Toward a semi-automated item nonresponse detector model for open-response data

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Outline

- Background and context
  - COVID-19 pandemic
  - Open-text data: value and challenges
  - Item nonresponse detection: the technology and development of the model
- Evaluating the model: our approach
- Evaluation results
- Discussion/Next steps

Background and context

COVID-19 pandemic

- Numerous new COVID-19 related survey items
- Circumstances prevented our usual approach: in-depth cognitive interviewing to inform closed-ended online survey web probes
- Adapted and innovated our methods to include both closed and open-ended probes and experimental designs for post-hoc evaluations

Open-text data: value and challenges

- Range of methodological uses for open-text data (Singer & Couper, 2017)
- Allows for responses without constraint (Schonlau & Couper, 2016) a particular advantage when little is known about a topic (Neuert et al., 2021, Scanlon, 2019; 2020)
- But higher response burden, more prone to item nonresponse, inadequate and irrelevant responses
- Coding and analysis can be labor intensive and time-consuming
- Recent advances in data science offer new efficiencies and opportunities

Item nonresponse detection: prior work

- Categorizing item non-response
  - “nonproductive” responses (Behr et al., 2012)
  - Indirect (soft) versus direct (hard) refusals (Meitinger et al., 2021)

Item nonresponse detection: prior work, cont'd

- Detecting item non-response
  - EvalAnswer* (Kaczmirek et al. (2017); available on GitHub)
    - **Complete non-response**: blank text box
    - **No useful answer**: "dfgjh"
    - **Don't knows**: "I have no idea"; "DK"; "I can't make up my mind"
    - **Refusals**: "no comment"; "see answer above"
    - **Other**: insufficient to code; "it depends"; "just do"; "just what it is"
    - **Single word**: "economy"
    - **Too fast**: < 2 seconds to answer

* https://git.gesis.org/surveymethods/evalanswer

Item nonresponse detection: prior work, cont’d

- Limitations of EvalAnswer
  - Relies on regular expressions (regex)
  - Missed some gibberish and don't know responses: "I dunno“; "no clue“
  - Flagged single word responses that are valid: "quarantine“; "furloughed“; "closings“
  - Flagged valid responses that include one of the rules:
    - “I have not bee unable to travel to see my grandsons who live away from me. I am **unsure** how this country is going to fare.” [emphasis added]
  - Marked some non-response as valid:
    - "this is not a good question“; "I think my answer is self explanatory"

Item nonresponse detection: Model development

- Trained a natural language processing (NLP) model to interpret responses.
  - Fine-tuned a Bidirectional Transformer for Language Understanding (BERT)* model using Simple Contrastive Sentence Embedding (SimCSE)**
- Refined training via human coding (active learning)

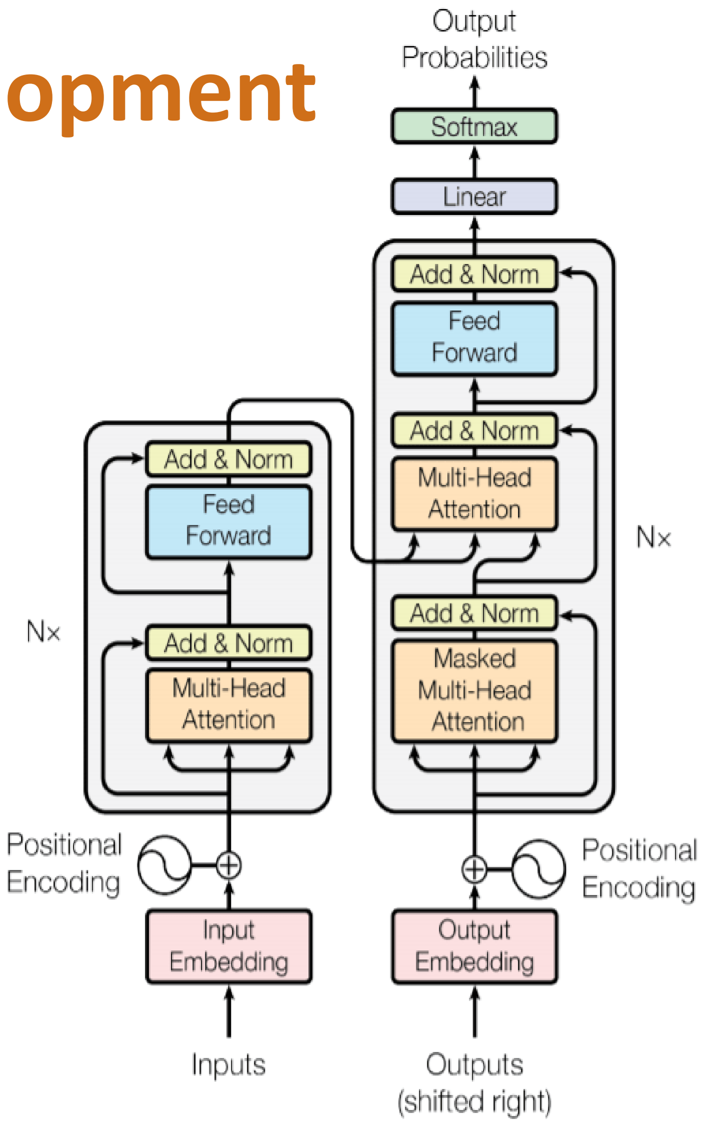

Figure 1: The Transformer - model architecture.

* https://arxiv.org/abs/1810.04805

** https://arxiv.org/abs/2104.08821

Item nonresponse detection: Model development, cont’d

- Our working taxonomy:
  - **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
- The model assigns a score (0-1) for the extent to which a response falls into each of the item non-response categories

Model development: Active learning

- Round 1
  - 5 coders hand-coded 1,400 each, 200 overlapping with one other coder; full overlap for 500
  - Good consistency with most categories (gibberish, DKs, refusals)
  - Less consistency between valid versus “other, high risk” item nonresponse
  - Good results for identifying item nonresponse, but flagged more valids than we wanted
- Round 2:
  - 2 coders reviewed and arbitrated the results to retrain the model
  - Uncertainty retained in the model when warranted

The data

- NCHS's Research and Development Survey (RANDS)
  https://www.cdc.gov/nchs/rands/index.htm
- RANDS During COVID-19 – Multi-round web/phone survey
- Topics: health, impacts of pandemic on health care access, COVID-19 related health care and behaviors
- Round 1 fielded June-July 2020: 13,020 Completes
  - 6,800 NORC's AmeriSpeak probability-based sample = 23.0% weighted cumulative response rate/78.5% completion rate
  - 6,220 Dynata opt-in panel

Model evaluation: our approach

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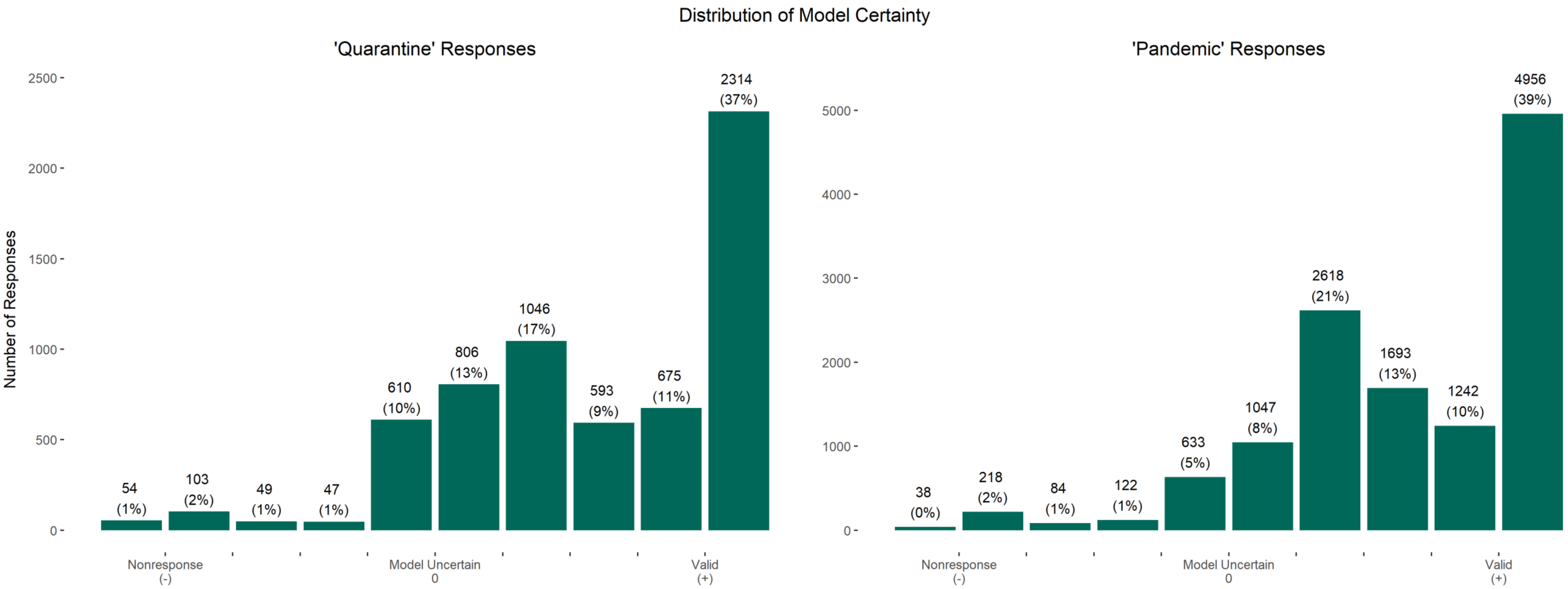
- Mixed-method evaluation of two web probe case studies
  - Quarantine probe
  - Pandemic time reference probe

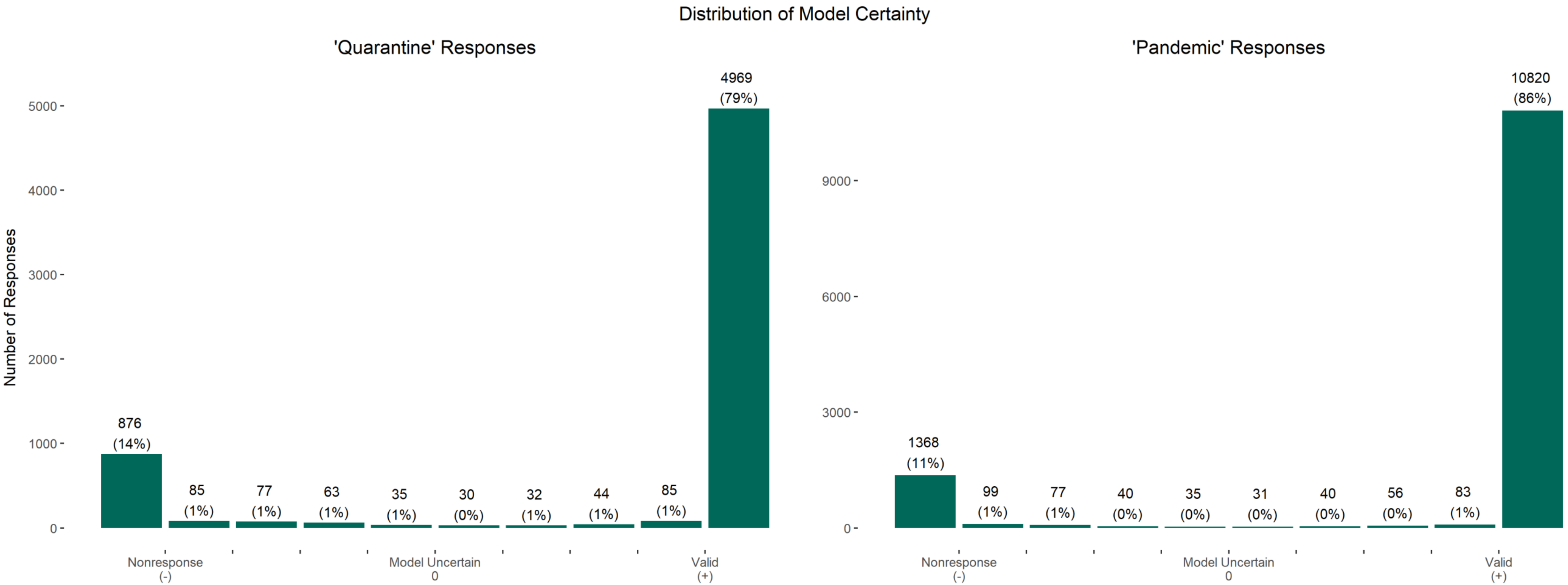
Evaluation results

Round 1: model was initially very uncertain



Model certainty is calculated by subtracting the highest nonresponse prediction score from the valid score.
Negative scores indicate model-predicted nonresponse. Positive scores indicate model-predicted valid response.

Round 2: model is now much more uncertain



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Quarantine probe

- Quarantine survey question: Have you isolated or quarantined yourself because of the Coronavirus? Yes/No
- Quarantine probe: When answering the previous question about isolating or quarantining because of the Coronavirus, what were you thinking about? (half the sample received (n=6,308), other half received a closed-ended version)
- Comparison with "source of truth": human coding (July-September 2020)
  - Sensitivity and specificity calculations

Quarantine probe: evaluation results

	Coded NR	Coded Valid	
Model NR	848	288	**1136**
Model Valid	392	4768	**5160**
Total	**1240**	**5056**	**6296**

Key take-away:
Model did a good job identifying "true" valids; less well identifying "true" item nonresponse

Sensitivity **68%** (848/1240)

False valids (human-coded NR):

- "None" (61)
- "Quarantine" (10)

Specificity **94%** (4768/5056)

False NR (human-coded valid):

- "If I had symptoms"
- "Did I need to quarantine because of a possibility of Coronavirus"
- "If I was knowingly exposed to the virus"
- Almost all "other, high risk"

Pandemic time reference probe

- The probes:
  - 1. When do you think that the Coronavirus pandemic began? Your best guess is fine.
  - 2. When did the Coronavirus pandemic first affect your daily life? Your best guess is fine.
  - 3. Why do you say that? (n=12,662)
- Different "source of truth"; hand-review but not full coding
- Full review of model-identified nonresponse (n=1,619); random sample (n=1,000) of valids
  - "Implied" sensitivity and specificity calculations

Pandemic time reference probe: evaluation results

	Coded NR	Coded Valid	Total
Model NR	1372	247	1619
Model Valid	*199 = (18/1000)*11043*	*10844 = (982/1000)*11043)*	11043
Total	1571	11091	12662

Key take-away:
Model did a good job identifying "true" valids; slightly less well identifying "true" item nonresponse

Sensitivity **87%** (1372/1571),
95% CI [83% , 93%]

Specificity **98%** (10844/11091),
95% CI [98% , 98%]

False valids (human-coded NR):

- "None"
- "Because it just doesn't"
- "I'm fine"
- "Best guess"
- "You asked"

False NR (human-coded valid):

- "because i sdyaty jhome"
- Almost all "other, high risk"

Discussion/next steps

Discussion/next steps

- Evaluation results show promise for our semi-automated item nonresponse detection model
- Next steps:
  - Further evaluation on additional open-text data on wider range of topics
  - Analysis to better understand the types and patterns of item nonresponse and possible subgroup differences
  - Work toward release of a generalized model (possibly web-based) to share with others

Thank you!!

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

For more information contact: Amanda Wilmot awlimot@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

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