Title: Predictive speech processing evolves across the adult lifespan

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Whereas healthy-aging older adults generally have preserved speech comprehension [1], they seem to use context information less efficiently than younger adults [2]. The N400 component, an event-related potential (ERP) related to sentence-level meaning and sensitive to context integration and how predictable words are, is consistently smaller in amplitude and delayed in older adults [2,3]. In a more ecologically valid experiment where participants listened to a naturally spoken story, researchers [4] found delayed peaks in older adults when investigating the relationship between the measured EEG and a speech model containing information about how surprising or unexpected a word is in its linguistic context, i.e. word surprisal (see [5]). However, this study did not control for acoustic and speech segmentation-related activity, hence responses were not specific to top-down predictive speech processing but also included bottom-up acoustic aspects [6]. To clarify the effect of age specifically on predictive speech processing, we explored the unique contribution of prediction-related speech features (while controlling for bottom-up processing) across the adult life span.

Fifty-two participants between 17 and 82 years of age listened to a 14-minutes-long story while 64-channel EEG was recorded (dataset recorded for [7]). Several speech features were derived from the stimulus and combined into 2 models for further analysis, i.e. (1) combining spectrogram, acoustic edges, phoneme onsets and word onsets and (2) containing these identical features plus predictive coding features such as phoneme surprisal, cohort entropy and word surprisal (for details see [6]). The delay between EEG data and the 2 feature combinations was modeled over time (integration window: 0-600ms), i.e. the temporal response function (TRF), and peak latencies were extracted. The TRF was further used for training and predicting estimated EEG responses to unseen story parts, which in turn were correlated with the original EEG data, referred to as prediction accuracy hereafter. To isolate the unique contribution of predictive speech processing, the prediction accuracies of model 1 were subtracted from model 2.

Participant age and prediction accuracies of the unique contribution of predictive speech processing features were significantly correlated when all electrodes were averaged (model: $R2adj=.1061$, $F(1,50)=7.054$, $p=.0106$; age effect: $beta=-2.962e-05$, $t=-2.656$, $p=.0106$). Regional analyses in which bilateral electrodes were grouped in frontal, temporal and centro-parietal electrode locations demonstrated that the correlation with age was only significant in the centro-parietal region (model: $R2adj=.2023$, $F(1,50)=13.93$, $p=.0004$; age effect: $beta=-6.027e-05$, $t=-3.733$, $p=.0004$). The more advanced the age of the participants was, the lower the prediction accuracies were. Furthermore, the TRF peak latencies were significantly longer in older participants for cohort entropy (model: $R2adj=0.06512$, $F(1,48)=4.413$, $p=.04094$; age effect: $beta=0.09836$, $t=2.101$, $p=.04094$) and word surprisal (model: $R2adj=0.1013$, $F(1,48)=6.521$, $p=.01389$; age effect: $beta=0.12271$, $t=2.554$, $p=.01389$), but not for phoneme surprisal.

These results converge with the N400 ERP literature and demonstrate aging effects in predictive speech processing, even when acoustic and speech segmentation-related effects are controlled for. Using natural speech to investigate predictive speech processing can provide a valuable tool for understanding the shift in speech processing dynamics across the adult lifespan and more specifically, in older age.

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