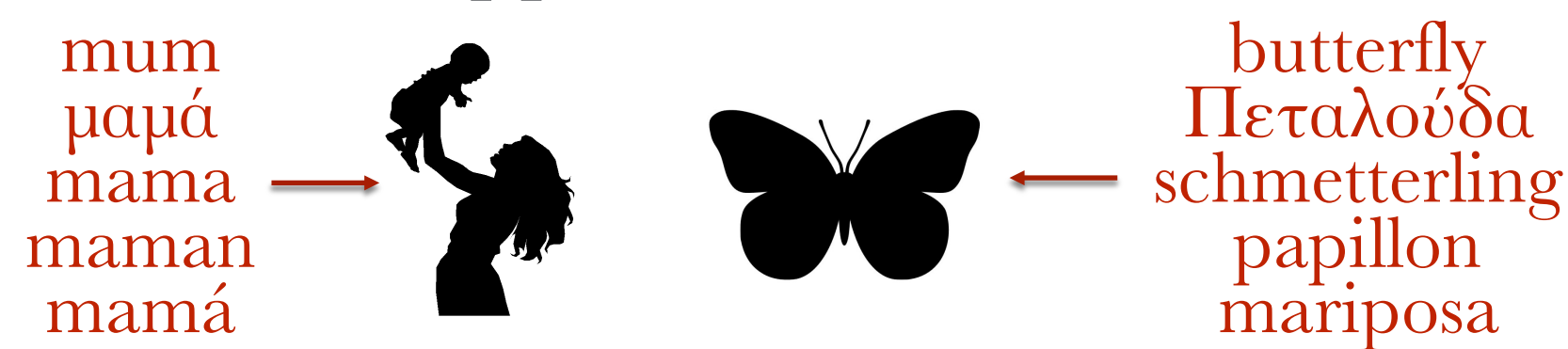


# Predictors of lexical stability in an artificial language

## Introduction

- Lexical items in the vocabulary are susceptible to change, but what predicts these changes? and what types of change are they subject to?
- Some words undergo changes much more rapidly than others, leading to some word forms being conserved across different languages, whilst others appear to be unrelated



- It has been shown that certain psycholinguistic properties of these words can be used to reliably predict the rate at which a word form is replaced by a new, unrelated form
- These are **FREQUENCY**, **LENGTH** and **AGE OF ACQUISITION (AoA)** (Pagel et al, 2008; Monaghan, 2014)
- Additionally, word forms can also be subjected to more minor changes where they are adjusted to provide optimal communicative efficiency, reducing effort in speech production (Zipf, 1949)
- Here, we aim to generate these findings using a novel artificial language learning paradigm in the lab

## Hypotheses

- Low frequency, long, late acquired words undergo more lexical replacements
- High frequency, short, early acquired words undergo more adjustments
- High frequency, short, early acquired words are conserved in the language during processes of cultural transmission

## Methods

- Artificial language with 12 images, each paired with an unfamiliar word (adapted from Kirby et al, 2015)



- Training phase where participants saw the image-word pairings over several blocks (total 120 trials), then tested in a production recall task
- 3 different experimental conditions:

### 1. Frequency:

Weight number of exposures during training (4 words per frequency condition)

training block	low	medium	high
1	1	3	6
2	1	3	6
3	1	3	6
total	3	9	18

### 2. Length:

Vary the number of characters in the words (either 4, 6, or 8 with 4 words per length condition)

training block	short	medium	long
1	5	5	5
2	5	5	5
total	10	10	10

### 3. AoA:

Present words early or late during training (6 words per acquisition condition)

training block	early	late
1	6	0
2	1	3
3	1	3
4	1	3
5	1	1
total	10	10

## Analysis

Each participant learned an artificial language and produced one new testing output language

- Compare words presented in training language to testing output
- Calculate error as *normalised Levenshtein edit distance (NLED)* by quantifying the number of character insertions, substitutions or replacements, then dividing that value by the longest word length

e.g. 'hello' → 'helicopter' = 7/10 = 0.7

- Classify errors based on the mean *NLED* between all words in the initial training language, producing a threshold value of 0.67:

**accurate:** 0, **adjustment:** 0 < 0.67, **replacement:** > 0.67

## Experiment 1 – One generation learning

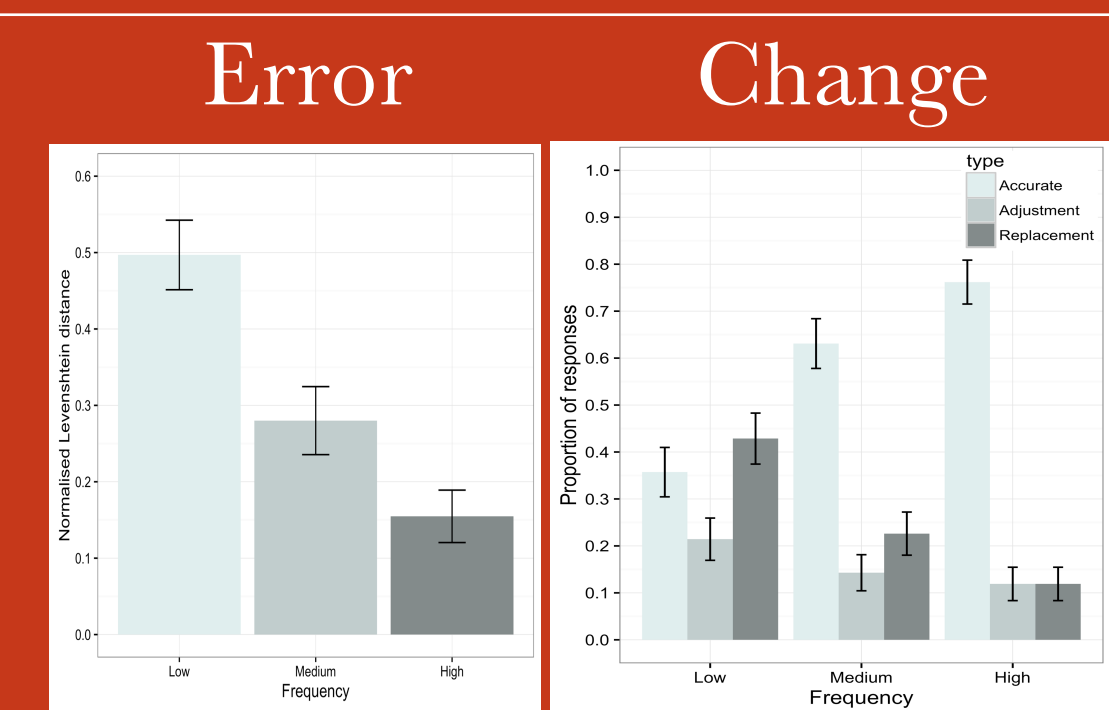
- 21 participants in each experimental condition (total  $n = 63$ )
- Analysis using three mixed-effects models for each *psycholinguistic property* (fixed effect), with *error*, *number of adjustments* and *number of replacements*, as dependent variables.

### Frequency

*Error:* decreases as frequency increases  $\chi^2(2) = 46.2$ ,  $p < .001$

*Adjustments:* no significant difference.

*Replacements:* decreases as frequency increases  $\chi^2(2) = 29.5$ ,  $p < .001$

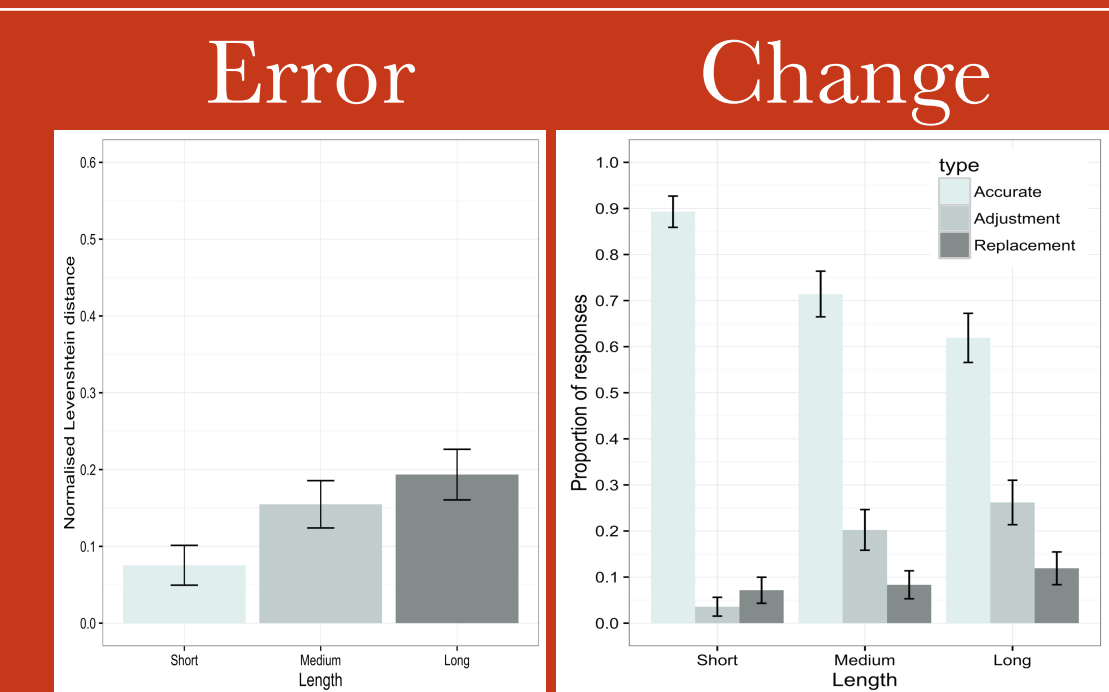


### Length

*Error:* increases as length increases  $\chi^2(2) = 10.8$ ,  $p = .005$

*Adjustments:* increases as length increases  $\chi^2(2) = 20.1$ ,  $p < .001$

*Replacements:* no significant difference.

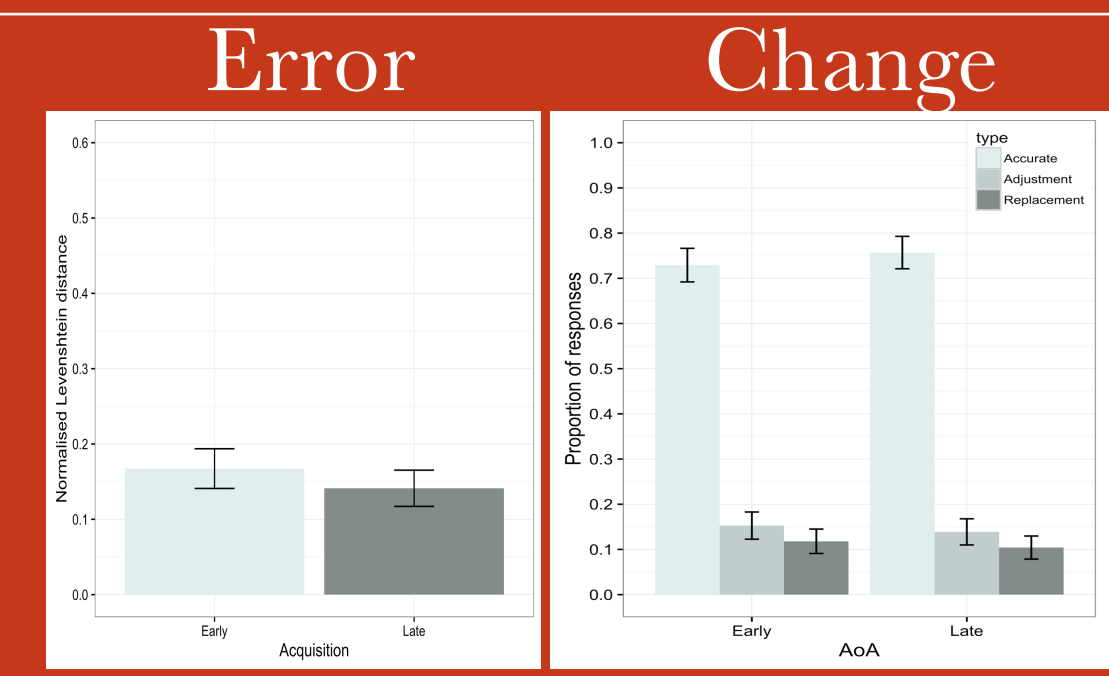


### AoA

*Error:* no significant difference.

*Adjustments:* no significant difference.

*Replacements:* no significant difference.



## Experiment 2 - Iterated learning

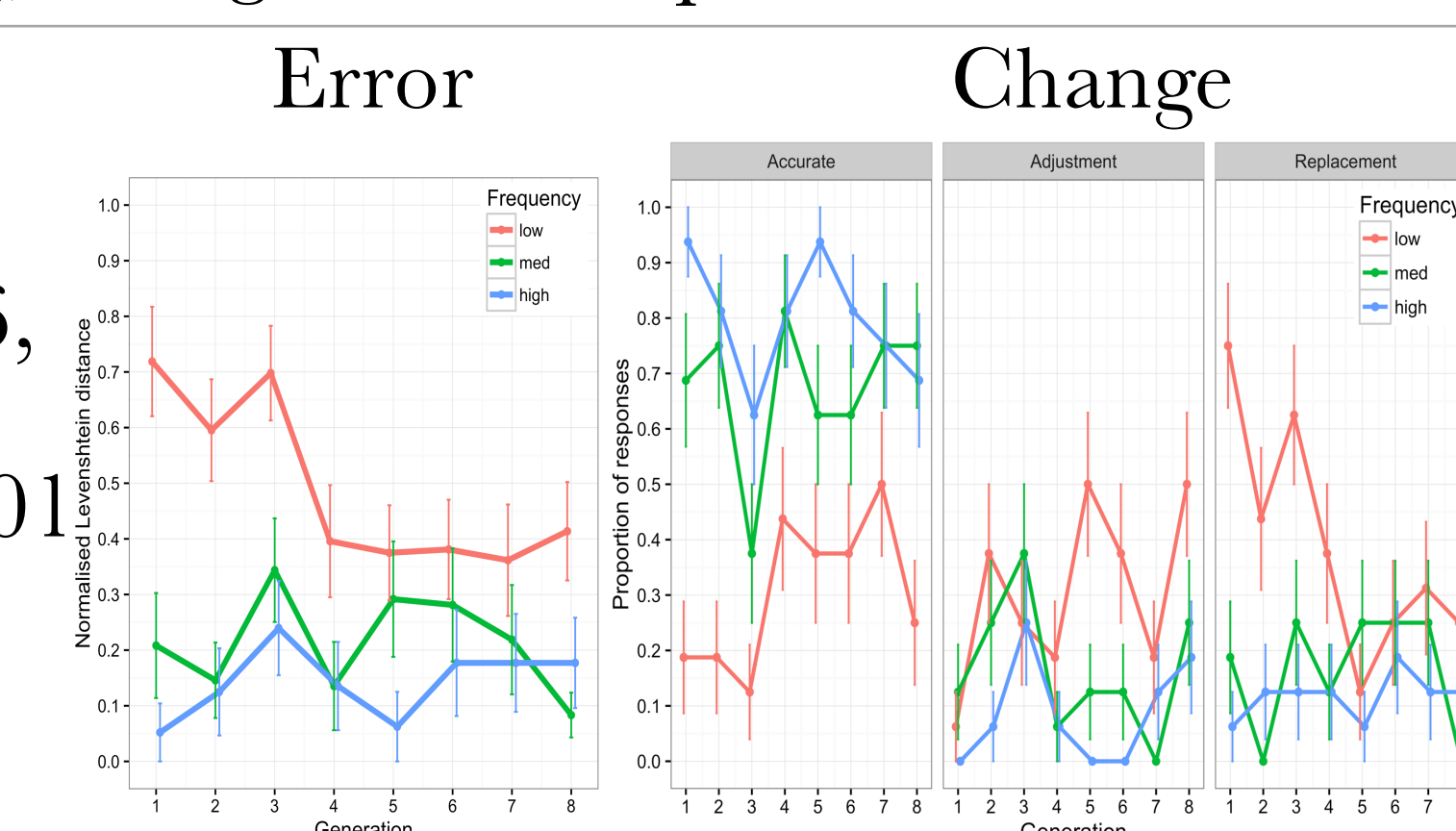
- Participant gets trained on previous participant's testing output, with 4 chains of 8 participants in each experimental condition (see Kirby et al, 2008) each participant representing a generation in the learning chain (total  $n = 96$ )
- Analysis using mixed-effects modelling, with *generation* as predictor variable

### Frequency

*Low:* error decreases:  $\chi^2(1) = 13.2$ ,  $p < .001$   
adjustments marginal increase:  $\chi^2(1) = 3.6$ ,  $p = .058$   
replacements decrease:  $\chi^2(1) = 13.6$ ,  $p < .001$

*Medium:* no significant changes.

*High:* no significant changes.

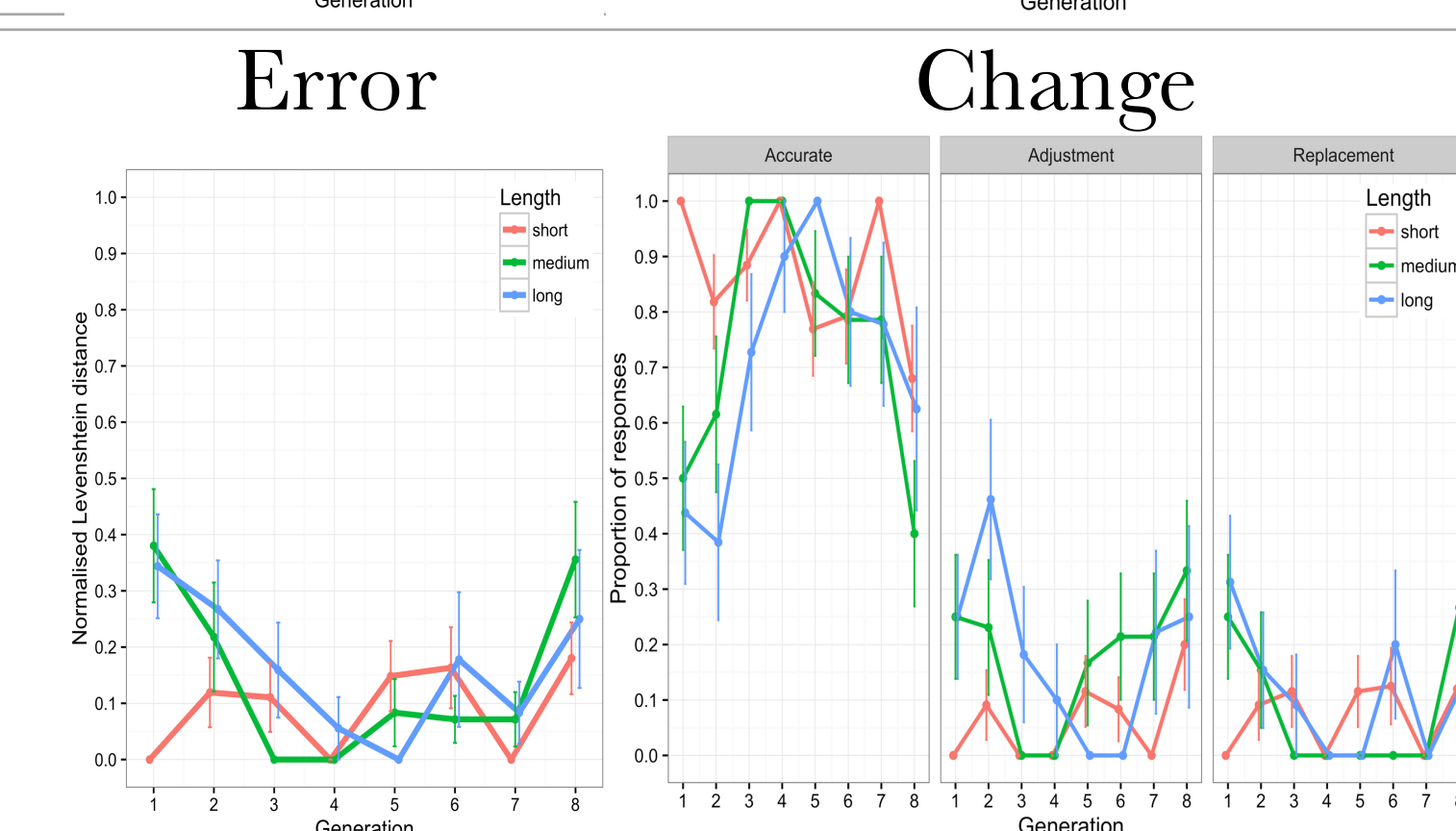


### Length

*Short:* no significant changes in error or replacements.  
adjustments increase:  $\chi^2(1) = 4.1$ ,  $p = .04$

*Medium:* no significant changes.

*Long:* no significant changes.

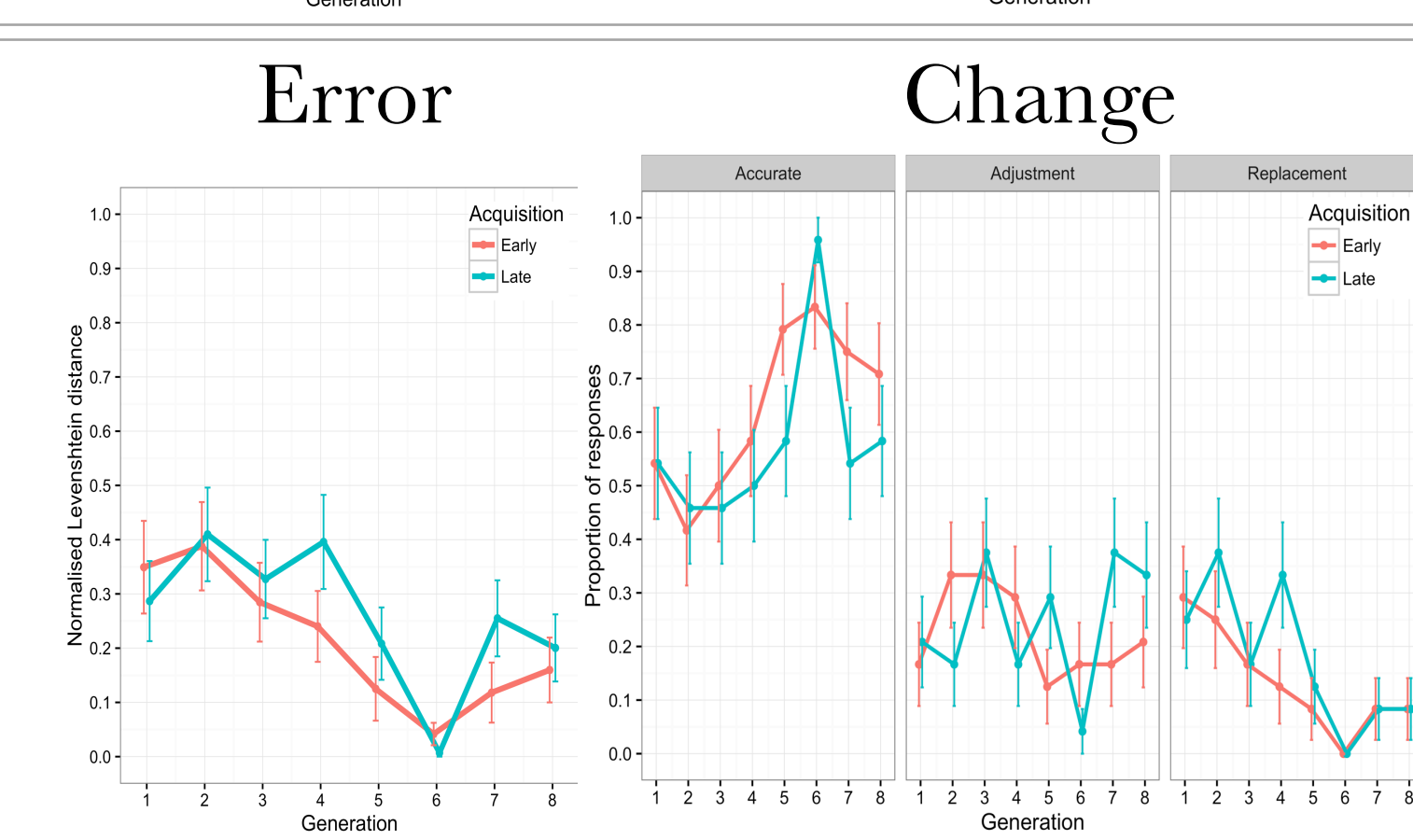


### AoA

*Early:* error decreases:  $\chi^2(1) = 16.9$ ,  $p < .001$   
no significant change in adjustments.  
replacements decrease:  $\chi^2(1) = 10.2$ ,  $p = .001$

*Late:* error decreases:  $\chi^2(1) = 7.4$ ,  $p = .01$   
no significant change in adjustments.

replacements decrease:  $\chi^2(1) = 11.3$ ,  $p < .001$



## Conclusions

- Low frequency words undergo more error, but over time can become more learnable, whilst high frequency words remain reliably recalled and transmitted with little change over time.
- Longer words undergo more error than shorter words, but over time shorter words are becoming adjusted more.
- No difference in AoA, but both early and late acquired words become more learnable over time.

### References:

- Kirby et al (2015). Compression and communication. *Cognition*.  
Kirby et al (2008). Cumulative cultural evolution in the laboratory. *PNAS*.  
Monaghan (2014). AoA predicts rate of lexical evolution. *Cognition*
- Pagel et al (2007). Frequency of word-use. *Nature*.  
Zipf (1949). *Human behavior and the principle of least effort*.