

Survey data contamination through Large Language Models: Predicting LLM-generated answers to open narrative questions

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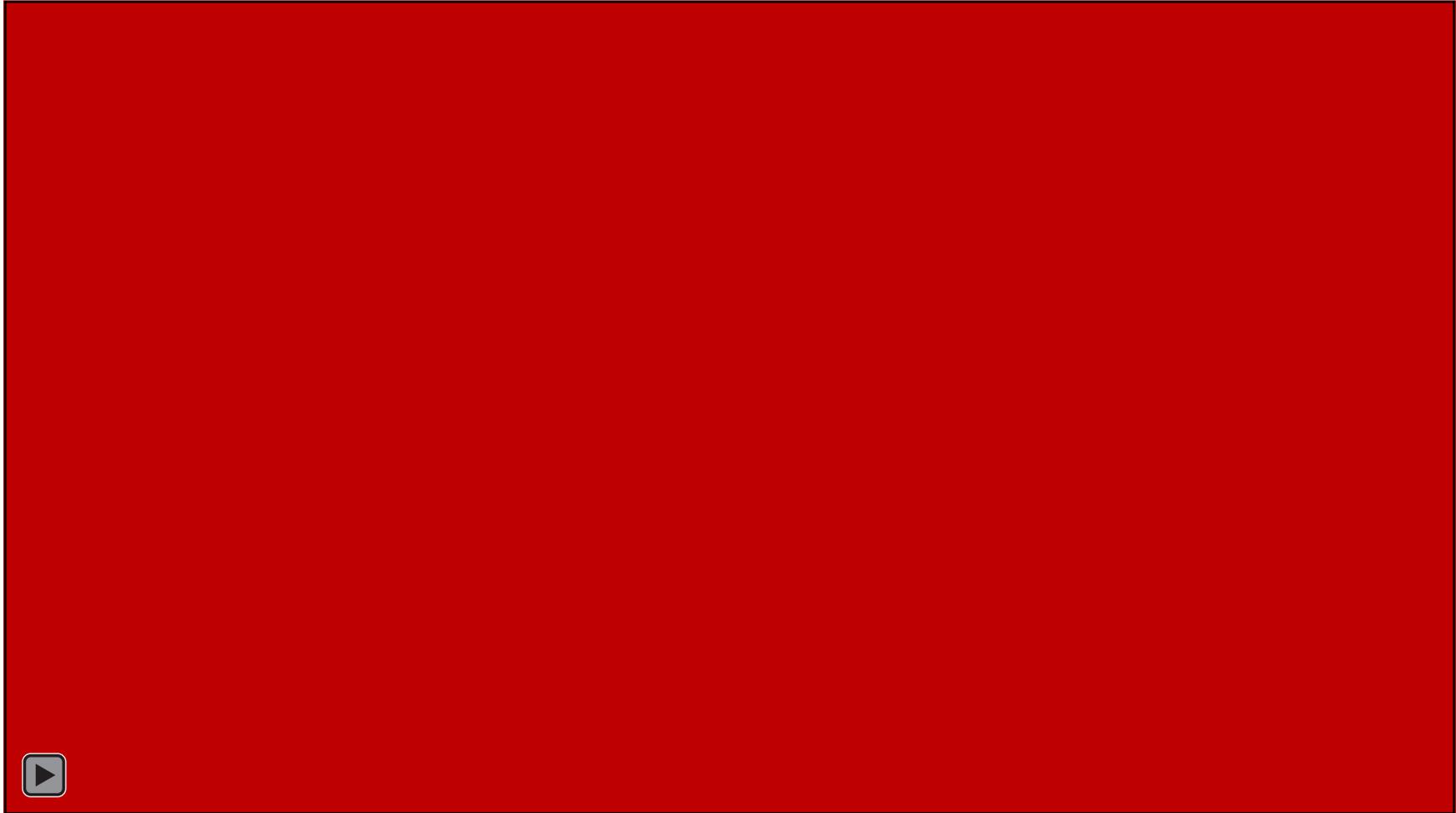
Introduction I

- Growing demand for high-quality survey data (Knowledge Sourcing Intelligence 2023)
- Cost-efficient and streamlined web surveys replace other survey modes, especially in-person interviews (Schober 2018)
- Web surveys may not be suitable for primary survey mode
 - *Depressed response rates* (Daikeler et al. 2020)
 - *Frequently struggle with achieving high data quality* (Callegaro et al. 2015)
- No interviewers for assistance and to create trust, motivation, and engagement
 - *Respondents are on their own without monitoring* (Höhne et al. 2020)
 - *Web offers numerous opportunities to cut corners: so-called “cheating”* (Scott & Jerrit 2016)
 - *The advent of Large Language Models (LLMs) has fueled the problem further* (Rilla et al. 2025)

Introduction II

- There is rumor about respondents prompting LLMs to answer open narrative questions
 - *Reducing response effort: formulating and entering answers is burdensome*
 - *Potential threat to the quality and integrity of survey outcomes*
 - *The extent of LLM-contaminated answers and how to detect them is unclear*
- In this study, we therefore address the following two research questions (RQs):
 - *What are the attributes of open narrative answers generated through LLMs? (RQ1)*
 - *Can we detect open narrative answers in web surveys generated through LLMs? (RQ2)*

Showcase: Contamination through LLMs



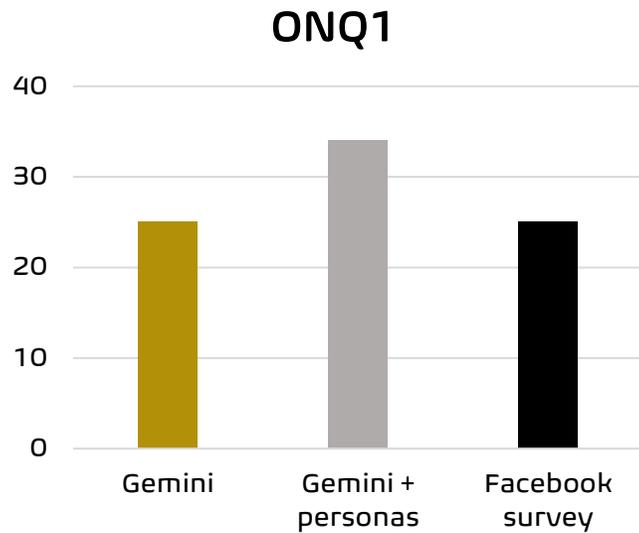
Method: Data and Analyses

- Web survey on same-gender partnerships programmed with Unipark
 - *Three open narrative questions: Child adoption, discrimination, and final comment*
 - *For each question, we prompted Gemini 1.5 Pro (Google 2024) 800 times in February 2025*
 - *Gemini adopted personas – age, gender, education, and party preference – in 50% of the cases*
 - *We also conducted a web survey through Facebook (N = 1,512) in February/March 2024*
- RQ1: Text-as-data methods in the form of answer length and word choice
- RQ2: Predicting robotic language
 - *Fine-tuning BERT for each ONQ: LLM-generated text = “yes” or LLM-generated text = “unclear”*
 - *Performance evaluation: Precision, recall, and F1 score*

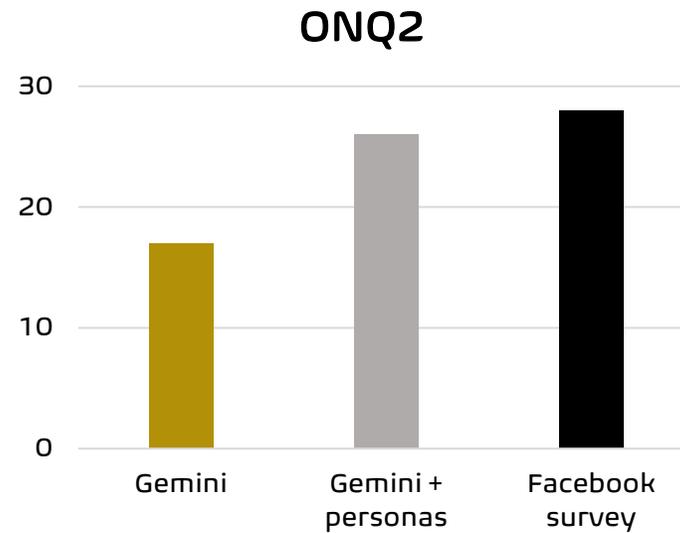
Results: Exemplary Answers

Gemini	Gemini + personas	Facebook survey
<p>Jeder sollte die gleichen Chancen haben, eine Familie zu gründen. Liebe ist Liebe.</p> <p><i>Translation:</i> <i>Everyone should have the same opportunities to start a family. Love is love.</i></p>	<p>Ein Kind braucht 'ne Mutter und 'nen Vater. So is das nun mal vorgesehen.</p> <p><i>Translation:</i> <i>A child needs a mother and a father. That's how it's meant to be.</i></p>	<p>Hauptsache es wird sich gut um das Kind gekümmert.</p> <p><i>Translation:</i> <i>The most important thing is that the child is well taken care of.</i></p>

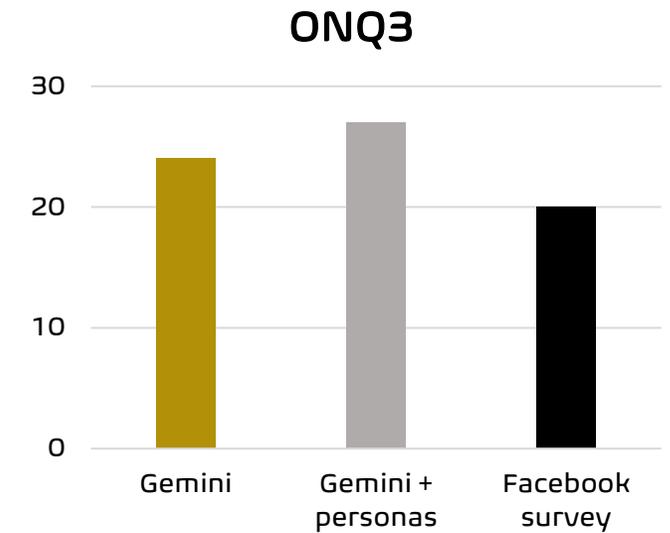
Results: Answer Length (RQ1)



Note. Average number of words.
One-way ANOVA: $p < 0.001$.



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One-way ANOVA: $p < 0.001$.

Results: LLM-generated Text (RQ2)

Table 1. Prediction performance

	ONQ1	ONQ2	ONQ3
Training set size (60%)	960	960	758
Validation set size (20%)	320	320	253
Test set size (20%)	320	320	253
Precision	0.98	0.97	0.99
Recall	0.99	1.0	0.97
F1 score	0.98	0.99	0.98

Note. We used the “bert-base-german-cased” model via the “Simple Transformers” library in Python. For ONQ1 and ONQ2, we used all 800 Gemini answers as well as 800 randomly selected Facebook survey answers, respectively, to create a balanced sample. For ONQ3, in contrast, we used all 632 Facebook survey answers as well as 632 randomly selected Gemini answers.

Discussion and Conclusion

- There are similarities between LLM-generated answers and those from the Facebook survey
 - *LLMs provide meaningful open narrative answers*
 - *No systematic differences regarding answer length*
 - *Word choice may offer clues when it comes to detecting LLM-generated answers*
- BERT reliably predicts LLM-generated answers
 - *Between 97 and 100 percent of the answers are correctly detected*
 - *Applies to answers from both Gemini and Gemini + personas*
- We currently explore further research possibilities
 - *Using BERT to predict prevalence of LLM-generated answers in web survey data*
 - *Making predictions based on closed questions*
 - *Examining other LLMs, such as GPT-4 and Llama 3.3*

Many thanks for your attention!

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Appendix A: Open Narrative Questions

- **ONQ1:** In the last question, you indicated to find it (very good | rather good | rather not good | not good at all) that married same-sex partners in Germany can adopt children. Please explain to us in your own words why you chose this response.
- **ONQ2:** In your opinion, to what extent is discrimination against gay, lesbian and bisexual people a problem or no problem in Germany?
- **ONQ3:** Finally, we would like to give you the opportunity to say something about our survey. Do you have any comments or suggestions on the survey as a whole or on individual questions?

Appendix D: Prompt (Baseline Design)

LLM version

gemini-1.5-pro-002.

Open narrative questions – Prompt design (Gemini)

Verhalte dich wie eine Person, die an einer Umfrage teilnimmt, und schreibe eine Antwort auf Deutsch basierend auf deren Denkweise/Eigenschaften für die folgende Frage: {question}

Gib eine kurze und prägnante Antwort.

Open narrative questions – Prompt design (Gemini + personas)

Verhalte dich wie eine {age} Jahre alte deutschsprachige {gender} Person mit {education} und {party preference} nahestehend, die an einer Umfrage teilnimmt, und schreibe eine Antwort auf Deutsch basierend auf deren Denkweise/Eigenschaften für die folgende Frage: {question}

Gib eine kurze und prägnante Antwort.

Berücksichtige dabei deine bisherigen Antworten: {history}"

Personas (Gemini + personas)

Age: 18 to 89 years

Gender: female or male

Education: low education, medium education, or high education

Party preference: SPD, CDU/CSU, Greens, FDP, AfD, or Left

Gemini parameters

generation_config = {"temperature": 1.0, "max_output_tokens": 2048}.

Appendix E: Token Analysis

LLM-generated text = "yes"				LLM-generated text = "unclear"		
	Token	Attribution score	Frequency	Token	Attribution score	Frequency
ONQ1	(1) Fin	0.78	126	(1) auch	0.25	30
	(2) ##d	0.52	111	(2) Kinder	0.20	71
	(3) is	0.20	38	(3) Eltern	0.19	38
	(4) Ein	0.19	28	(4) und	0.17	92
	(5) ich	0.16	140	(5) zu	0.17	37
ONQ2	(1) schon	0.59	71	(1) Problem	0.31	96
	(2) Is	0.49	35	(2) nicht	0.23	73
	(3) doch	0.42	43	(3) oder	0.22	31
	(4) is	0.39	27	(4) wird	0.21	40
	(5) Also	0.39	43	(5) werden	0.20	36
ONQ3	(1) Also	0.47	46	(1) der	0.20	48
	(2) verständlich	0.43	30	(2) es	0.16	34
	(3) waren	0.27	44	(3) ##en	0.16	31
	(4) Fragen	0.25	72	(4) nicht	0.15	47
	(5) Die	0.24	39	(5) den	0.15	26