# Inferring Respondents' Emotional States from Text and Voice Answers to Open Questions in a Smartphone Survey

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#### Introduction

- Open questions with requests for voice answers are promising
  - Content: Voice answers are longer and contain more topics (Gavras et al., 2022; Höhne & Claassen, 2024)
  - Data Quality: Voice answers have higher criterion validity (Gavras & Höhne, 2022)
  - Missing data: High dropout and high item-nonresponse (Revilla & Couper, 2021; Revilla et al., 2020)
- Voice answers contain tonal cues for inferring emotional states (Höhne et al., 2023)
  - In-situ inferences of emotional states in contrast to global measures
  - Shedding light on engagement and data quality
- Inferences from tonal cues have limitations
  - Time-consuming data processing
  - Do not consider textual content
  - Only possible for voice answers
- In this study, we therefore analyze both text and transcribed voice answers



### Research Questions (RQs)

- RQ1: Do respondents' emotional states inferred through sentiments and transformer models align with each other?
- RQ2: How sensitive are inferences of respondents' emotional states to manipulations induced by an environmental treatment?
- RQ3: Are respondents' emotional states related to data quality?

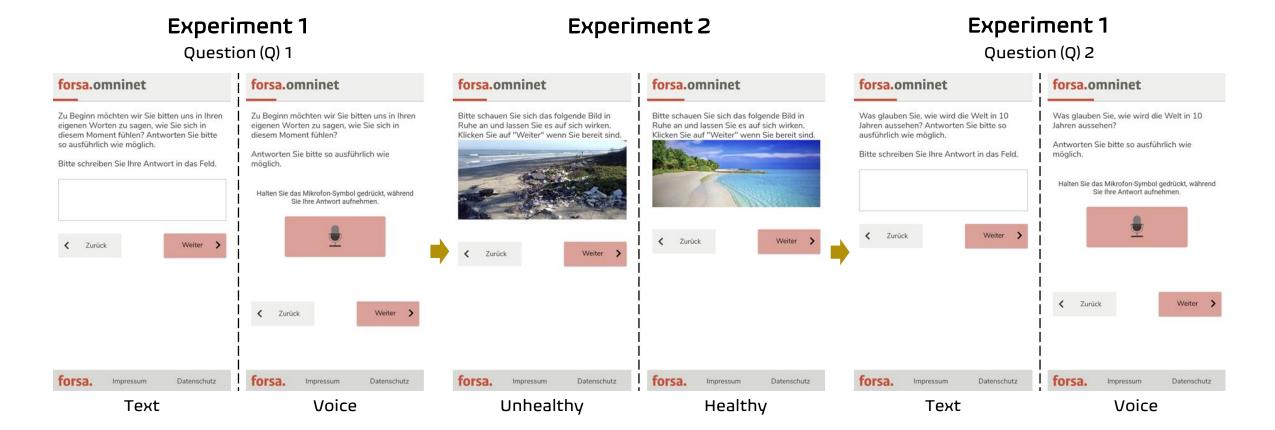


### Method: Study Design

- Smartphone survey (N = 1,001) in Germany in November 2021
  - Cross quota on age, gender plus quota on education
  - Average age: 48 years; female: 49%; medium education: 42%; high education: 28%
- Two open questions
  - Q1: To begin with, we would like to ask you to tell us in your own words how you feel at this
    moment? Please answer in as much detail as possible.
  - **Q2**: What do you think the world will look like in 10 years? Please answer in as much detail as possible.
- Two independent experiments
  - Experiment 1: Request for text or voice answers
  - Experiment 2: Picture of unhealthy or healthy environment
- Voice answers were collected with the open-source SurveyVoice tool (Höhne et al., 2021)



## Method: Study Procedure



### Method: Analytical Strategy

- Transcription of voice answers via OpenAl's Whisper (Radford et al., 2023)
  - Manual inspection of 20% of the recordings (n = 120)
  - High transcription quality
- Determining sentiments using SentiWS v2.0 (Remus et al., 2010)
- Determining emotion probabilities using a transformer model
  - "xlm-roberta-large-xnli" model from Hugging Face (<u>www.huggingface.com</u>)
  - Probability with which an emotion follows from an answer
  - Emotions: Anger, disgust, fear, joy, sadness, surprise, and contempt (Ekman & Friesen, 1986)
- Determining the number of words using Quanteda (R) (Benoit et al., 2021)
- Determining the number of topics using STM (R) (Roberts et al., 2014)



#### Results: Exemplary Answers

Table 1a. Exemplary **text** answers to Q1 including sentiments and emotion probabilities

Answer	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
I am depressed and lack motivation.	-6.16	0.22	0.81	0.47	0.00	0.99	0.86	0.74
Healthy and satisfied.	6.31	0.01	0.02	0.00	0.99	0.00	0.78	0.63

Note. Emotion probabilities >= 0.7 in bold.

Table 1b. Exemplary voice answers to Q1 including sentiments and emotion probabilities

Answer	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
I feel good, not stressed, and refreshed after my vacation.	0.66	0.02	0.02	0.01	0.99	0.00	0.90	0.51
Tired, unmotivated, annoyed, not good.	1.53	0.90	0.81	0.11	0.00	0.80	0.16	0.66

Note. Emotion probabilities >= 0.7 in bold.

Table 2a. Correlations between sentiments and emotion probabilities - Text

	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Sentiment (Q1)	-0.54	-0.57	-0.52	0.67	-0.61	0.02	-0.27
Sentiment (Q2)	-0.21	-0.40	<i>-</i> 0.39	0.33	-0.25	0.01	-0.21

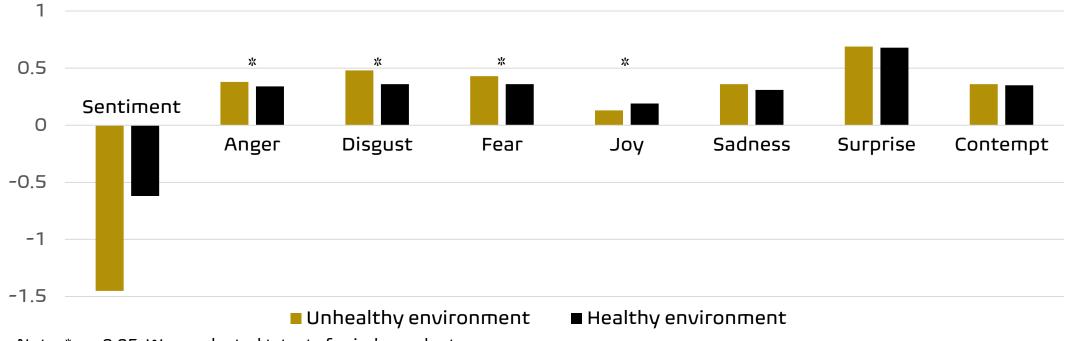
Note. Coefficients with p < 0.05 in bold.

Table 2b. Correlations between sentiments and emotion probabilities - Voice

	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Sentiment (Q1)	-0.51	-0.64	-0.58	0.71	-0.63	0.10	-0.30
Sentiment (Q2)	-0.19	-0.31	-0.35	0.29	-0.24	-0.12	-0.16

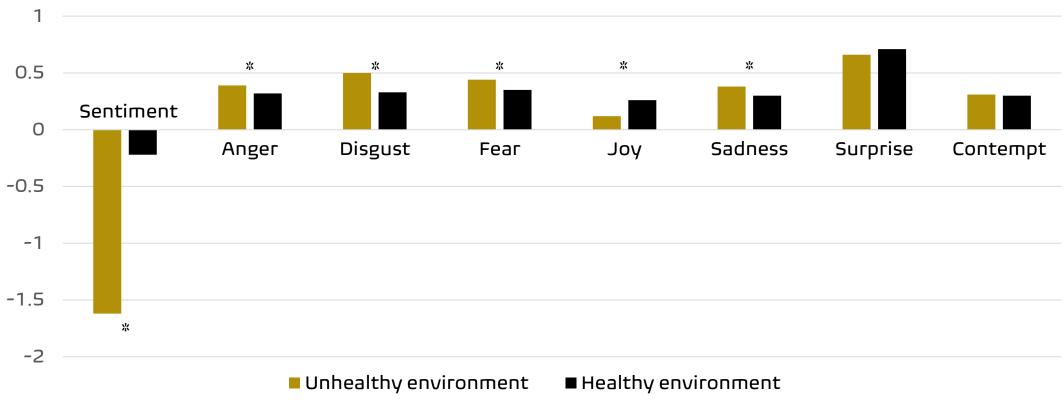
Note. Coefficients with p < 0.05 in bold.

Figure 1a. Emotional state differences between picture conditions (Q2) – <u>Text</u>



Note. \* p < 0.05. We conducted t-tests for independent groups.

Figure 1b. Emotional state differences between picture conditions (Q2) - Voice



Note. \* p < 0.05. We conducted t-tests for independent groups.

Table 3a. Correlations between sentiments, emotion probabilities, and answer length - Text

	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Answer length (Q1)	-0.11	-0.02	0.19	0.21	-0.13	0.06	-0.00	-0.13
Answer length (Q2)	0.00	-0.04	0.04	0.04	-0.11	-0.04	-0.12	-0.15

Note. Coefficients with p < 0.05 in bold.

Table 3b. Correlations between sentiments, emotion probabilities, and answer length - Voice

	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Answer length (Q1)	-0.18	0.21	0.31	0.30	-0.06	0.21	-0.03	0.21
Answer length (Q2)	0.10	0.23	0.21	0.18	0.12	0.20	0.02	0.18

Note. Coefficients with p < 0.05 in bold.

Table 4a. Correlations between sentiments, emotion probabilities, and number of topics - **Text** 

	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Topic number (Q1)	-0.14	-0.02	-0.05	-0.06	-0.07	0.03	0.01	-0.10
Topic number (Q2)	0.09	0.01	-0.02	-0.04	-0.01	-0.10	0.07	-0.06

Note. Coefficients with p < 0.05 in bold.

Table 4b. Correlations between sentiments, emotion probabilities, and number of topics - Voice

	Sentiment	Anger	Disgust	Fear	Joy	Sadness	Surprise	Contempt
Topic number (Q1)	-0.26	0.04	0.11	0.06	-0.23	0.13	-0.14	0.06
Topic number (Q2)	0.04	-0.03	-0.06	-0.06	0.07	-0.00	-0.05	-0.07

Note. Coefficients with p < 0.05 in bold.

#### Discussion and Conclusion

- Moderate to strong correlations between sentiments and emotion probabilities
  - Stronger correlations for question on in-situ feelings (Q1)
  - Patterns hold for both text and voice answers
- Emotional states are sensitive to environmental treatment text and voice
  - <u>Negative</u> sentiments and emotions are more prevalent in <u>unhealthy</u> environment condition
  - <u>Positive</u> sentiments and emotions are more prevalent in <u>healthy</u> environment condition
- Moderate correlations between emotional states and answer length
  - Strength and direction differs between text and voice answers
- Few correlations between emotional states and topic number text and voice
- Take home message: Emotional states can be inferred from text and transcribed voice answers and they inform about answer behavior



# Many thanks for your attention!

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#### Questions for Discussion

- 1) What alternative approaches can be used to infer sentiments and discrete emotions?
- 2) What additional data quality indicators should be considered?
- 3) How can we combine transcribed voice answers with tonal features to inferemotional states?



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