This is the supplementary information to the paper "Participants something something vocabulary something something age something something lexical decision task".

Links

The lit review is **here**.

The ms is **here**.

The code to run the experiments on Gitlab for pilot 1, pilot 2, and the main experiment are **here**, **here**, and **here**.

File structure and workflow

We ran two pilot experiments and a main experiment. In the paper, we mostly talk about the main experiment and don't like talking about pilot 1 and 2, much like people do about the East Pole and the West Pole.

The stimulus list for pilot 1 was based on a frequency list from Hungarian Webcorpus 2. We host this list in this repository. Cite us and the original if you want to use it. Subsequent stimulus lists were based on results from pilot 1.

- src: corpus data in various processed forms
- raw: raw output of the Gitlab scripts running the experiments
- scripts: scripts to create the word lists, process the raw data, create the tidy data, and check on the processing
- tidy: tidy data for pilot 1, 2, and main
- analysis: scripts to analyse the tidy data from the main experiment

The main experiment

Research questions

1. Does participant vocabulary size predict response time to visual word targets in a homogeneous participant sample?
2. Does participant age predict lexical decision times?
3. How do participant vocabulary size, participant age, and the relative familiarity of a word target interact in predicting response times by a participant to a word target?

Stimuli

We used real Hungarian words and nonce words in the main experiment. For real words, 900 word forms were sampled from a frequency dictionary built from a web-crawled and morphologically disambiguated corpus of Hungarian (Nemeskey (2020)). The corpus contains cca. 9 billion forms. For nonce words, we used a spelling dictionary (Szabó and Kovács (2018)) with a low-frequency cutoff to generate ngram models of valid Hungarian forms. We used these models to generate words of varying length and then hand-filtered the resulting list to arrive at a list of 300 nonce words.

A separate baseline experiment (our pilot 1) was used to benchmark our stimuli. The word list of 1200 (900 real + 300 nonce) forms was split in 50 frequency bins of 24 (18 real + 6 nonce) forms each based on log frequency for real words and at random for nonce words. Words were displayed in a lexical decision task in decreasing order of bins (from more frequent to less frequent) for each participant. Participants had to say "yes" the word if they were familiar with it or say "no" if they were unfamiliar with it or did not think it to be a word in Hungarian. Participants responded using the keyboard. They were instructed to be as fast as possible. A subset of words was sampled at random for each participant. The experiment was coded in Psychopy and run online on Pavlovia (Peirce (2007)).

The step-wise design was built on earlier work, such as (Hintz et al. (2020),Wolf et al. (2021)). We are grateful for the substantive feedback given by Florian Hintz. Participants were to encounter gradually more difficult stimuli, and the experiment terminated if they rejected too many words in a given difficulty bin. In practice, the vast majority of our participants reached the most difficult bin, indicating that the original design was not sufficiently challenging for this sample.

404 participants completed the baseline experiment (305 women, median age = 21) in mid 2020. We collected 19-60 responses per word, with a median of 37.

For real word targets, the log odds of "yes" / "no" answers correlated with the word's log frequency (r = .56). We fit a regression model predicting the log odds of "yes" / "no" answers from the word's frequency bin. Visual inspection of the model residuals revealed an outlier region of words that were comparatively rare in the corpus but participants knew them all the same. We used the residuals to exclude around 20% of words which fell in this category, that is, which received much more "yes" answers than predicted by their frequency bin. We did this for both the overall distribution and the individual frequency bins. We ordered the remaining words by the log odds of accept / reject answers (that is, their familiarity to the participant sample in the baseline experiment), split the set into 50 bins, and sampled 4 real words from each bin.

Subjective familiarity and word frequency are never a perfect match, especially in the written domain (Colombo, Pasini, and Balota (2006)). Some less common words are used in specific contexts while others are more evenly distributed (see our example of ‘lymphatic’ and ‘mantelpiece’ from earlier), compounds (like ‘darkroom’ or ‘blackbird’) might be primed by their constituents, some words are harder to parse than others, etc. We wanted to create stimuli that are a better fit for the expectations of our participant sample, which is why we used participant responses to calibrate word familiarity.

For nonce words, we sorted these across the ratio of correct answers (saying “no” to the word) and took the two-thirds with which participants were most accurate (in recognising that the word was not a real word in Hungarian). We sampled 50 forms from this set. Due to a sorting error, the stimulus set ended up with 199 real words and 51 nonce words.

The end result was a set of 250 words, with 199 real words split across 50 familiarity bins and 51 nonce words. Real words were singular nouns, adjectives, and 3sg. present verbs, containing 2 or 3 syllables. They each had a familiarity score between 1 and 50, predicated on responses in a baseline experiment (as detailed above). Nonce words matched real words in length and make-up, and were rated as sufficiently distinct from real words in the baseline experiment. These words were used in the main experiment.

List of nonce words in stimuli:

> “abeti, aragas, aurult, cséltás, csenyei, dohorpák, egant, ernyak, extuál, gyásos, hider, hitódó, jegedény, karnogó, kelől, kilukát, kocskesi, konyrúd, kosi, kunyai, lemesség, lublika, megpadék, méhezter, mihálóz, norvend, novagár, összalaj, ószeven, parkkói, pentez, retálhit, retta, rojtoz, rozintem, storító, szabotró, szelégül, szimboló, tajtásos, takorák, tömzsa, tortya, tröshet, úszamos, városló, vényegő, vésségi, vetézmés, vonzum, zomogyi”

List of real words in stimuli, from most to least familiar:

> “pohár (glass), extrém (extreme), törődik (cares), ellenfél (opponent), időszak (period), eszköz (tool), alkalom (occasion), szegény (poor), közhely (cliché), rejtőzik (hiding), tartalom (content), mítosz (myth), karakter (character), dolog (thing), törékeny (fragile), barát (friend), példakép (role model), gazdag (rich), profit (profit), kötődik (bound), dolgozik (work), lélek (soul), hatalom (power), hajlik (bend), gyűjtemény (collection), beton (concrete), jármű (vehicle), keresztény (Christian), könnyelmű (frivolous), űrlap (form), töredék (fragment), irány (direction), végbél (rectum), százalék (Percent), reagál (responds), örmény (Armenian), égitest (celestial body), ausztrál (Australian), régész (archaeologist), század (century), bélyeg (stamp), pereg (slick), nagyszámú (numerous), hálózsák (sleeping bag), tábornagy (Field Marshal), diktátor (dictator), balközép (centre left), kárpit (tapestry), komoly

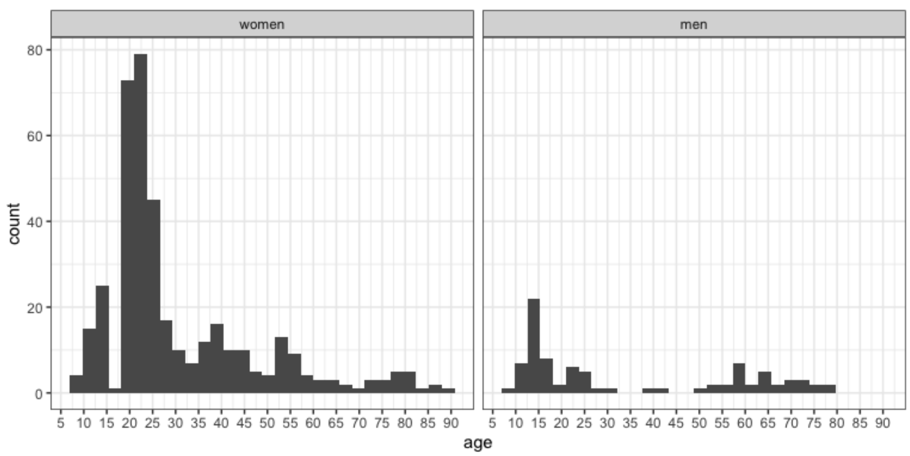
(serious), csatázik (battle), piktogram (pictogram), kislány (girl), sárgaréz (brass), csengettyű (bell), délceg (proud), kulcscsont (clavicle), komplex (complex), hidroxid (hydroxide), sugár (ray), igény (demand), iszlám (islam), olaj (oil), újgazdag (nouveau riche), nárcisz (narcissus), árus (vendor), szempont (aspect), rakódik (stack), sporthorgász (sport fisherman), tenger (sea), rövid (short), forgórész (rotor), csontdarab (bone fragment), fürkész (scan), orális (oral), látszik (seems), ómagyar (old Hungarian), tarol (sweep), színpad (stage), elegy (blend), horizont (horizon), darab (piece), nagybeteg (gravely ill), lépték (measure), ború (dour), selypít (lisp), kanalaz (spoon), glükóz (glucose), lágyék (crotch), népszerű (popular), sziszeg (hiss), grafikon (graph), változik (varies), luftballon (balloon), biliárd (billiards), gyapot (cotton), mellényzseb (vest pocket), tököl (fiddle), gyülemlik (accumulates), nyersarany (raw gold), testnedv (bodily fluid), referál (refer), csüggeszt (discourage), tangózik (tango), turné (tour), heveny (acute), derít (settle), hidegház (cold storage), viszkózus (viscous), lukaszt (aperture), puritán (puritan), reform (reform), nukleon (nucleon), kalcium (calcium), bacon (bacon), nimbus (nimbus), transzplantál (transplant), szalicil (salicyl), viszkóz (viscose), szokik (habituates), csüggedez (dispirited), abszint (absinthe), tropikus (tropical), kitin (chitin), szilikát (silicate), arzénsav (arsenic acid), bolgár (Bulgarian), ion (ion), gerencsér (lucky), svábtök (Solanum tuberosum), skubizik (scubic), komál (sympathise), kettősfém (bimetal), püffeszt (bloat), kondenzcsík (contrail), csapdáz (trap), anorák (anorak), lakotthely (dwelling place), koenzim (coenzyme), rücsök (jerk), báránytfark (Amaranthus caudatus), kurtít (curtail), genom (genome), csapattest (corps), neoprén (neoprene), árstop (driftstop), farkasbab (Lapinus luteus), konverzál (converge), törköly (dwarf), pauzál (pause), fertilis (fertilis), dádá (dada), kencéz (kencéz), alfél (bottom half), fajansz (faience), rotor (rotor), kúpol (cone), bizmut (bizmut), donhuán (donhuan), lazúroz (loose), káder (cadre), templomoz (temples), bajuszfű (Crypsis schoenoides), lejmol (scrounge), kurzív (cursive arch), türemlik (protrude), dipeptid (dipeptide), ingváll (shirt shoulder), áradmány (flooding), rámáz (ramp), cianid (cyanide), forrpont (boiling point), libling (favorite), glosszáz (gloss), viszonvád (counteraccusation), magmatit (magmatite), ifjít (rejuvenate), hübrisz (hybris), kollapszus (collapse), adszorbens (adsorbent), mimézis (mimesis), bajadér (bayadère), kvéker (Quaker), truccol (defy), kontrapunkt (counterpoint), rekvizit (props), petél (ovulate), orront (disdain), aggófű (Senecio asteraceae), infimum (infimum), döföl (stab), kurzivál (cursive), cugehőr (belongings), lalláz (slur), móringol (moor), piláf (pilaf), krakéler (roisterer), diffamál (slander), diviz (divident), vabank (all or nothing)”

Participants

507 participants completed the main experiment. Data were collected online in 2021-22. Participation was voluntary, participants either received course credit (if they were university students) or no compensation. **Put file number of Ethics approval here.**

From the final dataset, we removed trials with a response time larger than four seconds and participants who responded "yes" to more than 20 nonce words. This removed 4.3% of trials and 18 participants. In addition, 3 participants didn't provide their age and were also removed. This left 113705 "yes" and "no" responses from 475 participants to 250 existing and nonce words.

Participant demographics after filtering:



Procedure

Participants completed the task on their home computers. The experiment did not work on tablets and mobile phones. Each participant saw every stimulus word in a random order. The task was set up with two practice trials, one with a common Hungarian form that participants had to say "yes" to by pressing the right arrow on the keyboard, and a nonexistent form that they had to say "no" to by pressing the left arrow. The correct answer for the practice trials was spelt out in the instructions. The main experiment was coded in jspsych (De Leeuw (2015)) and run online on Pavlovia (Peirce (2007)). Participants saw each of the 250 trials once, in a random order.

The main experiment followed the practice trials. Each stimulus was displayed after a 500ms delay upon a button press. Participants were instructed to be as fast as possible.

Outcome and predictors

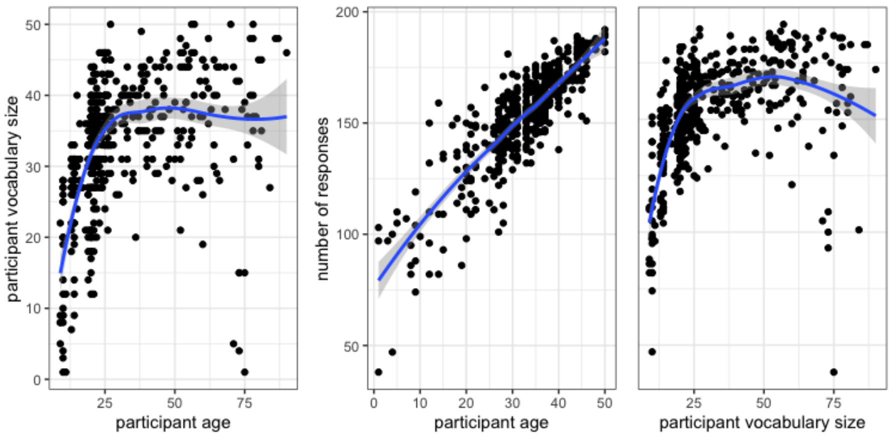
Our main analysis focuses on response times of "yes" responses to existing words in the experiment. Our outcome variable was untransformed reaction time in each trial, following Lo and Andrews (2015). The data have 72782 "yes" answers from 475 participants to 199 existing words.

Our predictors were the word's rate of familiarity and, the participant's age, and the participant's vocabulary size score.

Word familiarity had a score of 1 (highly unfamiliar, examples: 'diffamál' to slander, 'krakéler' roisterer) to 50 (highly familiar, examples: 'pohár' glass, 'extrém' extreme). It was established based on responses by a separate set of participants in the baseline experiment.

Participant vocabulary size was established as follows. Each participant responded to nonce words and real words. The real words were in pre-established familiarity bins (from 1, most familiar, to 50, least familiar). We identified the most familiar bin in which the participant responded "no" to more than one real word. The number of this bin became the participant's vocabulary size, used in the analysis. Here is an example. Bin 4, a relatively familiar bin, has four words in it: 'barát' (friend), 'dolog' (thing), 'törékeny' (fragile), 'karakter' (character). Bin 44, a relatively unfamiliar bin, has 'glosszáz' (to gloss), 'libling' (favorite), 'magmatit' (magnetite), 'viszonvád' (counter-accusation). Participant A might say "no" to both barát and dolog (no actual participant did this). This means they rejected more than one word in bin 4. We check that this hasn't happened in bins 1-3 meaning that 4 is the earliest bin where they did this. This means that their vocabulary size is 4. Participant B might say "no" to magmatit and libling and glosszáz. We check that hasn't happened in bins 1-43, where they only rejected one word per bin at most. This means that their vocabulary size is 44. What participant A does in bins 5-50 and what participant B does in bins 45-50 is not relevant for their vocabulary size. Note that participants see words in random order. Participant B might have responded to magmatit in trial 1, trial 250, or anywhere in between.

Vocabulary size correlates with age across participants, but imperfectly. Participants that know fewer words give fewer "yes" answers, meaning that we have fewer data from them. These two patterns can be seen below.



Modeling

The extent to which participant vocabulary size, age, and word familiarity explain variation in trial response time in the experiment was modeled using Generalized Additive Modeling (GAM) (S. Wood and Wood (2015),S. N. Wood (2017)) with thin plate regression splines for smooth terms, and participant and word as grouping factors. Models were fit using maximum likelihood (ML) optimisation. The choice of the k parameter was verified by basic dimension checking. The Akaike information criterion (AIC) and tests of the ML scores, were used for model comparison. Since response counts across word and participant (the grouping factors) vary widely and since some words and participants have very few "yes" responses, random slopes and factor smooths would have overfit the model, so we did not explore them.

Below is a table of GAMs fit on the "yes" responses to existing words. Models ranked from most complex (1) to least complex (12). Table shows model formula, AIC, and ML score, along with the significance level of a comparison between the model's ML score and Model 1's ML score. All smooths (s) fit as thin plate regression splines with k = 5. All 1+ dimensional interaction surfaces are modeled as tensor products. AIC and ML select Model 1 as the best model.

formula	aic	ml	sig
resp.rt ~ 1 + te(word_familiarity, participant_vocabulary_size, participant_age) + (1|participant) + (1|word)	97320	49648	
resp.rt ~ 1 + te(participant_age, word_familiarity) + te(participant_vocabulary_size, participant_age) + (1|participant) + (1|word)	97458	49703	***

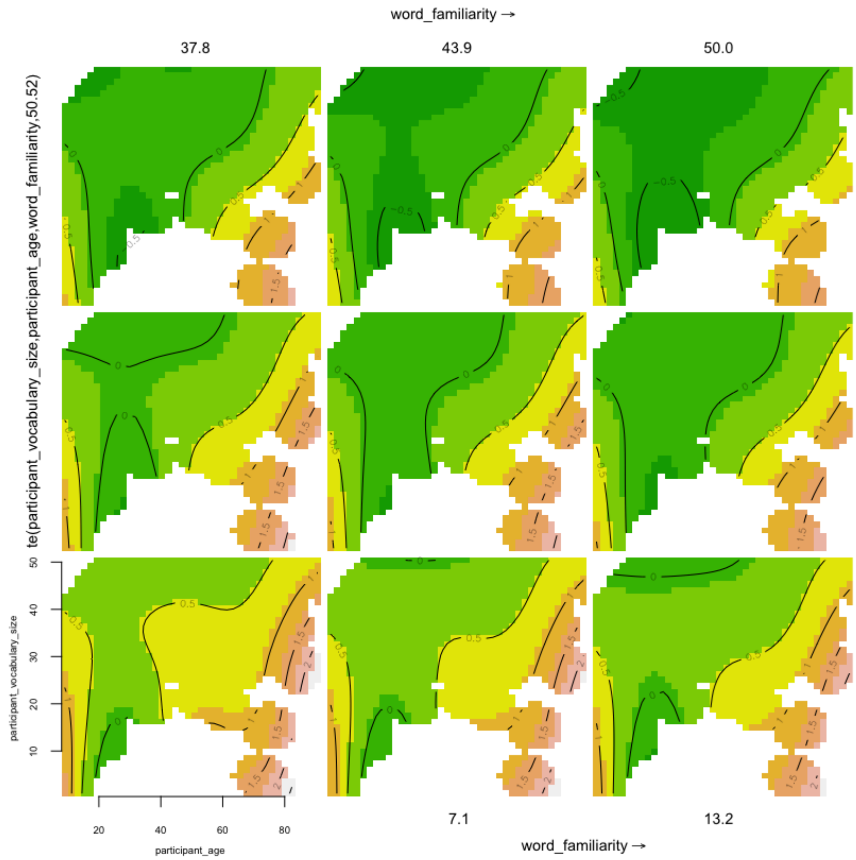
formula	aic	ml	sig
resp.rt ~ 1 + s(word_familiarity) + te(participant_vocabulary_size, participant_age) + (1|participant) + (1|word)	97530	49720	***
resp.rt ~ 1 + te(word_familiarity, participant_age) + (1|participant) + (1|word)	97461	49771	***
resp.rt ~ 1 + te(word_familiarity, participant_vocabulary_size) + (1|participant) + (1|word)	97413	49770	***
resp.rt ~ 1 + s(word_familiarity) + s(participant_vocabulary_size) + s(participant_age) + (1|participant) + (1|word)	97530	49756	***
resp.rt ~ 1 + s(word_familiarity) + s(participant_age) + (1|participant) + (1|word)	97532	49797	***
resp.rt ~ 1 + s(word_familiarity) + s(participant_vocabulary_size) + (1|participant) + (1|word)	97532	49824	***
resp.rt ~ 1 + s(participant_age) + (1|participant) + (1|word)	97536	49917	***
resp.rt ~ 1 + s(participant_vocabulary_size) + (1|participant) + (1|word)	97536	49944	***
resp.rt ~ 1 + s(word_familiarity) + (1|participant) + (1|word)	97534	49887	***
resp.rt ~ 1 + (1|participant) + (1|word)	97538	50007	***

We transformed the age predictor into a categorical variable with three levels, -14, 15-64, and 65+. We then refit the generalized additive model as a hierarchical linear model, predicting response time from word familiarity, participant vocabulary size, and the categorical age predictor, using the lme4 library (Bates et al. (2014)). Plots were made using `itsadug` (van Rij et al. (2022)) and `sjplot` (Lüdecke (2023)).

These two models are reported below.

Results

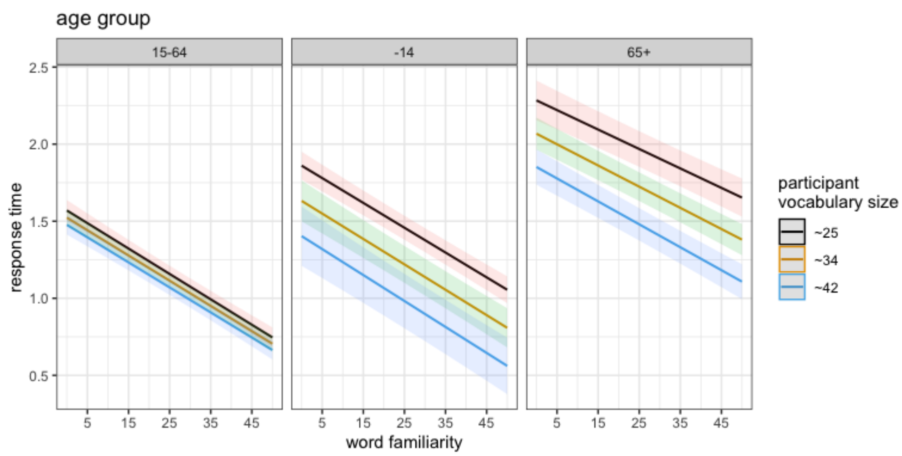
Participant vocabulary size, age, and relative word familiarity together predict response time in correct responses to visual targets of existing words in our participant sample. The best model of our responses posits non-linear relationships between our predictors and response times. Interpreting a three-way non-linear numeric interaction is daunting. The effect plot can be seen below.



This is a topography plot. Contours show response times. Hills are slow responses, valleys are fast responses. Each panel shows one range of word familiarity, from 1-6 (bottom left) to 44-50 (top right). Overall, as word familiarity goes up, the panels get greener: participants respond faster to more familiar words. The horizontal axis is participant age, the vertical axis is participant vocabulary size. As we saw above, some combinations of these don't exist. Only children and a small number of older adults have vocabularies that are smaller in size than 20. Children under 14 and adults over 65 are slower than the rest of the sample. These differences are more apparent when participants have smaller vocabularies and/or respond to less familiar words. Across participants with large vocabularies, younger and older participants are much less slower than the middle range of the sample. More or less everyone responds to very familiar words with the same speed. In sum, there is a U-shaped polynomial effect, participant age, that interacts with two more-or-less linear effects, participant vocabulary size and word familiarity.

We elected to explore this relationship by refitting the additive model using linear predictors for vocabulary size and word familiarity and a three-level factor for participant age: ages of 9-14, 15-64, and 65+. We kept the three-way interaction and the grouping factors for participant and word.

The effect plot for the linear model can be seen below.



The three panels show participant age group: adults (most of the sample) to the left, children (-14) in the middle, and older adults (65+) to the right. Participant vocabulary size is grouped into three thirds: low (around 25), mid (around 34-35) and high (around 42). The horizontal axis is word familiarity, the vertical axis is response time.

Participants get faster with more familiar words across the board. This is evident in each panel. Children are slower than adults and older adults are slower than children, as seen in the intercept of the lines in the three panels: they are higher in panels 2-3 than in panel 1. Vocabulary size matters, but mostly only for children and older adults. Finally, the error bars are thinner for predicted effects in the adult sample, as this was by far the most numerous.

It is true that our age groups are post hoc. The predictions of the linear model are useful to interpret the more complex results of the more fine-grained additive model, but the results themselves are very similar.

Discussion

Participant vocabulary size predicts response time of correct responses to visual targets of existing words in our sample, especially for younger and older participants. This suggests that lexical access is aided by a larger lexicon but that this will be especially manifest if it is constrained by other factors, like age. Note that there is a vocabulary size effect for our adult participants, but it is much smaller, in the hundred ms range, whereas vocabulary accounts for little under a second of a difference for older adults.

Participant age has a much larger effect on lexical decision times. Children converge to adult lexical decision speed in their mid-teens and adults start to slow down over the age of 65 or so. When we look at the topography plot of the model predictions, we see inflection points at the entrance to high school (12 or 14 in Hungary) and the age of retirement (62 or 64 in Hungary) meaning that the shifts can be as easily explained by lifestyle changes as by cognitive maturing and decline.

Responses to very familiar words constitute a threshold on response times (responses to these are very fast). This is an effect that a linear model has a harder time capturing. Overall, people respond to familar words faster, and this is by far the largest effect in our data, over one second.

Lexical decision data will have inherent structural properties that make it hard to analyze. Older people have larger vocabularies, on average. People with larger vocabularies will provide more "yes" responses, and, by proxy, response times. In a convenience sample, the 18-30 range will be most likely university students and so highly educated. The additive model is difficult to interpret, while the linear model, used to shed light on the directionality and interaction of the effects, might be broadly underfit.

Still, to our knowledge, ours is one in a limited set of examples that investigate the joint effect of vocabulary size and age in lexical decision. Our results strongly suggest that vocabulary size cannot be reduced to a function of age. This can be seen in the effect interactions in the linear model. It can also be seen when we look at the model comparisons for the additive model: we get a worse model fit both in terms of AIC and ML score if we take out either vocabulary size (AIC diff: 140.31, ML score diff: 122.99) or age (AIC diff: 93.02, ML score diff: 121.98). Note that though the vocabulary size measure was invented by us for this study while age is a biological eventuality, these numbers mean that vocabulary size proved to be the better predictor in terms of variable importance. To us, this is the enduring conclusion of our study.

References

Bates, Douglas, Martin Mächler, Ben Bolker, and Steve Walker. 2014. "Fitting Linear Mixed-Effects Models Using Lme4." *arXiv Preprint arXiv:1406.5823*.

Colombo, Lucia, Margherita Pasini, and David A Balota. 2006. "Dissociating the Influence of Familiarity and Meaningfulness from Word Frequency in Naming and Lexical Decision Performance." *Memory & Cognition* 34: 1312–24.

De Leeuw, Joshua R. 2015. "jsPsych: A JavaScript Library for Creating Behavioral Experiments in a Web Browser." *Behavior Research Methods* 47: 1–12.

Hintz, Florian, Marjolijn Dijkhuis, Vera van 't Hoff, James M McQueen, and Antje S Meyer. 2020. "A Behavioural Dataset for Studying Individual Differences in Language Skills." *Scientific Data* 7 (1): 429.

Lo, Steson, and Sally Andrews. 2015. "To Transform or Not to Transform: Using Generalized Linear Mixed Models to Analyse Reaction Time Data." *Frontiers in Psychology* 6: 1171.

Lüdecke, Daniel. 2023. *sjPlot: Data Visualization for Statistics in Social Science*. https://CRAN.R-project.org/package=sjPlot.

Nemeskey, Dávid Márk. 2020. "Natural Language Processing Methods for Language Modeling." PhD thesis, Eötvös Loránd University.

Peirce, Jonathan W. 2007. "PsychoPy—Psychophysics Software in Python." *Journal of Neuroscience Methods* 162 (1-2): 8–13.

Szabó, Gábor, and László Kovács. 2018. "Benchmarking Morphological Analyzers for the Hungarian Language." In *Annales Mathematicae Et Informaticae*, 49:141–66. Eszterházy Károly University Institute of Mathematics; Informatics.

van Rij, Jacolien, Martijn Wieling, R. Harald Baayen, and Hedderik van Rijn. 2022. "itsadug: Interpreting Time Series and Autocorrelated Data Using GAMMs."

Wolf, Merel C, Antje S Meyer, Caroline F Rowland, and Florian Hintz. 2021. "The Effects of Input Modality, Word Difficulty and Reading Experience on Word Recognition Accuracy." *Collabra: Psychology* 7 (1): 24919.

Wood, Simon N. 2017. *Generalized Additive Models: An Introduction with r*. CRC press.

Wood, Simon, and Maintainer Simon Wood. 2015. "Package 'Mgcv'." *R Package Version* 1 (29): 729.