

gemini paper

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the einleitung

inspired by the paper *Empirical evidence of Large Language Model's influence on human spoken communication* Yakura et al. (2025), who indeed found (evidence) for GPT influenced human language after the introduction of chatGPT we tried to replicate the pipeline of building an AI vocabulary (gpt preferred lemmata) and compare frequencies of gpt-typical words across pre- and post chatGPT human language corpora. The first draft essay proves their hypothesis that LLM generated language manifests within human natural language.

the embedding of that investigation into the context of the class subject *germanische sprachen im vergleich* is still due; first idea is the projection of the Yakura et al. (2025) findings onto a german language corpus and see if these are still valid although that may rather be a pragmatics investigation.

preliminary

Our findings are still limited to a yet very small corpus of texts after the introduction of the google gemini chat agent to the german public in 03/2024, cf. Wikipedia and Google (2026). In contrast to Yakura et al. (2025) and out of resources considerations we decided for gemini as basis for our AI generated vocabulary and for another text corpus (german bundestag plenary protocols, DIP (2026)) than youtube/podcast audio for the same reasons. That limits our post-AI corpus to a small timeframe between 03/2024 up to now. With expanding that corpus to a wider spectrum with including other sources we may harden our results.

hypothesis

following Yakura et al. (2025) we assumed that the consuming of LLM generated language influences the human production of language such that vocabulary typical for LLM output will be found with higher frequencies in human language corpora dating after chat agent introduction.

next methods

methods

snc

16062.1.2.16063.1

please cf. Schwarz (2026) for the corpus building and evaluation script (still messy.)

data

our human langugae data consists of raw texts from german bundestag plenary protocols (DIP (2026)). the LLM corpus consists of model summaries of a first subset of these texts generated with the following prompt: Section .

corpus subsets

target	tokens
gemini	3895
human-pre	1437497
human-post	1363467

gemini prompt

```
[1] "System prompt: "  
[2] "You are a member of german parliament. Prepare a summary of the text provided to present  
[3] "Text:"
```

computation

we first devised AI-typical lemmata in the model corpus which are distinctive for that corpus using a linear regression model (R, package lme4::glmer(): Bates et al. (2015)) that calculates a score for each lemma in the corpus, see Figure 1 and Figure 2.

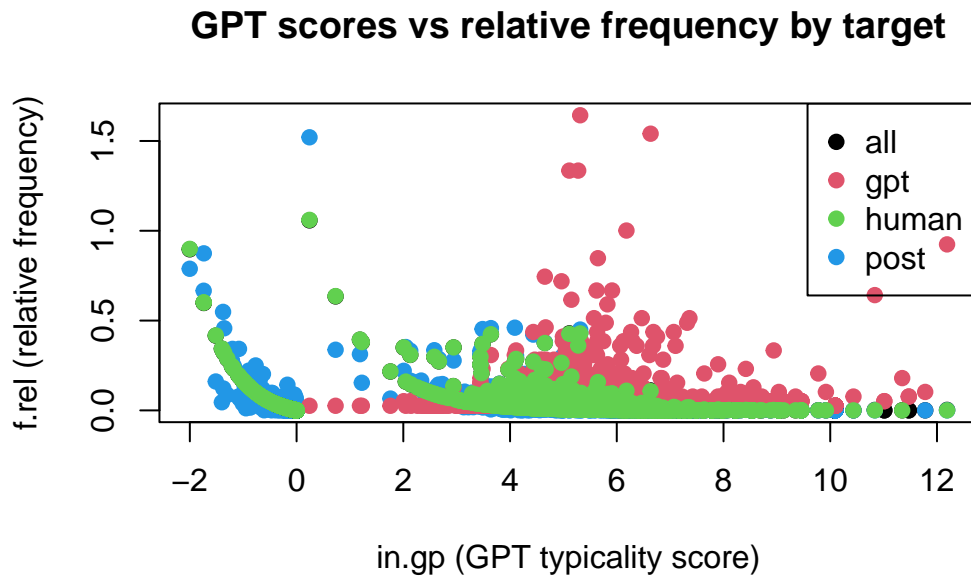


Figure 1: lemma gpt scores over targets



Figure 2: target gpt density

evaluation

basic descriptive

to first gather an insight, yet with simple descriptive stats comparing the raw frequencies of gpt-preferred lemmas in pre- and post-gemini onset we find that in the target corpus the occurrences of these lemma increase, only by small amount (see Table 2) and hard to visualise (see Figure 3). if these findings become relevant, we'll see in Section where we evaluate the frequencies with a linear regression model.

Table 2: GPT lemma frequencies (table) over target. (freq / vH)

target	freq
human	0.3708
post	0.3890
DIFF:	0.0182

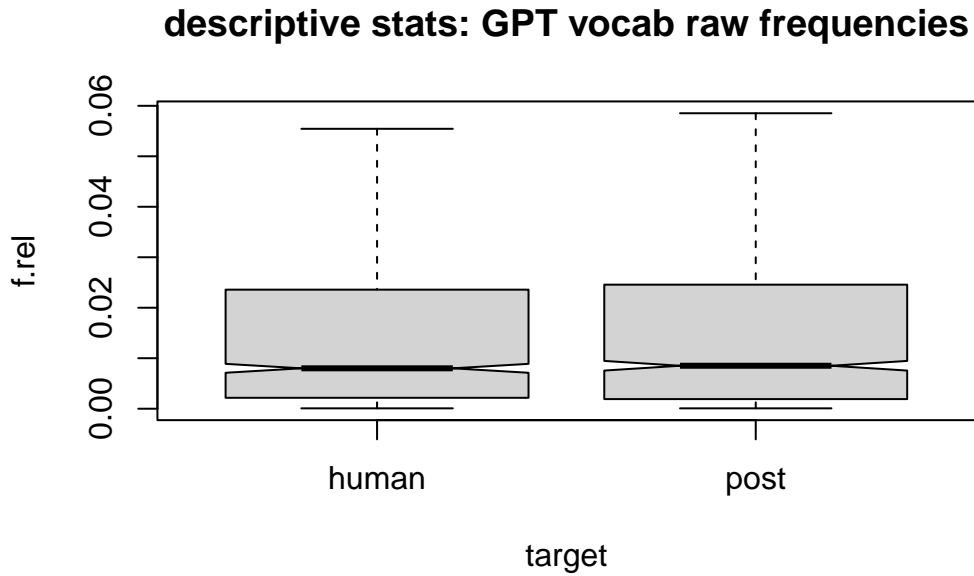


Figure 3: GPT lemma frequencies (boxplot) over target. (freq / Mtoken)

responsible lemmata

selection of first 20 lemma that are responsible for the increase of frequency in general

[1] müssen	deutschland	menschen	liebe
[5] stehen	mehr	sagen	einsetzen
[9] herausforderungen	wichtig	aktuell	interessen
[13] partei	wichtiger	arbeiten	arbeitsplätze
[17] berlin	bleiben	bürger	bürgerinnen

348 Levels: abgeordnete aktiv aktuell alice all alltag ... zusammenhalt

linear regression

to prove descriptive results, we compute the stability of the frequency increase for target- vs. reference corpus with a linear regression model using R's `lme4::lmer()` function, cf. Bates et al. (2015). coefficients are printed below, where frequency are the relative lemma frequencies over corpus; target defines reference resp. target corpus[post-gpt] (human/post) and in.gpt as numerical variable representing the gpt-score of the corresponding lemma i.e. whether it scores high (positive values) or low (negative values) in terms of being preferred by the chat agent.

basic (lm)

formula: frequency.relative ~ target * in.gpt

Call:

```
lm(formula = f.rel ~ target * in.gp, data = lmdf.c)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.04285	-0.00099	-0.00099	-0.00077	1.57754

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.061e-03	5.421e-05	19.570	< 2e-16 ***
targetall	5.864e-06	7.666e-05	0.077	0.9390
targetgpt	6.128e-02	1.370e-03	44.733	< 2e-16 ***
targetpost	9.944e-05	7.899e-05	1.259	0.2081
in.gp	2.535e-03	6.791e-05	37.333	< 2e-16 ***
targetall:in.gp	-2.157e-04	9.387e-05	-2.298	0.0215 *
targetgpt:in.gp	-1.922e-03	2.404e-04	-7.996	1.30e-15 ***
targetpost:in.gp	3.859e-04	9.731e-05	3.965	7.33e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0149 on 223173 degrees of freedom

Multiple R-squared: 0.1278, Adjusted R-squared: 0.1278

F-statistic: 4672 on 7 and 223173 DF, p-value: < 2.2e-16

mixed effects model (lmer)

formula: frequency.relative ~ target * in.gpt +(1|lemma)

Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]

Formula: f.rel ~ target * in.gp + (1 | lemma)

Data: lmdf.c

REML criterion at convergence: -1319734

Scaled residuals:

Min	1Q	Median	3Q	Max
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-70.063 -0.031 -0.028 -0.017 115.436

Random effects:

Groups	Name	Variance	Std.Dev.
lemma	(Intercept)	8.870e-05	0.009418
Residual		9.543e-05	0.009769

Number of obs: 223181, groups: lemma, 110393

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	9.193e-04	4.795e-05	2.101e+05	19.171	< 2e-16 ***
targetall	-5.765e-06	5.026e-05	1.447e+05	-0.115	0.9087
targetgpt	-1.781e-02	1.015e-03	1.676e+05	-17.535	< 2e-16 ***
targetpost	-3.930e-05	5.911e-05	1.937e+05	-0.665	0.5061
in.gp	2.216e-03	6.094e-05	1.992e+05	36.359	< 2e-16 ***
targetall:in.gp	1.262e-04	6.200e-05	1.463e+05	2.035	0.0419 *
targetgpt:in.gp	1.096e-02	1.772e-04	1.672e+05	61.847	< 2e-16 ***
targetpost:in.gp	2.781e-04	6.444e-05	1.469e+05	4.315	1.6e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	trgtll	trgtgp	trgtps	in.gp	trgtl:. trgtg:.
targetall	-0.524					
targetgpt	-0.028	0.026				
targetpost	-0.585	0.425	0.027			
in.gp	-0.118	0.063	0.034	0.070		
trgtll:n.gp	0.065	-0.121	-0.034	-0.053	-0.540	
trgtgpt:n.g	0.025	-0.023	-0.938	-0.023	-0.218	0.214
trgtpst:n.g	0.082	-0.059	-0.003	-0.140	-0.512	0.501 0.175

helper interpretation, to be tested

the coefficients interesting for us are the in.gp and targetpost:in.gp estimates. here we test the association between the gpt score of a lemma and its estimated frequency and its showing that a general increase of frequency is estimated if the score rises (=the lemma is within the lemmas preferred used by gemini) and that for the post-gpt corpus that increase 2.78×10^{-4} (30.25%) is significant (and not random in data).

in the fixed effects correlation output of the lmer() model we see that the gpt score increases the target corpus frequency for lemma by 0.0695357.

anova of mixed effects model

- Bates, Douglas, Martin Mächler, Ben Bolker, and Steve Walker. 2015. “Fitting Linear Mixed-Effects Models Using Lme4.” *Journal of Statistical Software* 67 (1): 1–48. <https://doi.org/10.18637/jss.v067.i01>.
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