Inferring Respondents' Emotional States from Transcribed Voice Answers to Open Questions in a Smartphone Survey

Claaßen[1,2], Höhne[1,2], Kern[3], & Avetisyan[1]

[1] German Center for Higher Education Research and Science Studies (DZHW)

[2] Leibniz University Hannover

[3] University of Munich

5th Mobile Apps and Sensors in Surveys (MASS) Workshop

Washington, DC (USA) - 6th March 2024

CS3 lab

Computational Survey and Social Science

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 the content of 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?

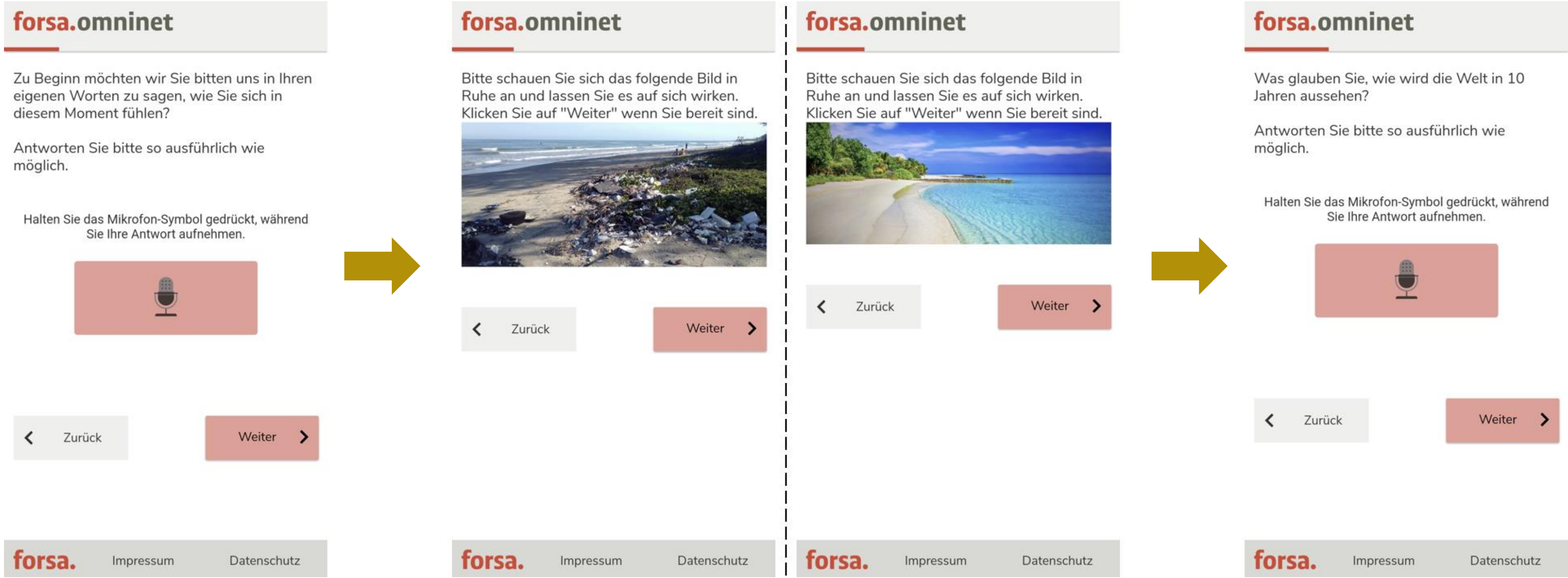
Method: Study Design

- Smartphone survey (N = 501) in Germany in November 2021
    - *Cross quotas on age, gender, and education*
    - *Average age: **48 years**; female: **49%**; low education: **30%**; medium education: **42%**; high education: 28%*
- Two open questions with voice answer requests
    - ***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.*
- Experiment: Picture of unhealthy or healthy environment between Q1 and Q2
- Voice answers were collected with the open-source SurveyVoice tool (Höhne et al., 2021)

Method: Study Procedure

Experiment

Question (Q) 1 | Unhealthy | Healthy | **Question (Q) 2**



Method: Analytical Strategy

- Transcription of voice answers via OpenAI'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 (www.huggingface.com)*
  - *Probability with which an emotion follows from an answer*
  - *Seven 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: Research Question 1

Table 1. Exemplary 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

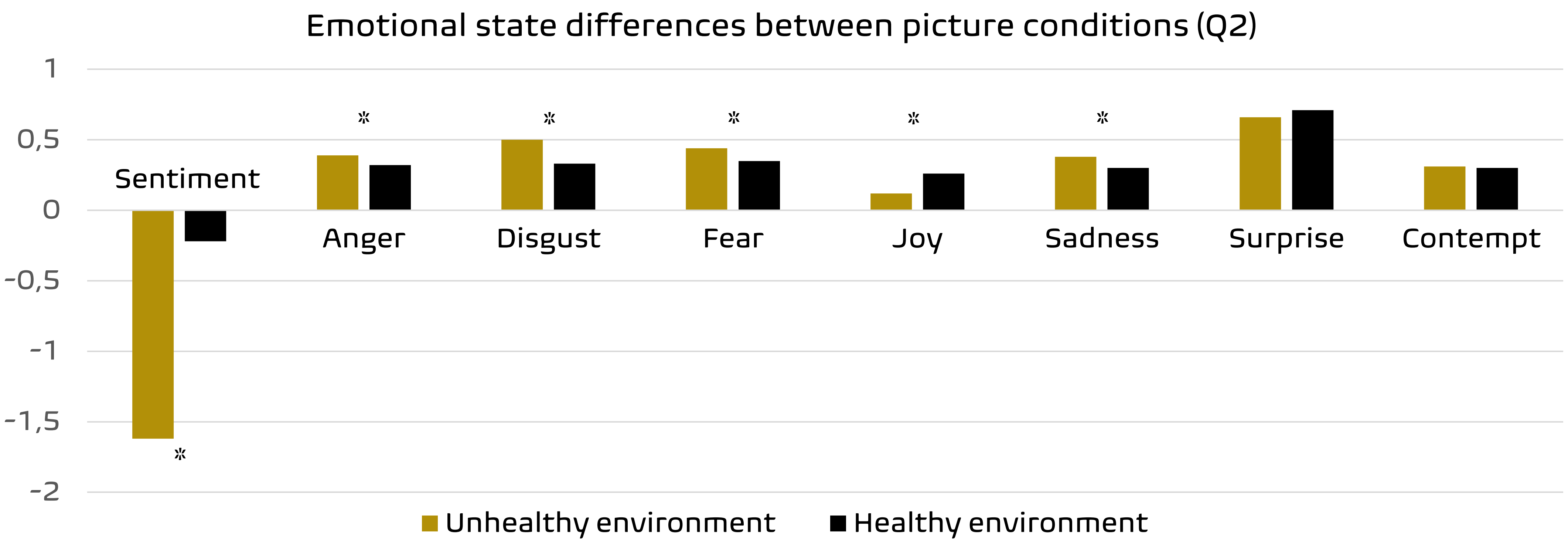
Note. Emotion probabilities >= 0.8 in bold.

Table 2. Correlations between sentiments and emotion probabilities

	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.

Results: Research Question 2



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

Results: Research Question 3

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

	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 4. Correlations between sentiments, emotion probabilities, and number of topics

	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
  - *Patterns hold for both questions*
  - *Stronger correlations for question on in-situ feelings (Q1)*
- Inferred emotional states are sensitive to environmental treatment
  - *Negative sentiments and emotions are more prevalent in unhealthy environment condition*
  - *Positive sentiments and emotions are more prevalent in healthy environment condition*
- Moderate correlations between emotional states and answer length
- Few substantive correlations between emotional states and number of topics
- Take home message: Emotional states can be inferred from transcribed voice answers and they inform about answer behavior

Many thanks for your attention!

claassen@dzhw.eu
@JClaass

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 infer emotional states?

Literature I

- Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., Matsuo, A., Lowe, W., & Müller, C. (2018). Quanteda: R package for quantitative analysis of textual data. https://cran.rproject.org/web/packages/quanteda/quanteda.pdf
- Ekman, P., & Friesen, W. V. (1986). A new pan-cultural facial expression of emotion. Motivation and Emotion, 10(2), 159-168. doi: 10.1007/BF00992253
- Gavras, K., & Höhne, J. K. (2022). Evaluating political parties: Criterion validity of open questions with requests for text and voice answers. International Journal of Social Research Methodology, 25, 135-141. doi: 10.1080/13645579.2020.1860279
- Gavras, K., Höhne, J.K., Blom, A., & 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), 185, 872-890. doi: 10.1111/rssa.12807
- Höhne, J. K., & Claassen, J. (2024). Examining final comment questions with requests for written and oral answers. International Journal of Market Research. doi: 10.1177/14707853241229329
- Höhne, J. K., Gavras, K., & Qureshi, D. D. (2021). SurveyVoice (SVoice): A comprehensive guide for collecting voice answers in surveys. GitHub. https://github.com/JKHoehne/SVoice/tree/v1.0.0
- Höhne, J.K., Kern, C., Gavras, K. & Schlosser, S. (2023). The sound of respondents: Predicting respondents' level of interest in questions with voice data in smartphone surveys. Quality and Quantity. doi: 10.1007/s11135-023-01776-8
- Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., & Sutskever, I. (2023). Robust speech recognition via large-scale weak supervision. Proceedings of the 40th International Conference on Machine Learning, 28492–28518. doi: 10.5555/3618408.36 19590
- Remus, R., Quasthoff, U. & Heyer, G. (2010) SentiWS - a Publicly Available German-Language Resource for Sentiment Analysis. Proceedings of the 7th International Language Resources and Evaluation, 1168–1171.
- Revilla, M., & Couper, M. P. (2021). Improving the use of voice recording in a smartphone survey. Social Science Computer Review. doi: 10.1177/0894439319888708

Literature II

- Revilla, M., Couper, M. P., Bosch, O. J., & Asensio, M. (2020). Testing the use of voice input in a smartphone web survey. Social Science Computer Review, 38(2), 111-244. doi: 10.1177/0894439318810715
- Roberts, M.E., Stewart, B.M., & Tingle, D. (2014). stm: R package for structural topic models. https://cran.r-project.org/web/packages/stm/vignettes/stmVignette.pdf

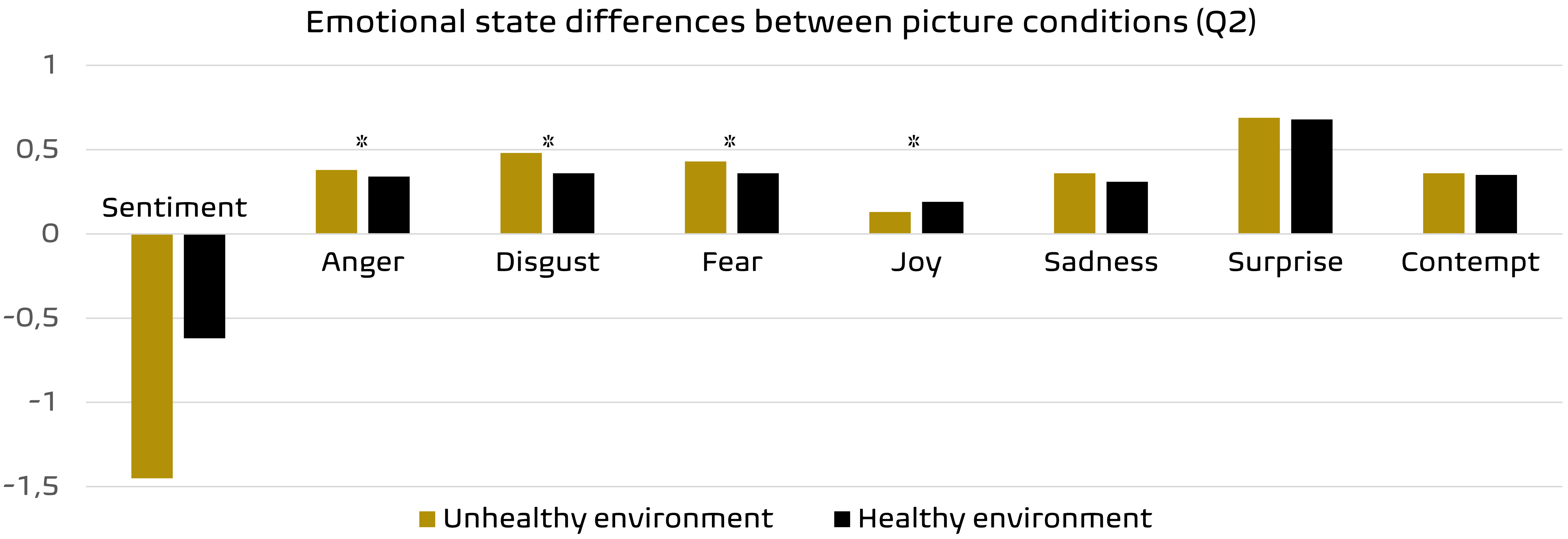
Appendix: Results for Text Answers I

Table A1. Correlations between sentiments and emotion probabilities

	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**	**-0.39**	**0.33**	**-0.25**	0.01	**-0.21**

Note. Coefficients with $p < 0.05$ in bold.

Appendix: Results for Text Answers II



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

Appendix: Results for Text Answers III

Table A2. Correlations between sentiments, emotion probabilities, and answer length

	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 A3. Correlations between sentiments, emotion probabilities, and topic number

	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.