Do the kinds of features that patients generate during Semantic Feature Analysis affect treatment outcomes?



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BACKGROUND

- Semantic Feature Analysis (SFA) is an aphasia treatment that improves naming for trained words and untrained, semantically-related words.¹
- Gravier et al.² found that the number of patient-generated features was predictive of naming for both direct training and generalization.
- Suggests that patient-generated access to semantic features is important for generalization.

<u>BUT</u> do the **types** of features generated matter? <u>OR</u> does **diversity** in feature generation improve response?

Hypothesis 1: Description (imageability) and personalassociation (salience) categories will be predictive of gains on all items for both *total number* and *unique* number of features.

Hypothesis 2: Effects will depend on whether successful repeated retrieval (total features) or activated semantic diversity (unique features) is key.

METHODS

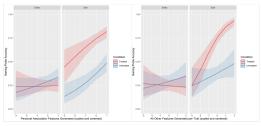
Separate trial-level **logistic mixed-effect regression** analyses³ for self-generated semantic features **for each feature type** and for **total** and **unique** features generated.

RESULTS

Question 1: For four feature categories (excluding personal association), generating more features was related to improved naming more for trained items than untrained items (table 2.)

 Likelihood ratio⁴ & bayes factor⁵ suggest personal association features affected direct training and generalization equally.

Question 2: **No evidence** that the number of **unique** features generated in any category was related to naming improvement. (table 3.)



DISCUSSION

- Repeated, successful feature retrieval is predictive of treatment outcomes; greater feature diversity is not.
- Generation of personally-relevant features may be associated with greater generalization.
- · Effect sizes were relatively small.

The total number of features
generated, not feature diversity,
is associated with better outcomes
in Semantic Feature Analysis

Generating personal association features is equally related to naming improvement for direct training and generalization





PARTICIPANTS

Table 1. Participant Demographics (n = 38)

	Mean (sd)	Median	Range
Age (years)	60.4 (12.4)	63.5	24 - 78
Education (years)	15.1 (3.3)	14	10- 25
Months post-onset	68.7 (58.7)	57	7 - 245
Aphasia Severity	52.1 (4.5)	51.1	45.3 - 62.3
		Frequency	Percentage
Gender	Male (Female)	33 (5)	86.8 (13.2)
Race	W (AA+NA+H)	31 (7)	81.6 (18.4)
Handedness	Right (Left)	34 (4)	89.5 (10.5)

Aphasia Severity = CAT mean T-Score AA = African-American, NA = Native American, H = Hispanic, W = White

TREATMENT

Feature Types:

Personal Association Location/Context Superordinate Description Use/Function

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ANALYSIS

Outcome measure: naming accuracy at entry and exit.

Fixed Effects: Item-type (treated/untreated), Time (entry/exit), Feature

Generation (with interactions)

Question 1: Total number of features generated

Question 2: Number of unique features generated

Covariate: Severity Random intercepts: participants and items

Likelihood Ratio: Bits of Evidence^{4:} -1.97

Given the data, Likelihood of no difference is 4:1

BIC Estimated Bayes Factor5: 32: strong evidence for 'no difference'

Table 2. Mixed Logistic Model Coefficients for the total number of features per feature category

	Location/ Context	Description	Use/ Function	Superordinate	Personal Association
Fixed Effects	Coef.(se)	Coef.(se)	Coef.(se)	Coef.(se)	Coef.(se)
Main effects of time	1.31(.11)***	1.33(.11)***	1.32(.11)***	1.31(.11)***	1.29(.11)***
Main effects of condition	-0.68(.12)***	70(.12)***	-0.67(.12)***	-0.69(.12)***	-0.67(.12)***
Main effects of feature category	0.22(.09)	0.22(.10)*	0.01(.09)	0.32(.09)***	0.27(.09)**
Aphasia Severity	0.53(.11)***	0.51(.11)***	0.56(.12)***	0.46(.11)***	0.54(.10)***
Time*Condition	1 -1.82(.21)***	-1.86(.21)***	-1.84(.21)***	-1.83(.21)***	-1.82(.21)***
Time*features category	0.27(.11)	0.46(.11)***	0.37(.11)***	0.38(.11)***	0.32(.11)**
Condition* feature category	017(.12	-0.22(.12)	-0.07(.11)	-0.17(.12)	0.10(.11)
Time*condition*features category	43(.22)	-0.78(.21)***	-0.60(.21)***	-0.61(.22)***	-0.17(.22)
Random Effects	S^2	S^2	s^2	s ²	52
Participant	.30	.30	.41	.28	.27
Îtem	.59	.61	.58	.59	.58

Note Excluding intercepts, Coef = estimation of the effect on naming accuracy in log odds, SE = standard error. * <0.5 **<.01***<.001. Personal Association Features Model: Bits of Evidence: 4:1; Bayes Factor, BP₀₁ = 33.8; Posterior probability: 97

Table 3. Mixed Logistic Model Coefficients for number of unique features per feature category

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		Location/ Context	Description	Use/ Function	Superordinate	Personal Association		
Fixed Effects	С	oef.(se)	Coef.(se)	Coef.(se)	Coef.(se)	Coef.(se)		
Main effects of	time	1.31(.11)***	1.32(.11)***	1.32(.11)***	1.34(.11)***	1.31(.11)***		
Main effects of condi	ition	-0.64(.12)***	-0.63(.12)***	-0.65(.12)***	-0.66(.12)***	-0.65(.12)***		
Main effects of feature cate	gory	.17(.08)*	0.16(.08)	0.27(.09)**	0.10(.07)	0.15(.08		
Aphasia Seve	erity	.55(.12)***	0.54(.12)***	0.53(.13)***	0.57(.12)***	0.56(.13)***		
Time*Condi	ition	-1.82(.21)***	-1.83(.21)***	-1.82(.21)***	-1.83(.21)***	-1.82(.21)***		
Time*features cate	gory	-0.015(.10)	-0.10(.1)	-0.06(.10)	-0.14(.10)	0.05(.1		
Condition* feature cate	gory	-0.13(.11)	-0.22(.11)	-0.09(.11)	-0.11(.11)	-0.12(.11		
Time*condition*features cate	gory	0.19(.20)	0.21(.20)	0.076(.20)	0.01(.20)	-0.014(.21		
Random Effects	5		s^2	s^2	s^2	s^2		
Particip	ants	0.43	0.45	.50	.44	.41		
Īt	tems	0.55	0.58	56	55	. 5		

Note. Excluding intercepts, Coef = estimation of the effect on naming accuracy in log odds, SE = standard error: * <.05 **<.01***<.001

Literature Cite

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