Informativity affects memory precision in the agreement attraction effect

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Language use is under the tension between predictability and informativity. On the one hand, linguistic units with higher predictability are more easily processed, motivating an influential line of psycholinguistics theories [1-2]; on the other, language is often used to deliver newsworthy messages in real communication, implicating some forms of cognitive strategies to deal with the linguistic information that is novel and less predictable [3]. However, compared to the effect of predictability, the role of informativity in language processing remains understudied.

Hypothesis. The current study hypothesizes that, although the less predictable linguistic units induce higher processing difficulty, this would actually help comprehenders construct a memory representation that is more precise and robust against the noise in communication, as more cognitive resources are allocated [4-5]. We test this hypothesis through the lens of the widely documented agreement attraction effect in English, where the ungrammatical main verb whose number feature mismatches with the target NP in the matrix clause (as in (1)) are less noticeable for comprehenders if there is a plural intervening distractor NP [6-7]. The prediction is that the less predictable target NP should have more robust memory representation, reducing the likelihood that the subject-verb agreement is interfered with by the distractor NP.

Procedure. In a self-paced-reading experiment (n=59) conducted on PCIbex Farm, we adapted the design of [7] by manipulating the predictability of the target NP (item=16; examples in (1)). In each trial, participants first self-paced read a subject relative clause sentence, and then rated its acceptability on a 0-100 slider scale, with 100 being the most acceptable. The target NP in the matrix clause is in the form of *Det Adj N*, where the adjective is manipulated into a typical and an atypical condition; the distractor NP in the relative clause does not contain any modifier.

Results. Bayesian linear mixed-effect models were performed both on acceptability rates and on log RTs for the critical and the spill-over regions with brms package [8] in R. The critical fixed-effect predictor is the Grammaticality x Predictability interaction. Data collection is ongoing. Given current results, for online RTs, the data numerically supports a reduced interference effect for less predictable target NP in the critical region (Estimate=0.018, 95%CrI=[-0.007, 0.044], $P(\beta>0)=0.92$), as shown in Figure 1. Consistent with our prediction, this is indicative of a more precise memory representation for target NP when it is less predictable. For offline acceptability rates, no effect has yet been detected. We conducted a post-hoc power analysis targeting the Grammaticality x Predictability interaction on the critical region of our reading time data with simr package [9] in R. With the 0.02 effect size (~45ms) and 32 items, approximately 175 participants are needed to achieve 80% power given the current experimental design. This will guide the scale-up of our study in the next step.

Conclusion. So far the results support an account of online language comprehension where memory resources are allocated strategically to store more robust representations of some linguistic units rather than others. In particular, more informative and newsworthy units get more robust representations. This is compatible with resource-rational models of language comprehension [10-13], where limited memory resources are allocated rationally to words that are more informative.

(1) Sample stimuli ("/" indicates SPR regions; critical and spill-over regions underlined)

a) The registered nurse/ who/ cared for/ the widows/ definitely/ {was/were} reluctant/ to work/ long shifts. [typical target NP]

b) The illegal nurse/ who/ cared for/ the widows/ definitely/ {was/were} reluctant/ to work/ long shifts. [atypical target NP]

Figure 1. Mean reading times

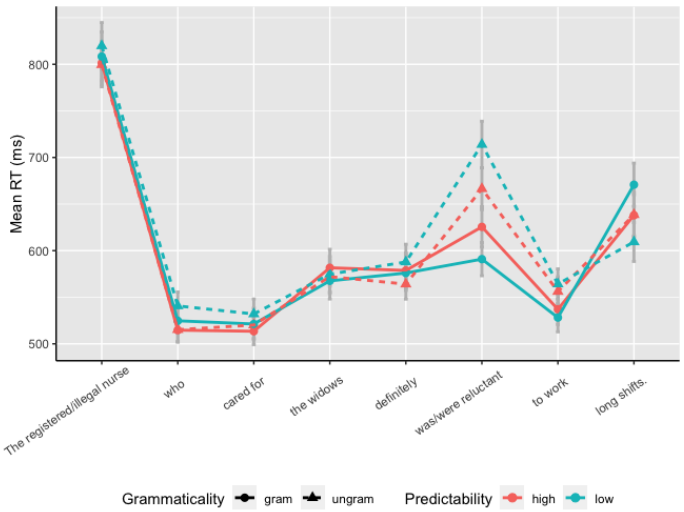

Figure 2. Mean acceptability rates

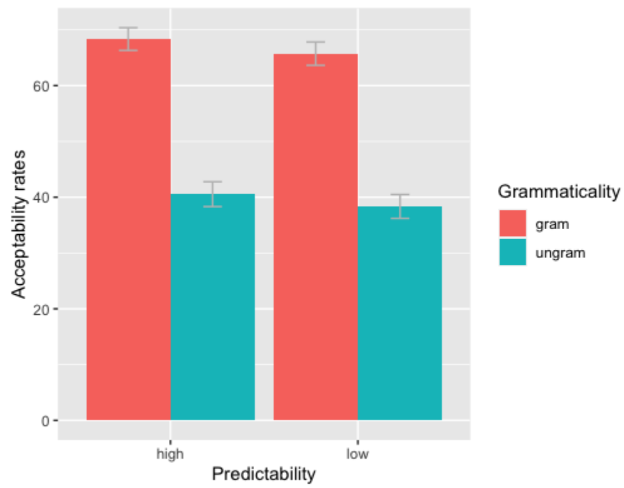

Table 1. Model results for log RTs

	Estimate	Est. Error	95% CrI	Region
Gram	-0.060	0.014	[-0.089, -0.032]	critical
Pred	0.002	0.012	[-0.022, 0.026]	
Gram:Pred	0.018	0.013	[-0.007, 0.044]	
Gram	-0.019	0.018	[-0.055, 0.015]	spill-over
Pred	-0.003	0.011	[-0.024, 0.018]	
Gram:Pred	0.005	0.012	[-0.019, 0.029]	

Table 2. Model results for acceptability rates

	Estimate	Est. Error	95% CrI
Gram	13.696	1.784	[10.135, 17.214]
Pred	0.997	0.974	[-0.921, 2.929]
Gram:Pred	-0.218	1.096	[-2.346, 1.977]

Model 1. log reading times

logRT ~ logRT.previous.region + Grammaticality*Predictability
+ (Grammaticality*Predictability|Subj) + (Grammaticality*Predictability|Item)

Model 2. Acceptability judgment rates

AJ ~ Grammaticality*Predictability
+ (Grammaticality*Predictability|Subj) + (Grammaticality*Predictability|Item)

References. [1] Hale (2001) *NAACL*. [2] Levy (2008) *Cognition*. [3] Rohde, Futrell & Lucas (2021) *Cognition*. [4] Hofmeister (2011) *Lang Cogn Process*. [5] Bruning & Lewis-Peacock (2020) *Scientific Reports*. [6] Wagers, Lau & Phillips (2009) *JML*. [7] Dillon, Mishler, Sloggett & Phillips (2013) *JML*. [8] Bürkner (2017). *Journal of Statistical Software*. [9] Green & MacLeod (2016) *Methods in Ecology and Evolution*. [10] Lewis, Howes & Singh (2014) *Top Cogn Sci*. [11] Gershman, Horvitz & Tanenbaum (2015) *Science*. [12] Lieder & Griffiths (2020) *Behav Brain Sci*. [13] Hahn, Futrell & Gibson (2020) *CUNY*.