# gemini paper

## index

### 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 essai proves their hypothesis that LLM generated language manifests within human natural language.

### 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 public in 03/2024. In contrast to Yakura et al. (2025) and out of resources reasons 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 agents introduction.

### next methods

## methods

### snc

16062.1.2

### 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 presen
[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.

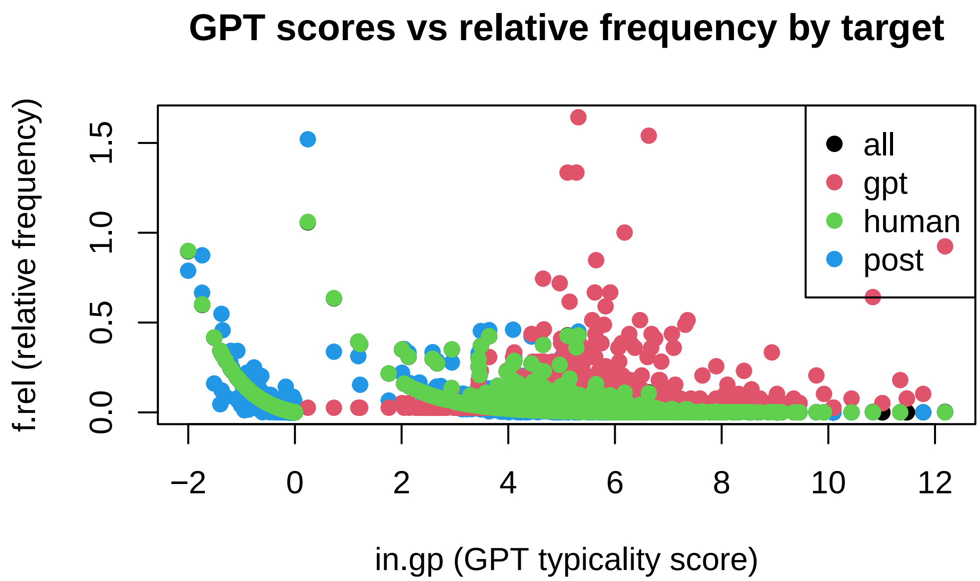


Figure 1: lemma gpt scores over targets


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 occurences 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 |

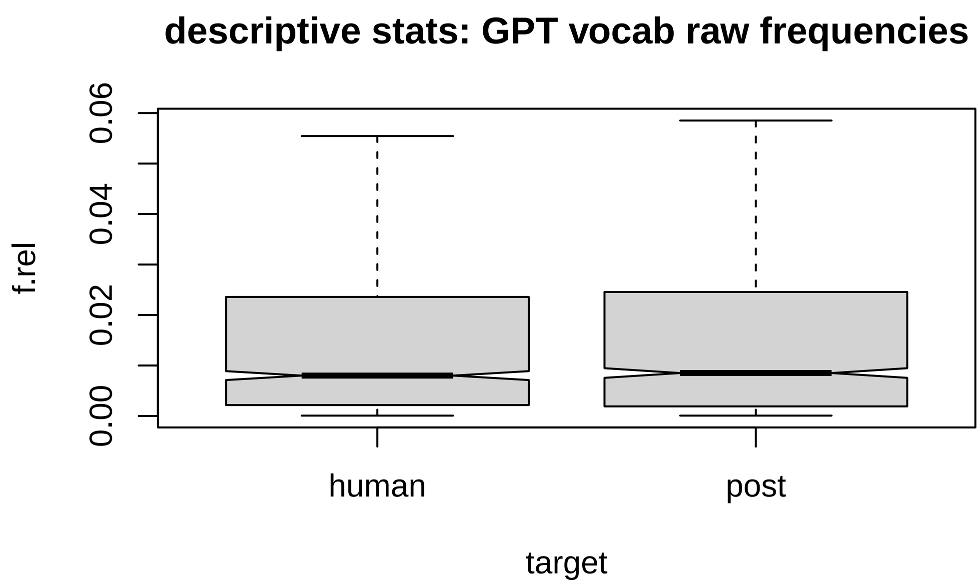


Figure 3: GPT lemma frequencies (boxplot) over target. (freq / Mtoken)

#### 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). coefficents 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. wether it scores high (positive values) or low (negative values) in terms of being preferredly used 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
-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 and that for the post-gpt corpus that increase is significant (and not random in data).

in the 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.

DIP. 2026. "DIP - Bundestagsprotokolle." Docs. *DIP - API*. Berlin. https://dip.bundestag.de/%C3%BCber-dip/hilfe/api#content.

Yakura, Hiromu, Ezequiel Lopez-Lopez, Levin Brinkmann, Ignacio Serna, Prateek Gupta, Ivan Soraperra, and Iyad Rahwan. 2025. "Empirical Evidence of Large Language Model's Influence on Human Spoken Communication." arXiv. https://doi.org/10.48550/arXiv.2409.01754.