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SOUNDS, ATTITUDES, AND MEANING

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How do we feel about /x/ ?

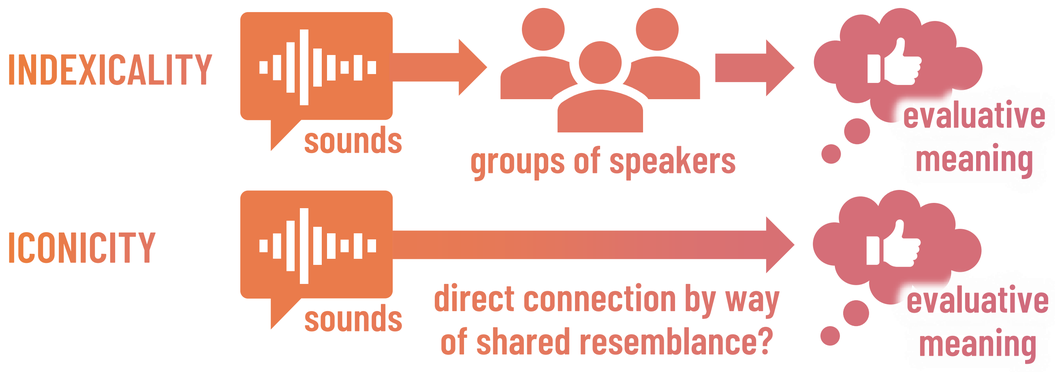
The role of iconicity and indexicality for language attitudes

French sounds beautiful and romantic.

German sounds harsh and aggressive.

language attitudes[1–28]

But why?[29–33] Indexicality[34–37] versus iconicity[38–51]



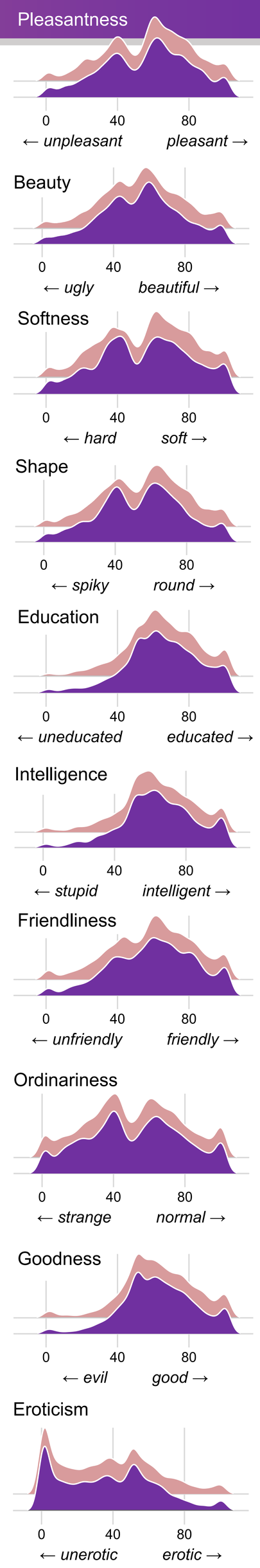
Methodology Creation of new languages[52–54]

PLACEHOLDER A
METHODOLOGY SLIDES
scroll down in PDF to see slides

1 **software development** new pseudotext generator called SSPG
2 **text generation** with and without /x/, other properties the same
3 **speech synthesis** with different languages, engines, voices[55]
4 **rating study** semantic differential scale sliders, 501 listeners[56–57]
5 **modeling** mixed models with `lme4`[58–59], `randomForest`[60] in `R`[61]

Results All semantic scales

PLACEHOLDER B
RESULTS SLIDES



In short You rate /x/ worse only if you're exposed to it, plus:

- Language sounds worse to you if you perceive it as being less **familiar**.[62–64, cf. 30, 32, 33]
- You rate language worse if you're **male**. Gender of voice also affects ratings.[20, 65–70]
- You rate language worse if you **feel** like it's similar to a specific **language group**, such as those associated with "harshness", like 'Middle East' or 'Germanic'.[71–72, cf. 30, 32]

/x/ doesn't sound as terrible as you'd think—unless sociocultural factors *make* it sound bad.

This supports the idea of iconicity being embedded into and constrained by a deeply indexical system.[35, 73–81]

REFERENCES, DATA, SCRIPTS

2 Text generation with the Sonority-Sensitive Pseudotext Generator SSPG

	Control			Stimulus		
Speaker	1	2	3	1	2	3
Mean sonority 1–17	10.91	10.94	10.92	10.94	10.95	10.92
Consonants %	47.62	46.9	47.26	47.33	47.44	47.13
Obstruents %	25.32	23.97	23.73	24.52	26.07	26.43
Vowels %	52.4	53.1	52.7	52.7	52.6	52.9
Voicing %	79.44	80.37	79.51	79.53	78.21	78.28
Syllable structures	CV, V	CV, V	CV, V	CV, V	CV, V	CV, V
Syllable weights 0–1	0.9, 0.1	0.9, 0.1	0.9, 0.1	0.9, 0.1	0.9, 0.1	0.9, 0.1
Number of words in text	100	100	100	100	100	100
Max number of syllables	4	4	4	4	4	4
Sound inventory	base	base	base	base, x	base, x	base, x

Overview of properties of convariety texts in both conditions, stimulus and control, after verification. The sound inventory base refers to the baseline inventory /p, t, k, b, m, n, s, l, w, j, i, u, a, e, o/. The crucial difference between control and stimulus conditions is the /x/ added to the baseline inventory.

2 Text generation with the Sonority-Sensitive Pseudotext Generator SSPG

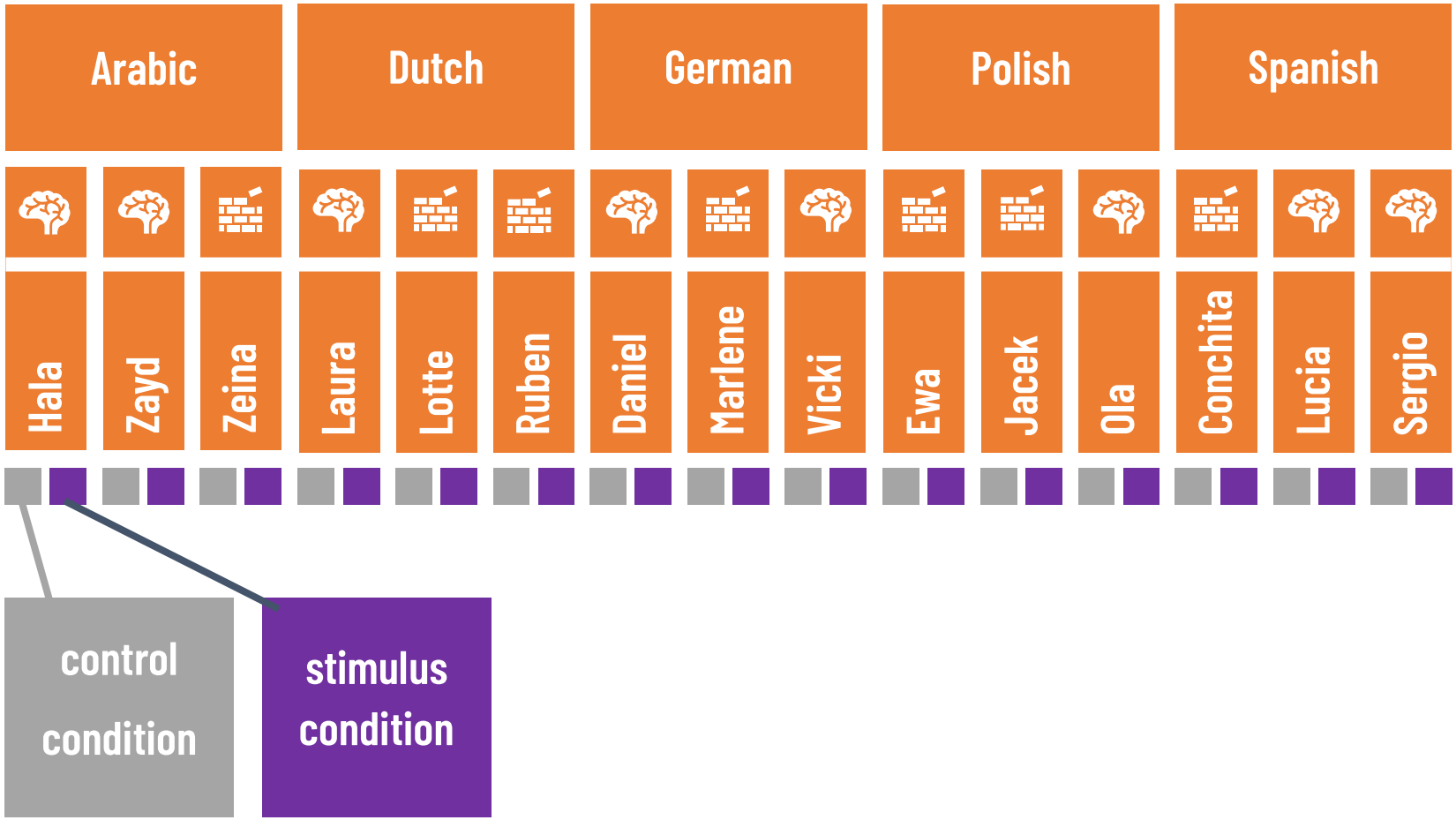
EXAMPLE OF TEXT FROM CONTROL CONDITION

Mo mutu kima le napo soteoi lubita bisi mabumopi tapesi satiu sue sobabise si painu nopu wupeto je sipawi bu nake muba no pa. Pe ne jako u po munilawi o jetuwi nu mo kuloa wiwiji somawejo. Nosobape juji pu kopopobo waka toajonu mi takeka jabakeja tisu tuelu kepe jewo luwo jesoa wejoniwe kasajo jujianu. Wulusa sa ma mieto ta tojimu motutasa lo we no pika. Nomewiju sau ta seili ni puwoja nase ju lelemi wawamonu bo pukebopo. Wa bakolimu kuuali jiku ke sobi tosisabo kikitebi nitiwusu jupike lipu enibu mopobewa ti iwibaja kinotu wa busu bibuase kuine kosumewe. Toinu.

EXAMPLE OF TEXT FROM STIMULUS CONDITION

Sauxi nuopo pu xo boxiliwa limuwua muneu tasasupe banepoku bano jumabise kuta wi pu pa tixu meja tupi tobimo boma. Ku jewia mujaxito li ta. Teloju ana epoo xitexi xotiwo no pexu kuwuto epa muwubu isiju. Wipoxai nubunipe niopawa xane joluxoka xo buipu owilu no pu mile sitokame mupaje. Xine nekosu. Mapejo ja xunujiwi esi si epa naji nuxu to. Ma naemexe beame jesobu betetumu bajotu mioxi lalo. Pibila bi wuneomo nonamito wo pelejiwe xo pa jo. Wokiwabi jopu xia ta masa ne jubuja sunasato ataxibu josakuto buxuwuxu telouna mele ku. Misa monapo ta miwi jeu so jumu enilepe lolami.

3 Speech synthesis with Amazon Polly



Overview of Amazon Polly voices used to create the recordings, together with their language optimizations and engines.

4 Participant quota sampling by PRIMARY LANGUAGE

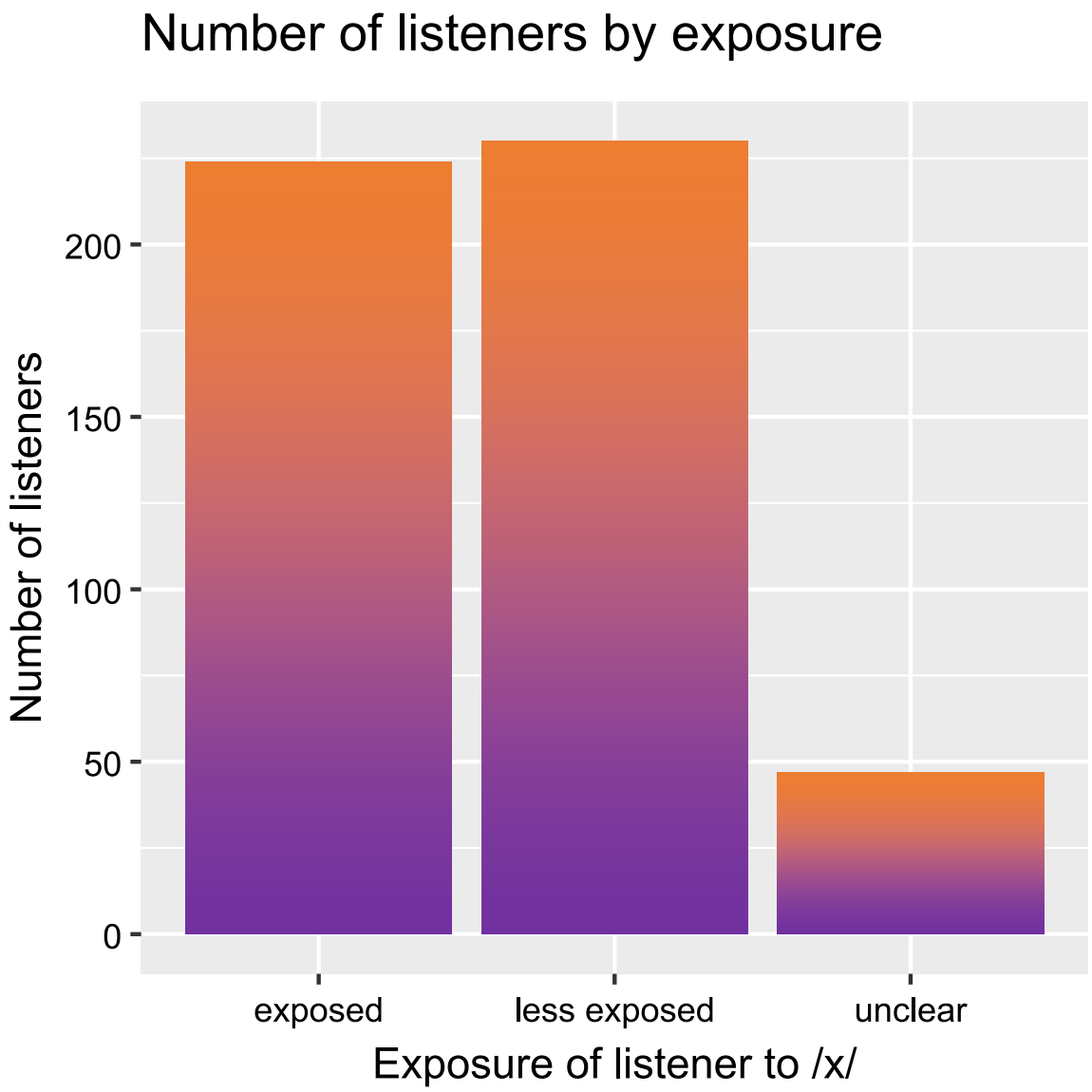
Arabic	Dutch	German	Polish	Spanish
10 %	10 %	10 %	10 %	10 %
50	50	50	50	50

English	Italian	Japanese
17 %	17 %	16 %
86	85	80

Prolific

= 100 %
= 500

4 Some participant demographics n = 501



277 male 213 female 11 non-binary

age 18–72 (mean = 32, median = 29)

382 computer 99 phone 10 tablet

207 speakers 172 in-ear 121 over-ear

446 at home 46 office 9 elsewhere

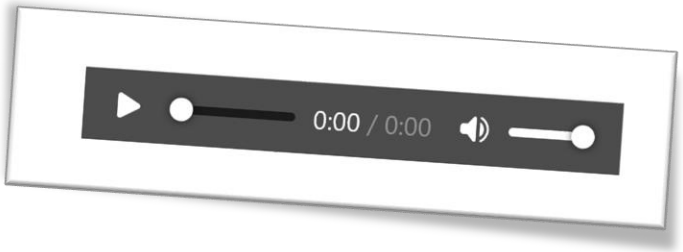
4 Questionnaire

In the far future, you encounter a colony of human-like robots on a distant planet. Your task on this expedition is to try to understand robot society and communication.

Every individual robot speaks in a different language, accent, or dialect, but they can all understand each other by using internal translation programs. Some of the robots sound very similar, for example because they happened to get a similar voice program when they were built, or because their dialects happen to be close to each other. But you quickly notice that just like humans, every robot is unique.

You want to improve your ability to distinguish the robots and their roles in society based on their speech. To do this, you will listen to three pairs of robots. Each of the two robots in a pair will sound similar, but slightly different. You will try to rate the speech of each robot on different attributes.

4 Questionnaire



How does the robot sound?

unpleasant	pleasant
ugly	beautiful
hard	soft
spiky	round
uneducated	

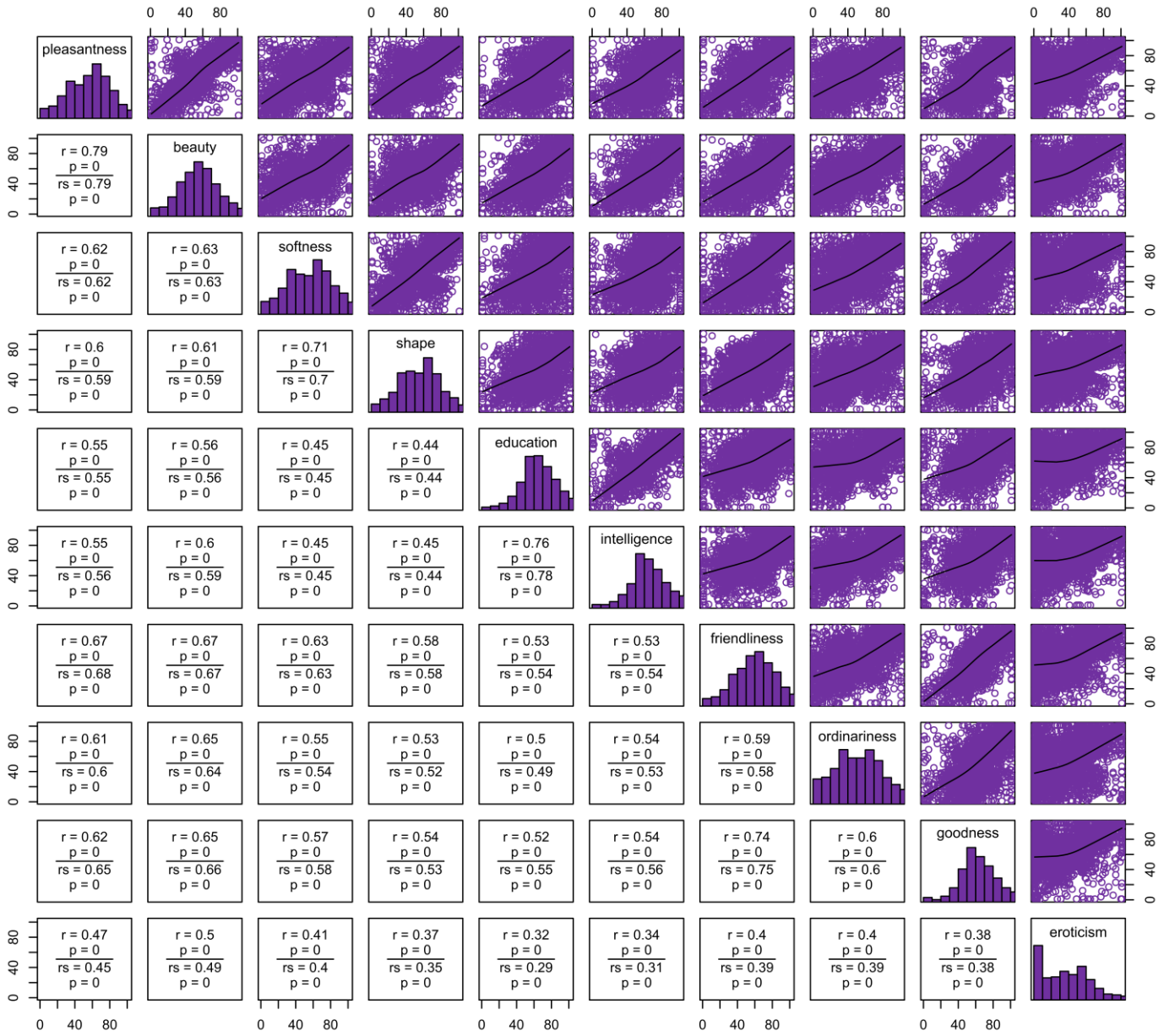
How familiar does this language sound to you?

not at all familiar — very familiar

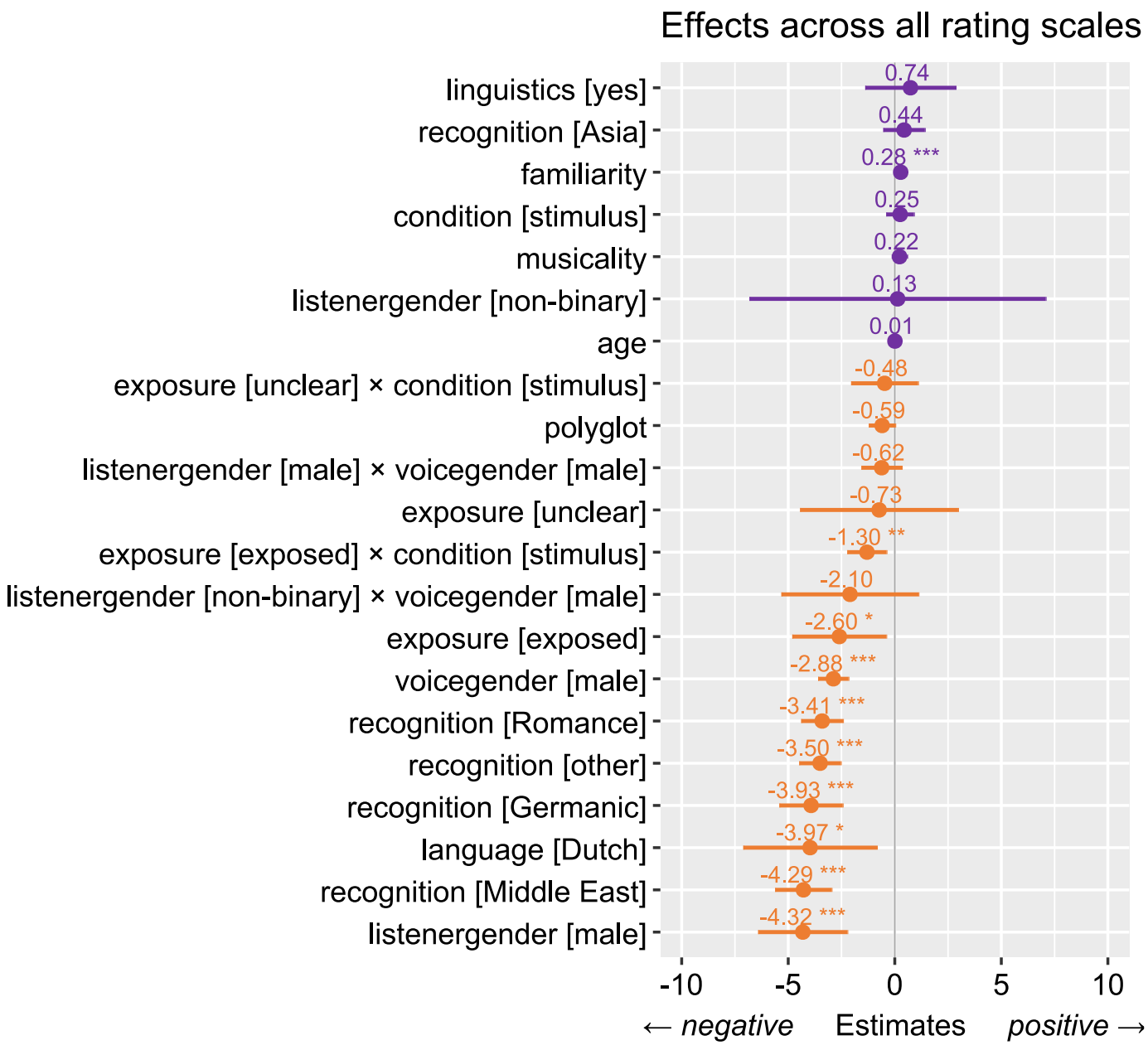
Which real language or dialect, do you think, does this language resemble the most?

5 Modeling

$$
\begin{aligned}
\text{RATING} \sim\ & \text{CONDITION} * \text{EXPOSURE} + \\
& \text{RECOGNITION} + \\
& \text{FAMILIARITY} + \\
& \text{LANGUAGE} + \\
& \text{LISTENER GENDER} * \text{VOICE GENDER} + \\
& \text{POLYGLOT} + \\
& \text{AGE} + \text{MUSICALITY} + \text{LINGUISTICS} + \\
& \text{INPUT} + \text{OUTPUT} + \text{LOCATION} + \\
& \text{SCALE} + \\
& (1 \mid \text{PARTICIPANT})
\end{aligned}
$$



Correlation matrix of the ratings from all ten semantic differential scales with data from 501 participants, 3060 ratings per scale. All scales are arranged from their negative (0) to their positive (100) valence.



Summary of across-scale linear mixed-effects regression model regressing the predictors against RATING, with INPUT, OUTPUT, LOCATION, and SCALE omitted. Reference levels are:

EXPOSURE `less exposed`

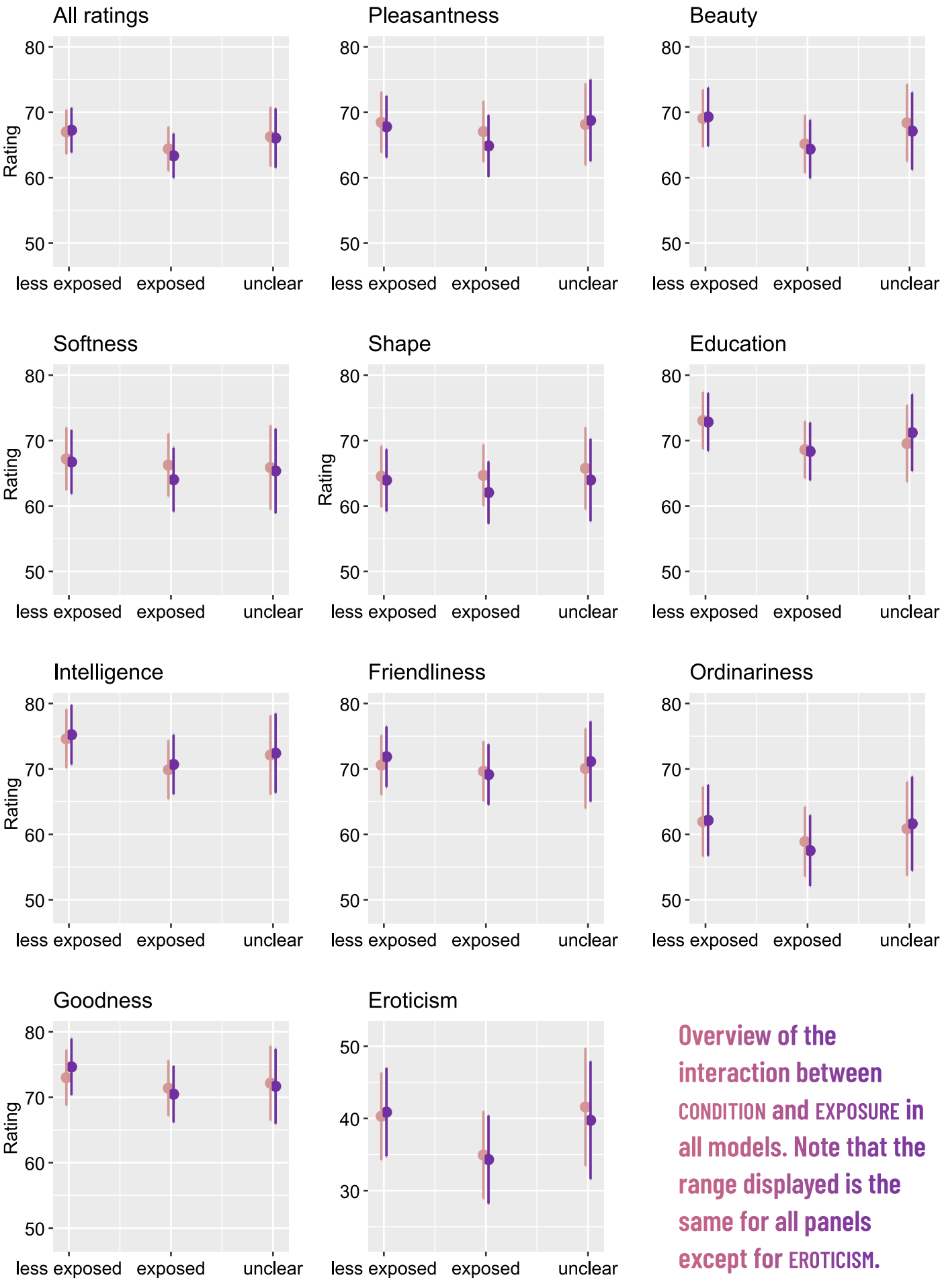
CONDITION `control`

RECOGNITION `Africa`

LANGUAGE `Dutch`

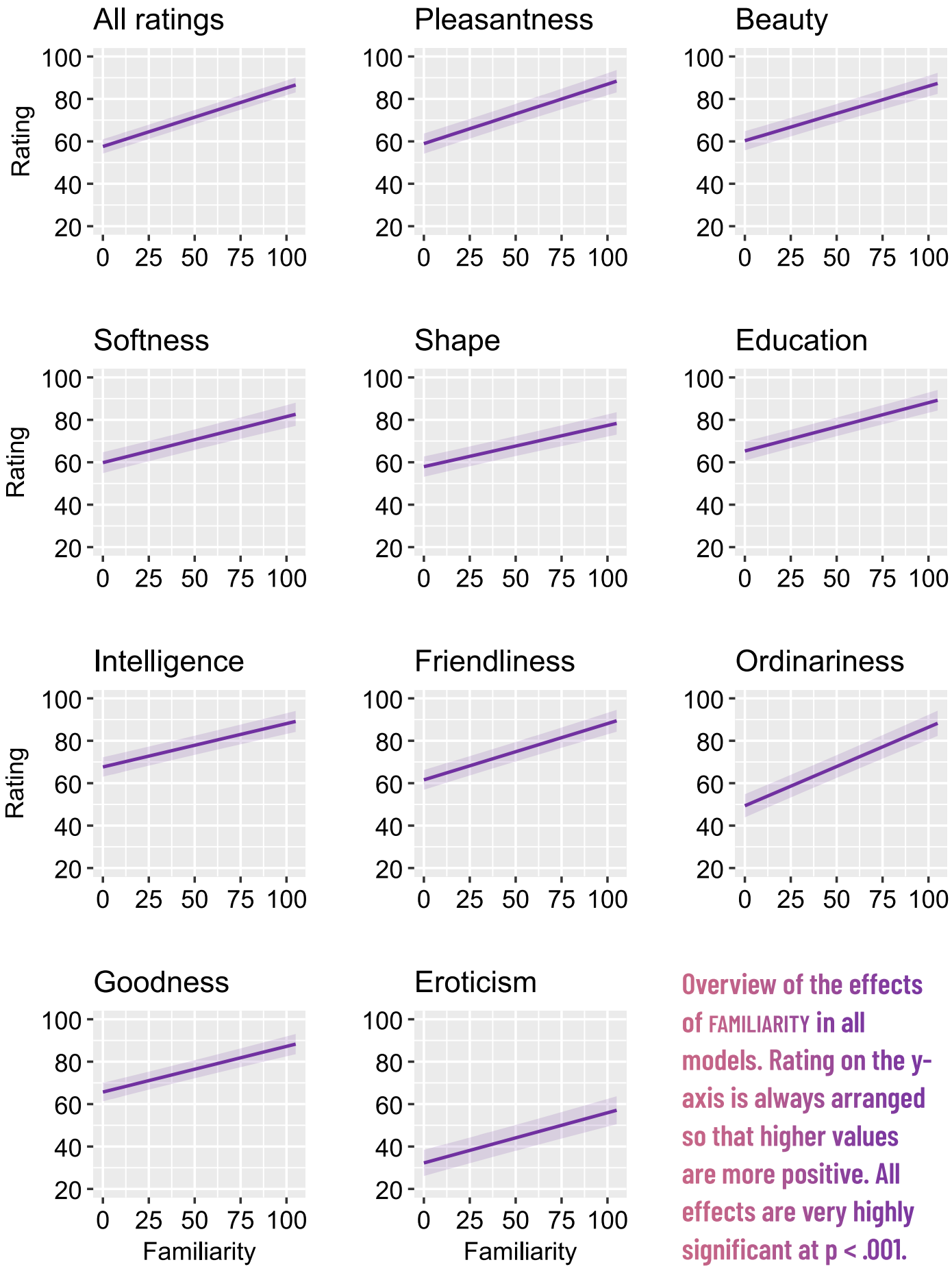
GENDER OF LISTENER `female`, GENDER OF VOICE `female`

LINGUISTICS `no`

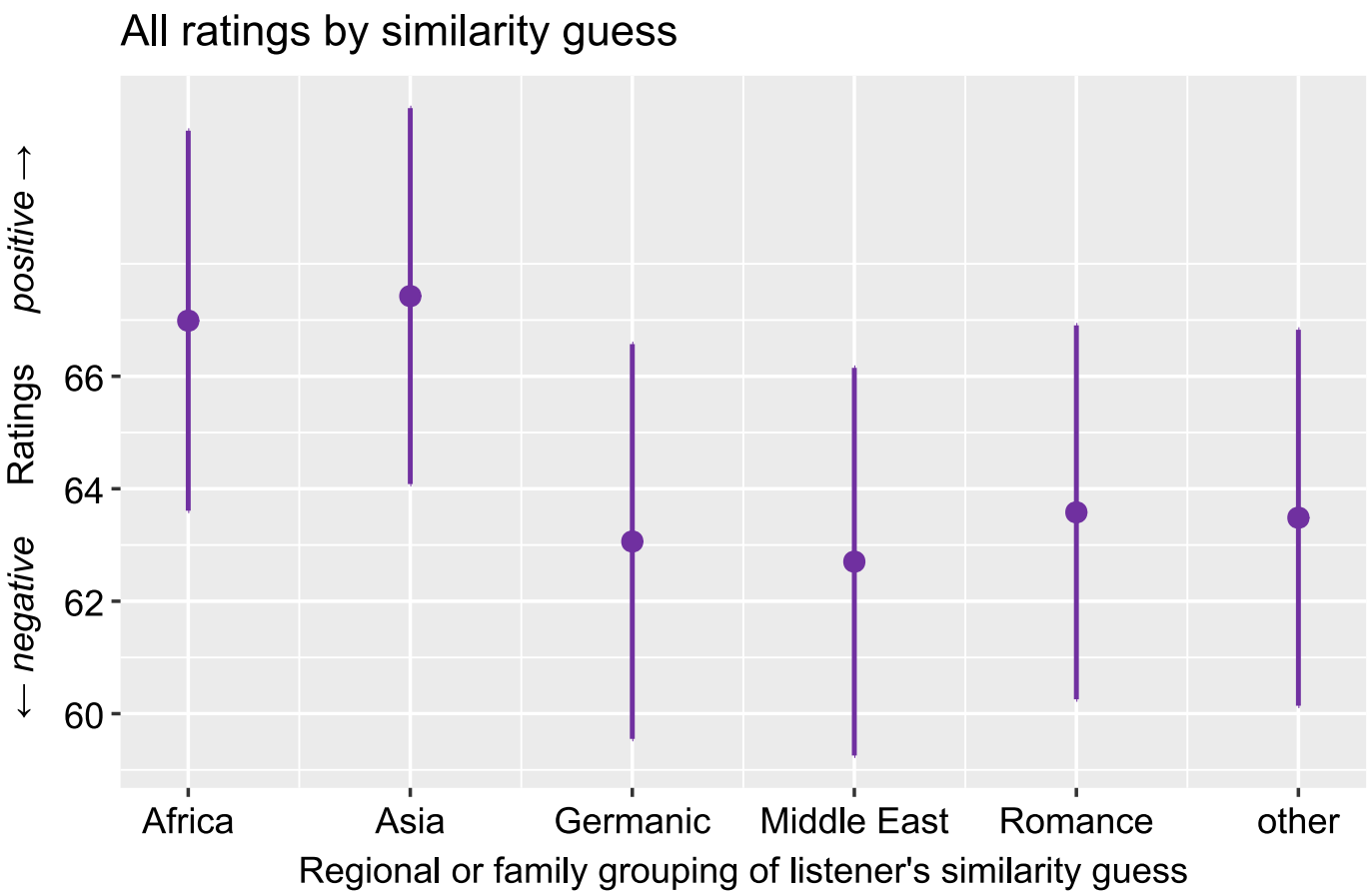


Overview of the interaction between CONDITION and EXPOSURE in all models. Note that the range displayed is the same for all panels except for EROTICISM.

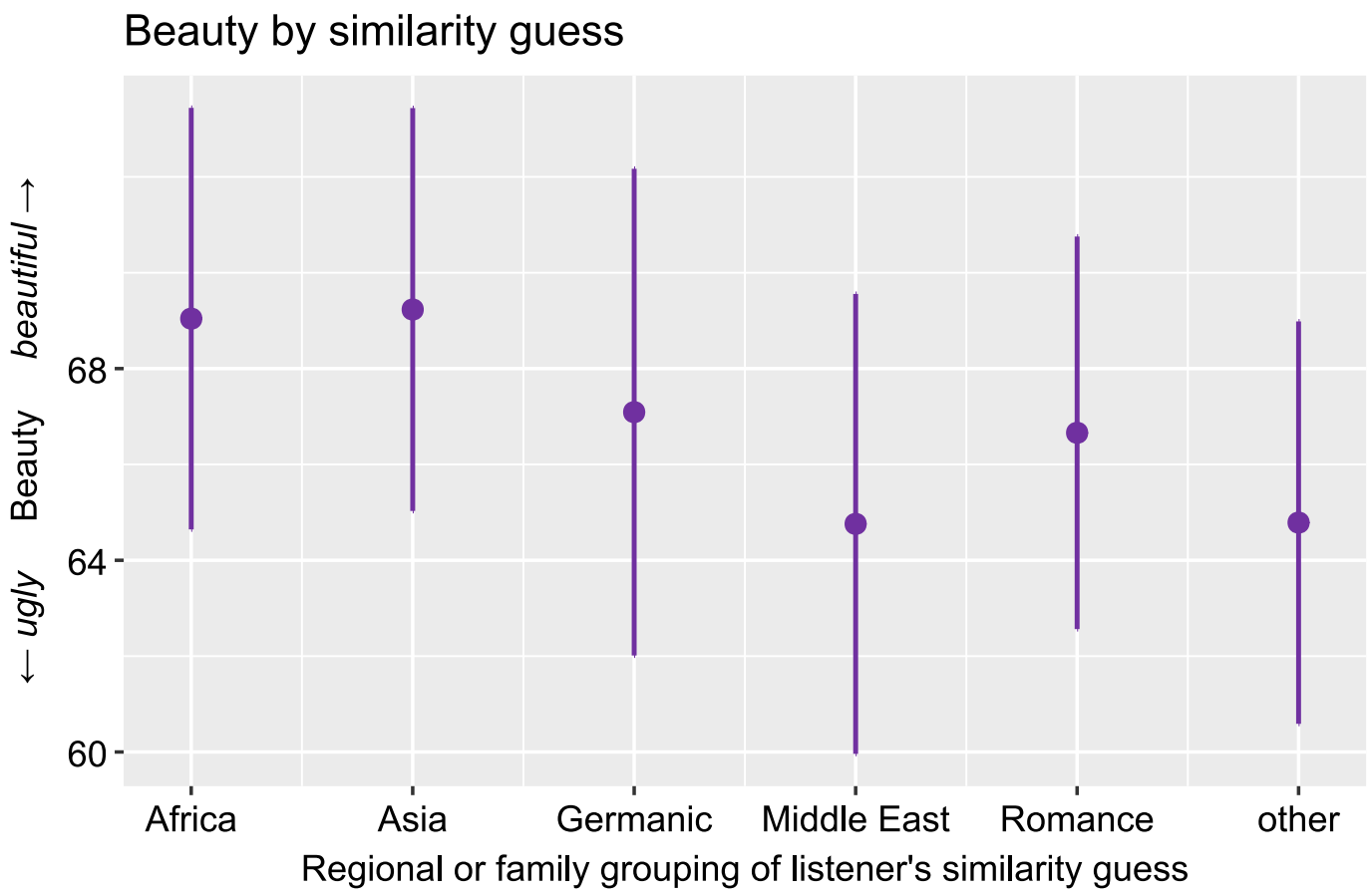
Effect of FAMILIARITY across all semantic scales. Effect is very highly significant at $p < .001$.

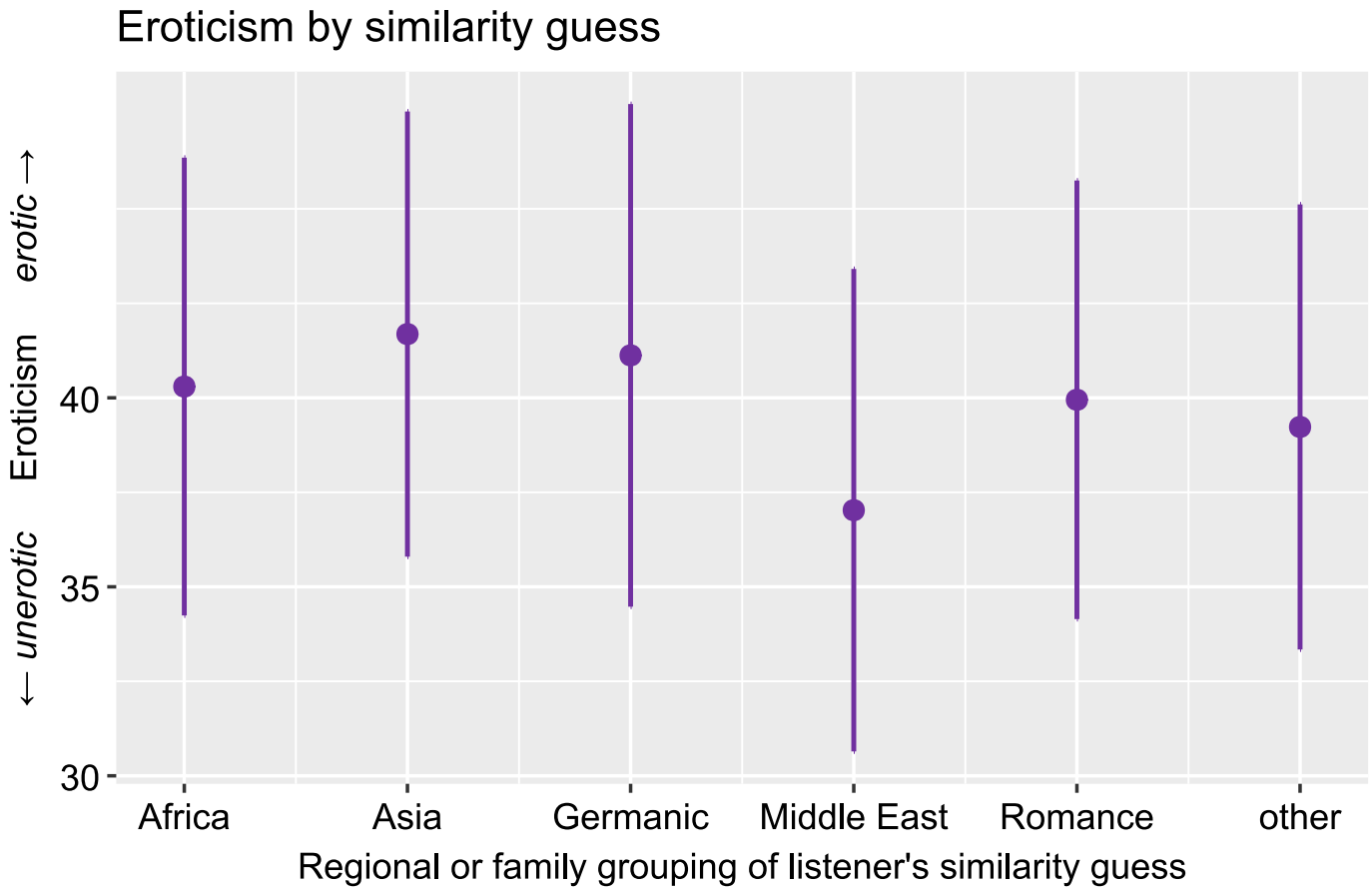


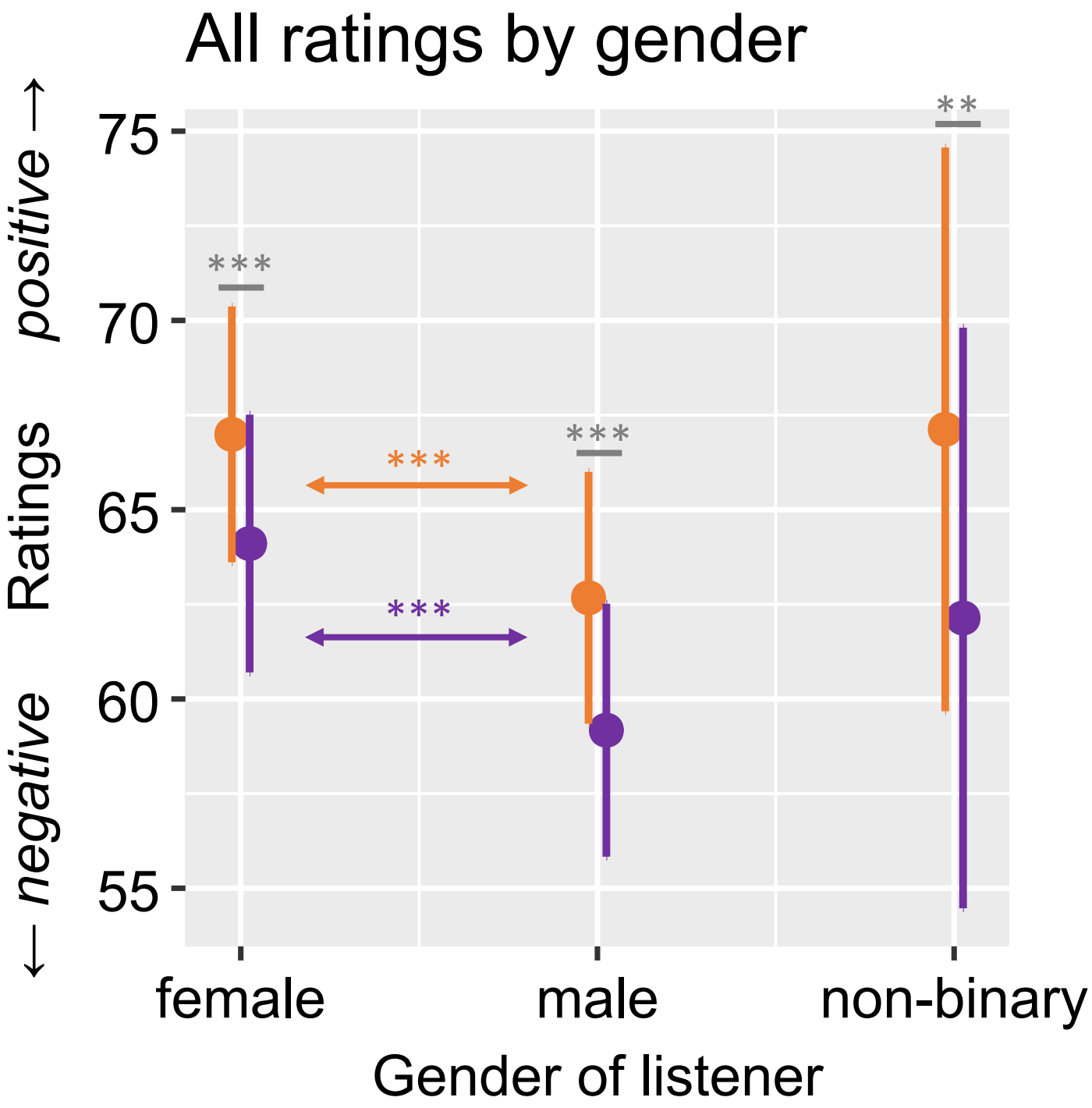
Overview of the effects of FAMILIARITY in all models. Rating on the y-axis is always arranged so that higher values are more positive. All effects are very highly significant at $p < .001$.



Overview of the effects of RECOGNITION for the across-scale model.


Beauty by similarity guess
← ugly Beauty beautiful →
68
64
60
Africa
Asia
Germanic
Middle East
Romance
other
Regional or family grouping of listener's similarity guess

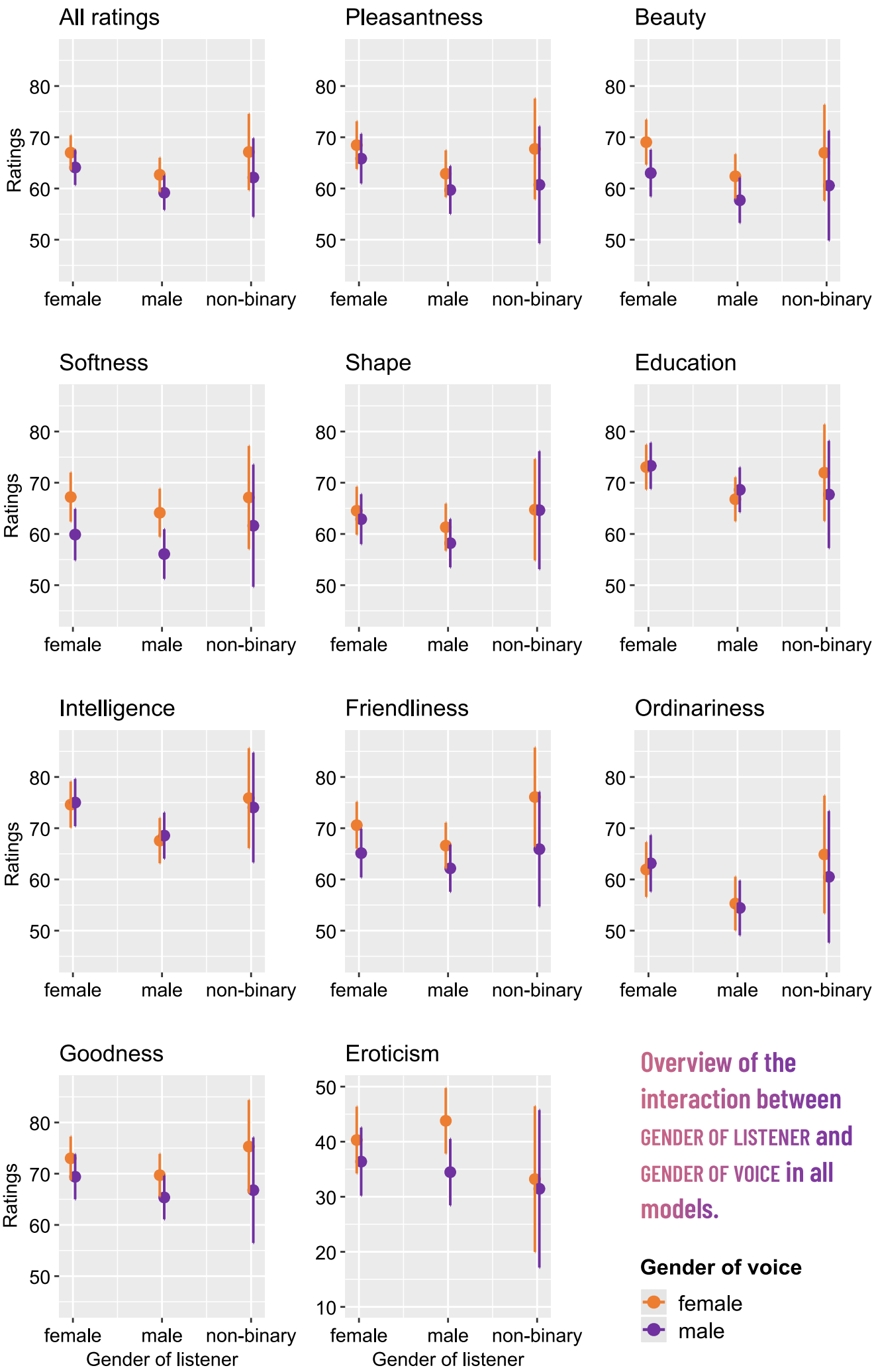

Eroticism by similarity guess
← unerotic Eroticism erotic →
40
35
30
Africa
Asia
Germanic
Middle East
Romance
other
Regional or family grouping of listener's similarity guess

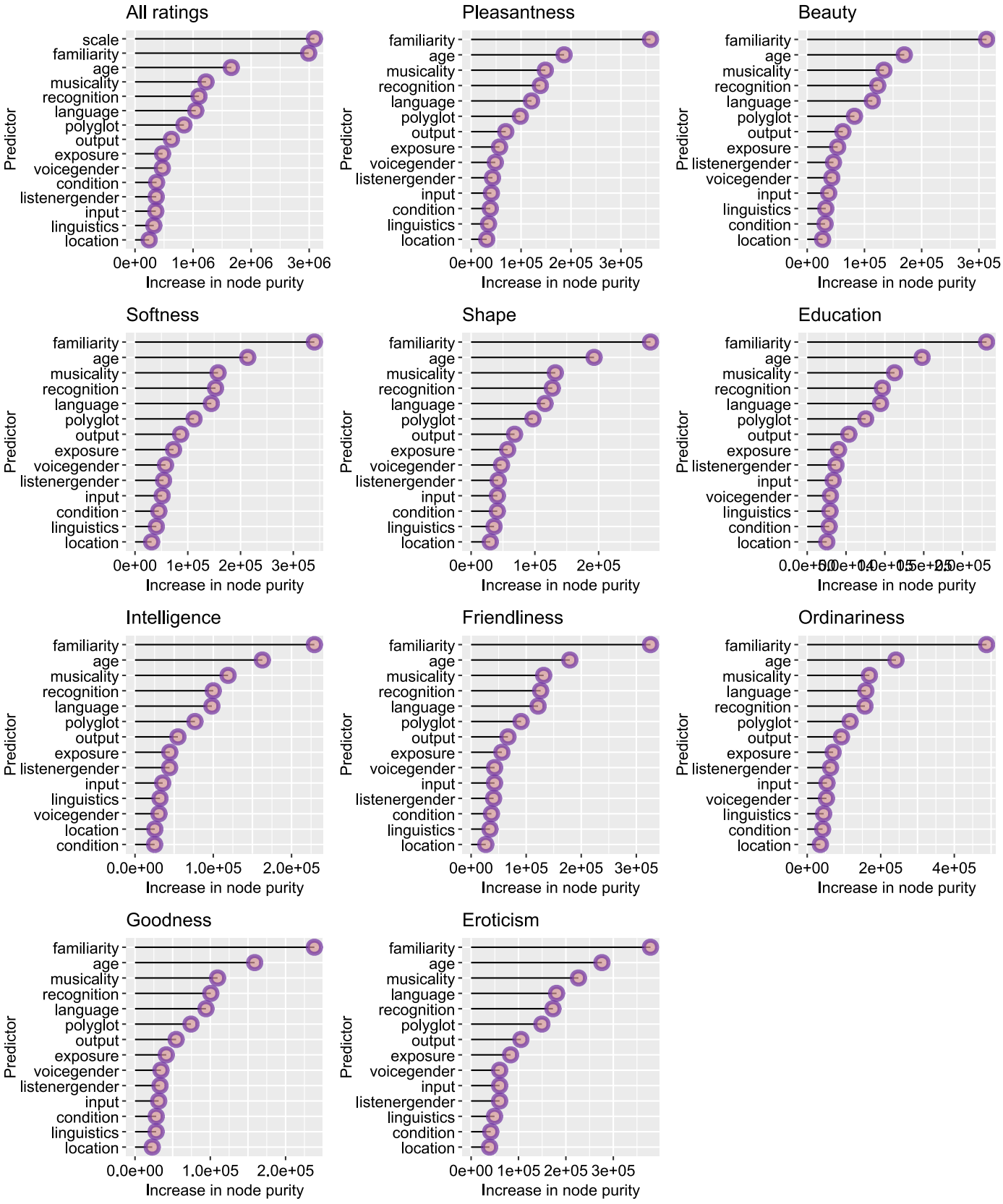


Overview of the effects of GENDER OF LISTENER in interaction with GENDER OF VOICE for the across-scale model.

Gender of voice

- female
- male


All ratings
Pleasantness
Beauty
Softness
Shape
Education
Intelligence
Friendliness
Ordinariness
Goodness
Eroticism
Ratings
female
male
non-binary
Gender of listener
Overview of the interaction between GENDER OF LISTENER and GENDER OF VOICE in all models.
Gender of voice
female
male



Overview of variable importance for all models in predicting the ratings, based on the increase in node purity in 500-tree random forests.