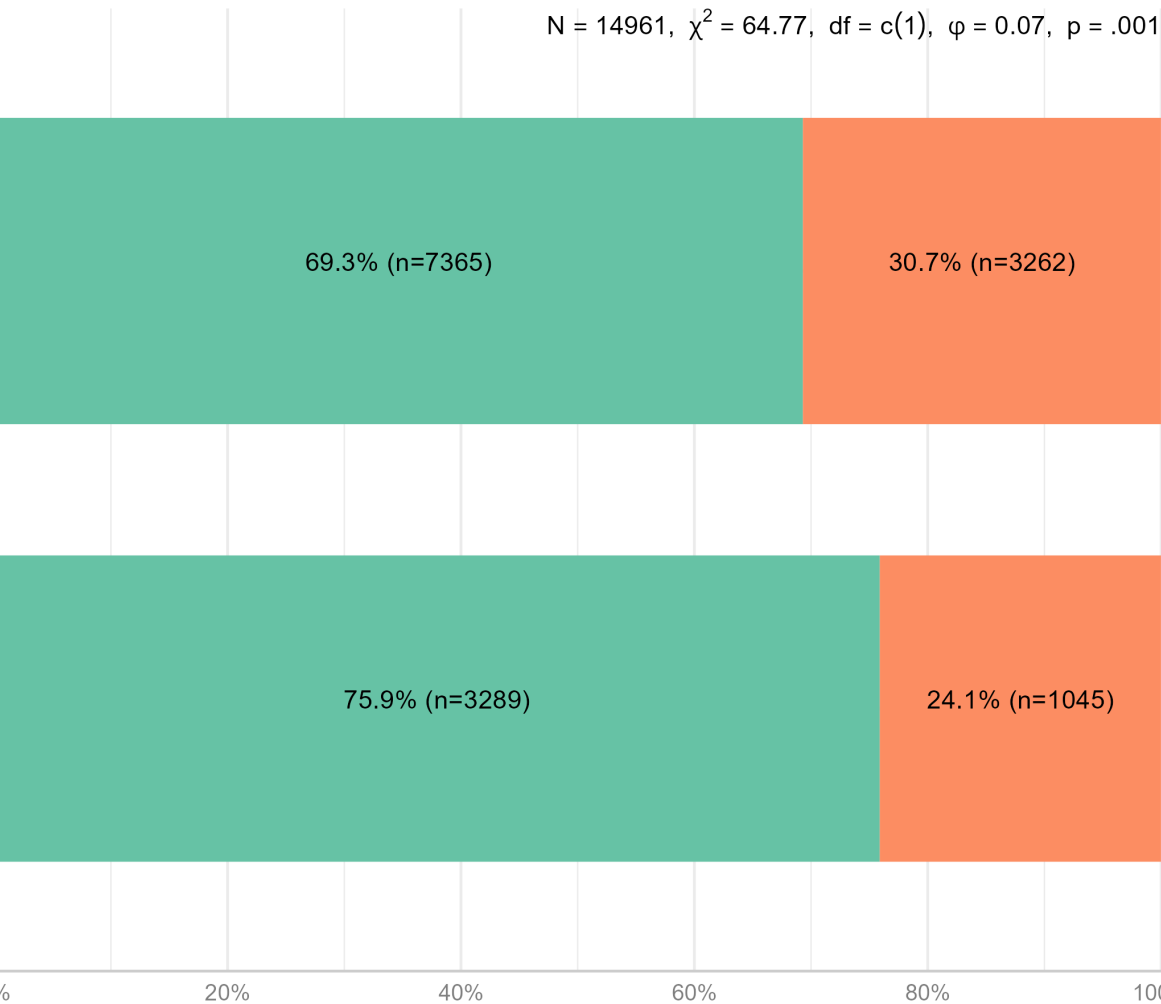
Item Nonresponse and Race/Ethnicity, Social Distancing



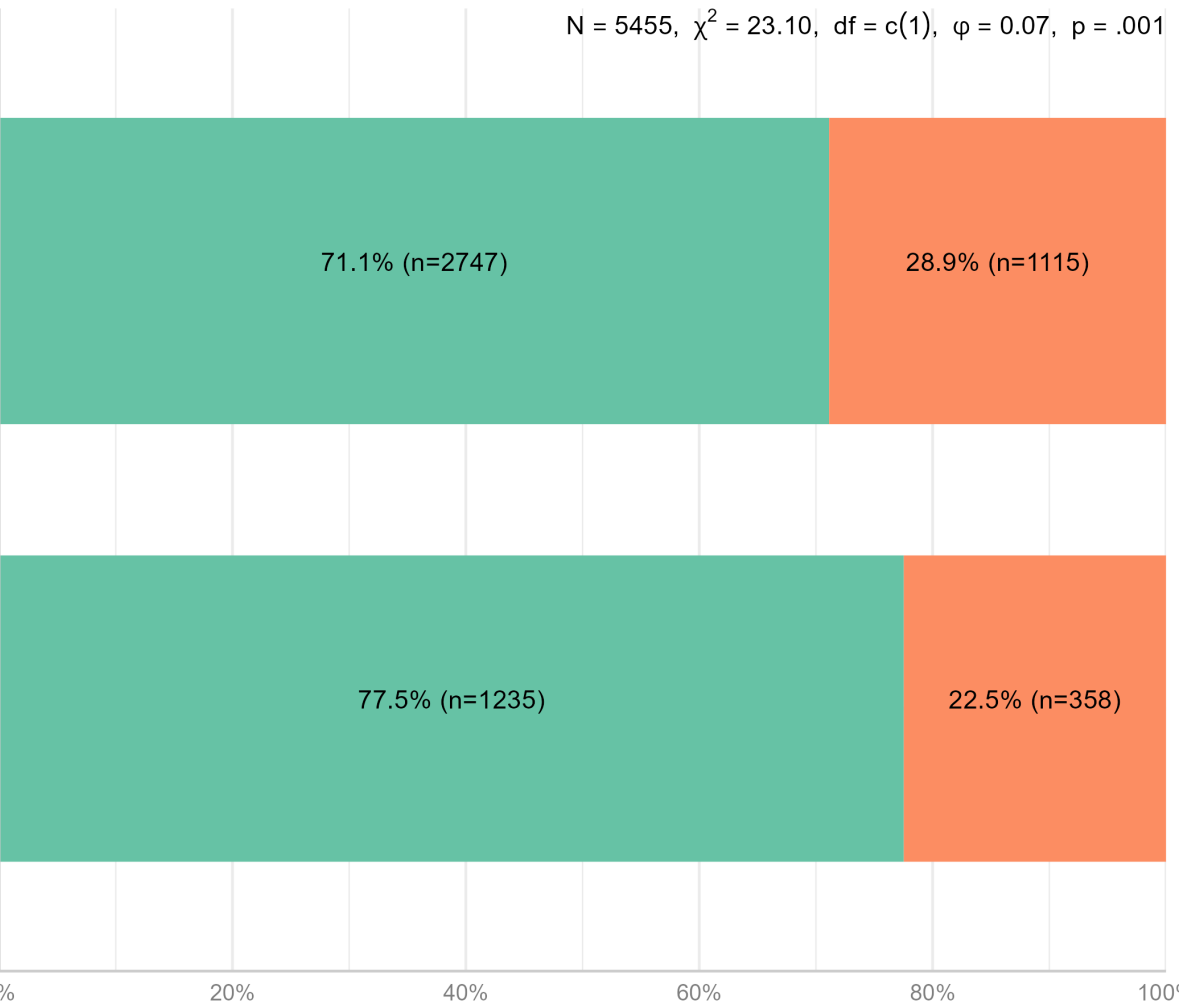
Response Type Coded Valid Coded Nonresponse

Subgroup variation: education

Item Nonresponse and Education, All Probes

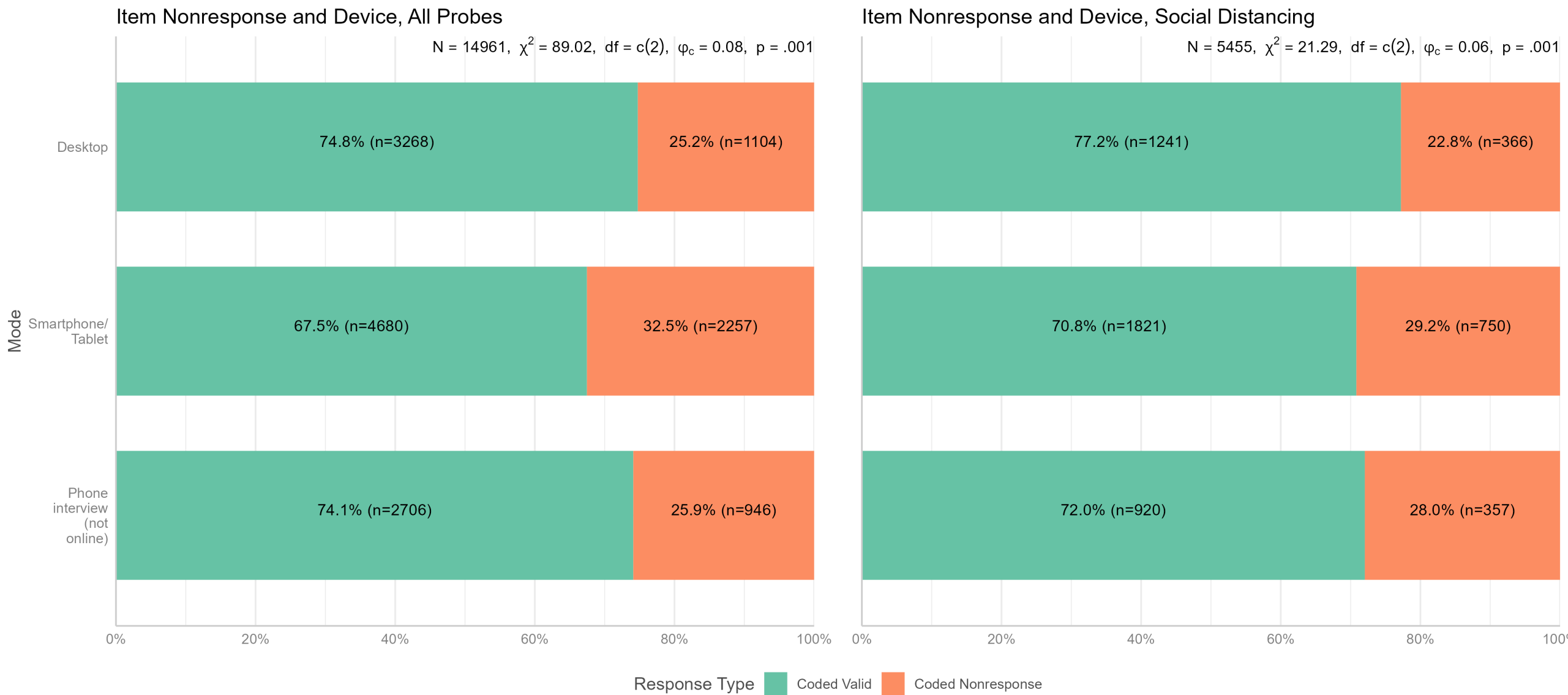


Item Nonresponse and Education, Social Distancing



Response Type Coded Valid Coded Nonresponse

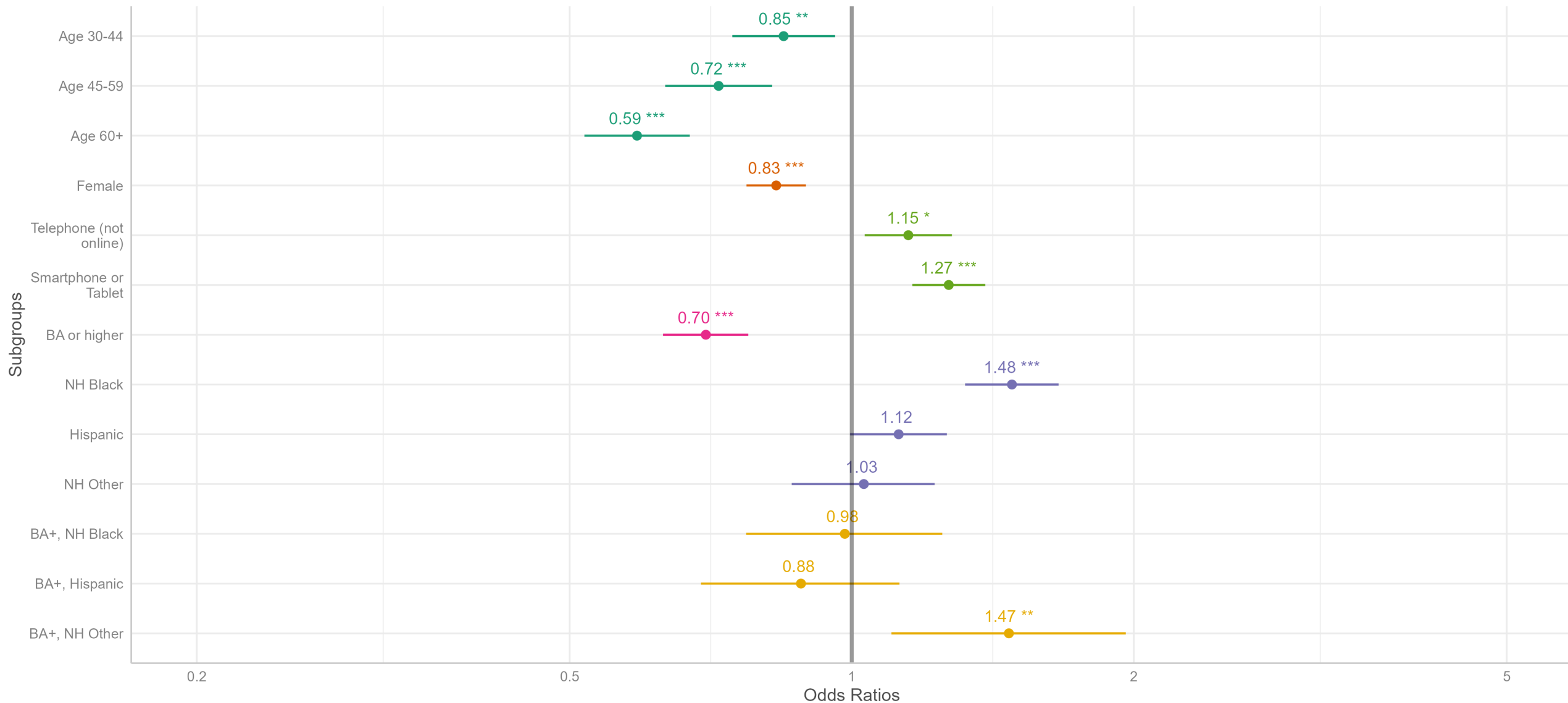
Subgroup variation: device



Pulling all the data together

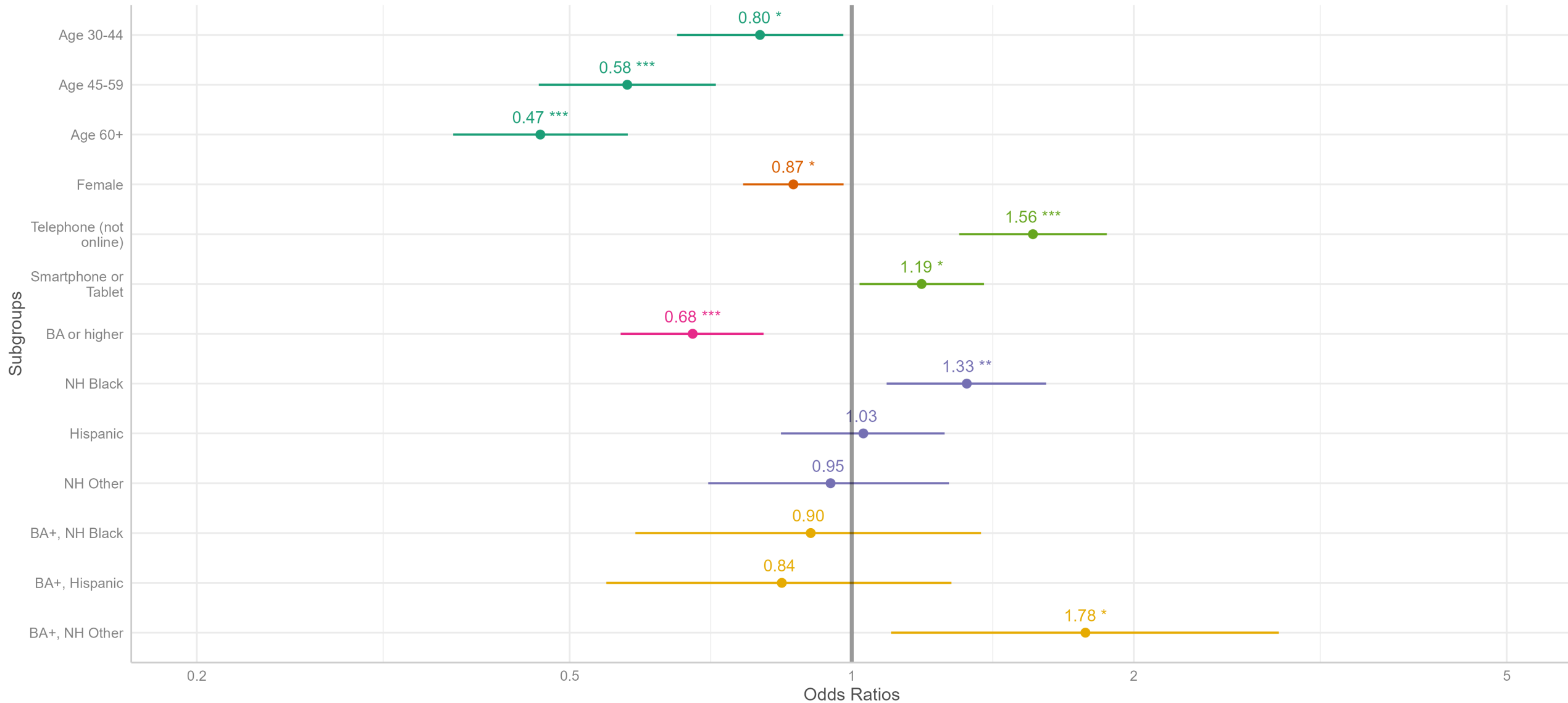
- Logistic regression to estimate odds of nonresponse by subgroup for a) all probes and b) the social distancing probe
- Reference categories:
 - Age: 18-29
 - Gender: Male
 - Race/ethnicity: Non-Hispanic White
 - Education: Some college or less
 - Device: Desktop computer
 - Interaction of race/ethnicity and education: NH White, Some college or less
- 95% confidence intervals shown
- Analysis run in R 4.2.0 and Rstudio 2022.02.03 using *tidyverse* and *sjPlot* packages

Odds of Nonresponse by Subgroup, All Probes



* p < 0.05, ** p < 0.01, *** p < 0.001; SOURCE: National Center for Health Statistics Research and Development Survey During COVID-19, Round 3, N = 14,961 responses

Odds of Nonresponse by Subgroup, Social Distancing



* p < 0.05, ** p < 0.01, *** p < 0.001; SOURCE: National Center for Health Statistics Research and Development Survey During COVID-19, Round 3, N = 5,455 responses

Implications for question evaluation



How can this model assist in question evaluation?

- Speedily categorizes open-text data with reasonable sensitivity and specificity
- Clear understanding of demographics of non-responders – potential for insight into patterns of nonresponse that can improve question design
- But, some dangers: reliance on the coded valid dataset excludes:
 - Potentially valid responses missed by the model (false negatives)
 - The voices of groups systematically more likely to be categorized as nonresponse

Thank you!

For more information contact: Zachary Smith, zsmith@cdc.gov

Q-Bank: providing access to survey question evaluation reports, question design and performance <https://wwwn.cdc.gov/qbank/>

Q-Notes: designed to facilitate the management and analysis of cognitive interviews <https://www.cdc.gov/nchs/ccqder/products/qnotes.htm>

For more information, contact CDC
1-800-CDC-INFO (232-4636)
TTY: 1-888-232-6348 www.cdc.gov

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

