

Body Language Without the Body

Lecture 09 (Bonus Track)

Alessandro Vinciarelli



University
of Glasgow



Social AI



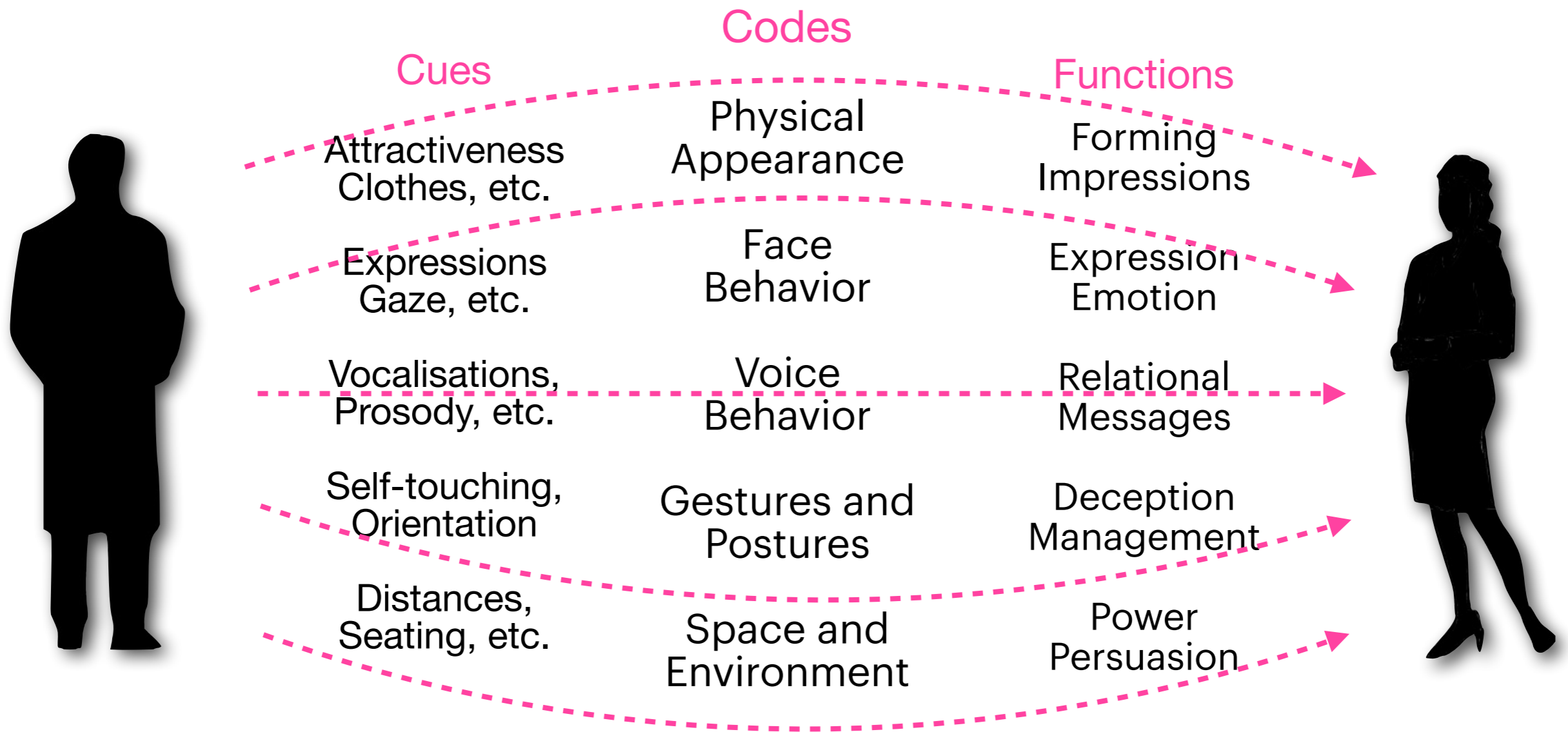
Engineering and
Physical Sciences
Research Council

Outline

- Body Language Without a Body
- Example: Typing Behaviour
- Example: Favs and Personality
- Conclusions

Outline

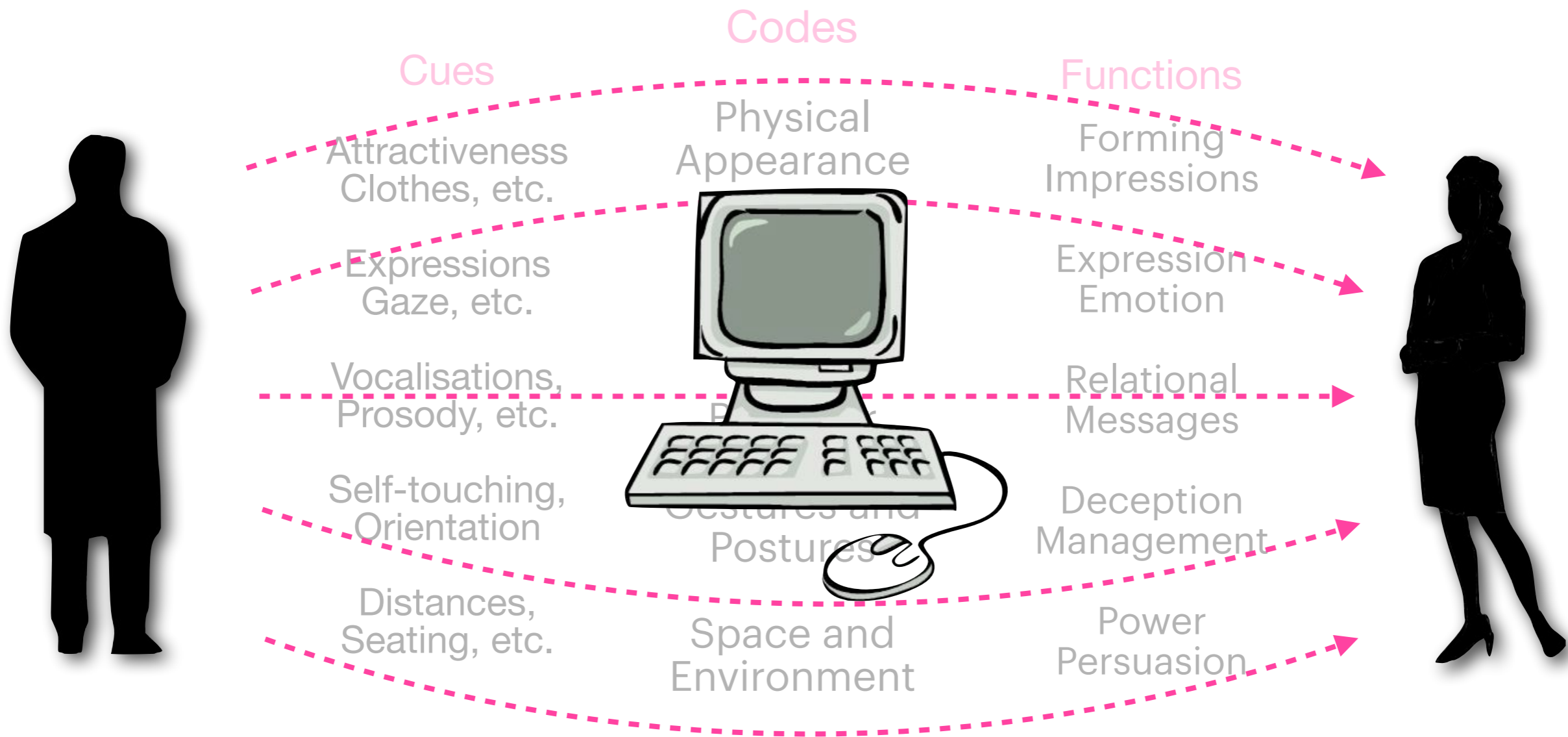
- Body Language Without a Body
- Example: Typing Behaviour
- Example: Favs and Personality
- Conclusions



Richmond and McCroskey, "Nonverbal Behaviors in Interpersonal Relations", Allyn and Bacon, 1995



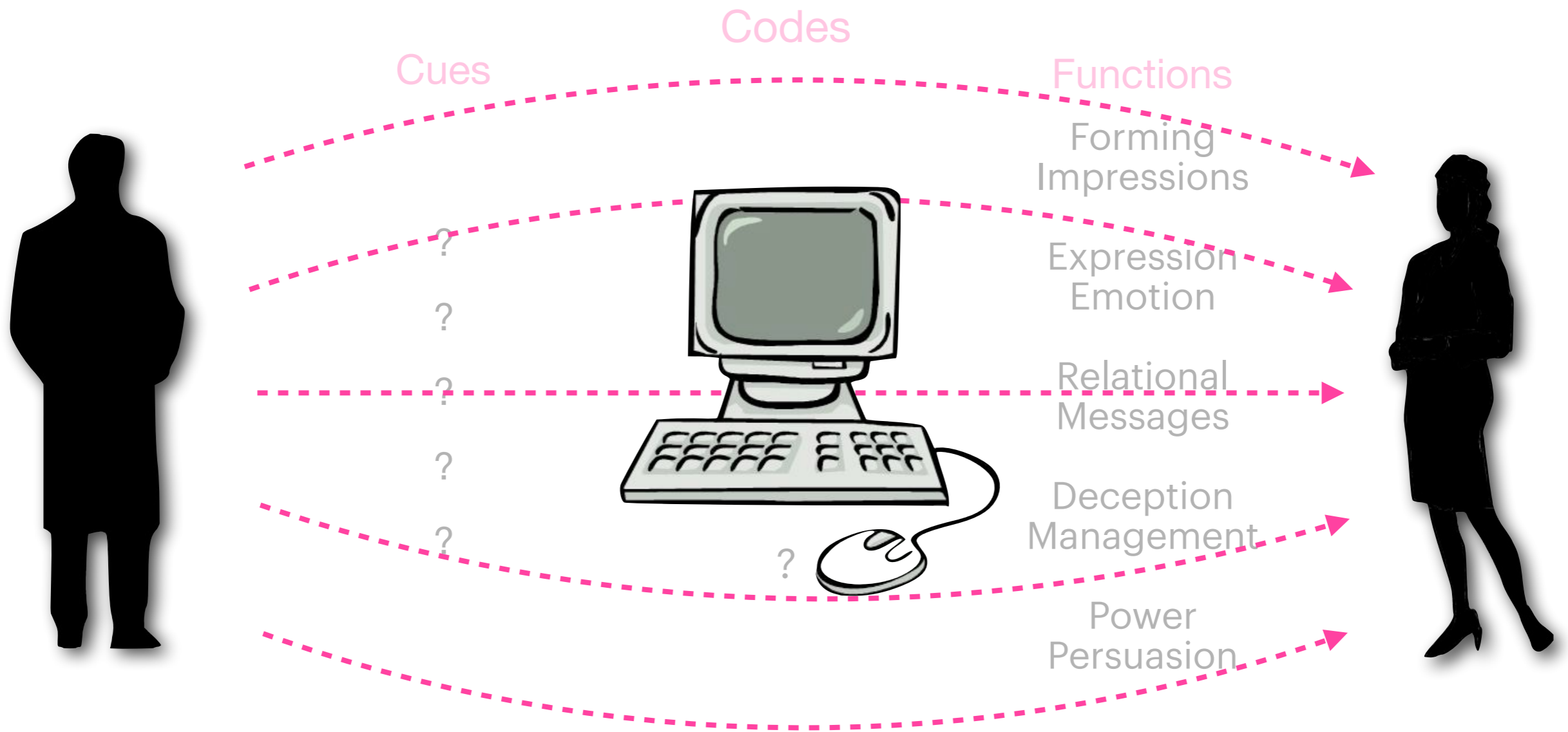
University
of Glasgow



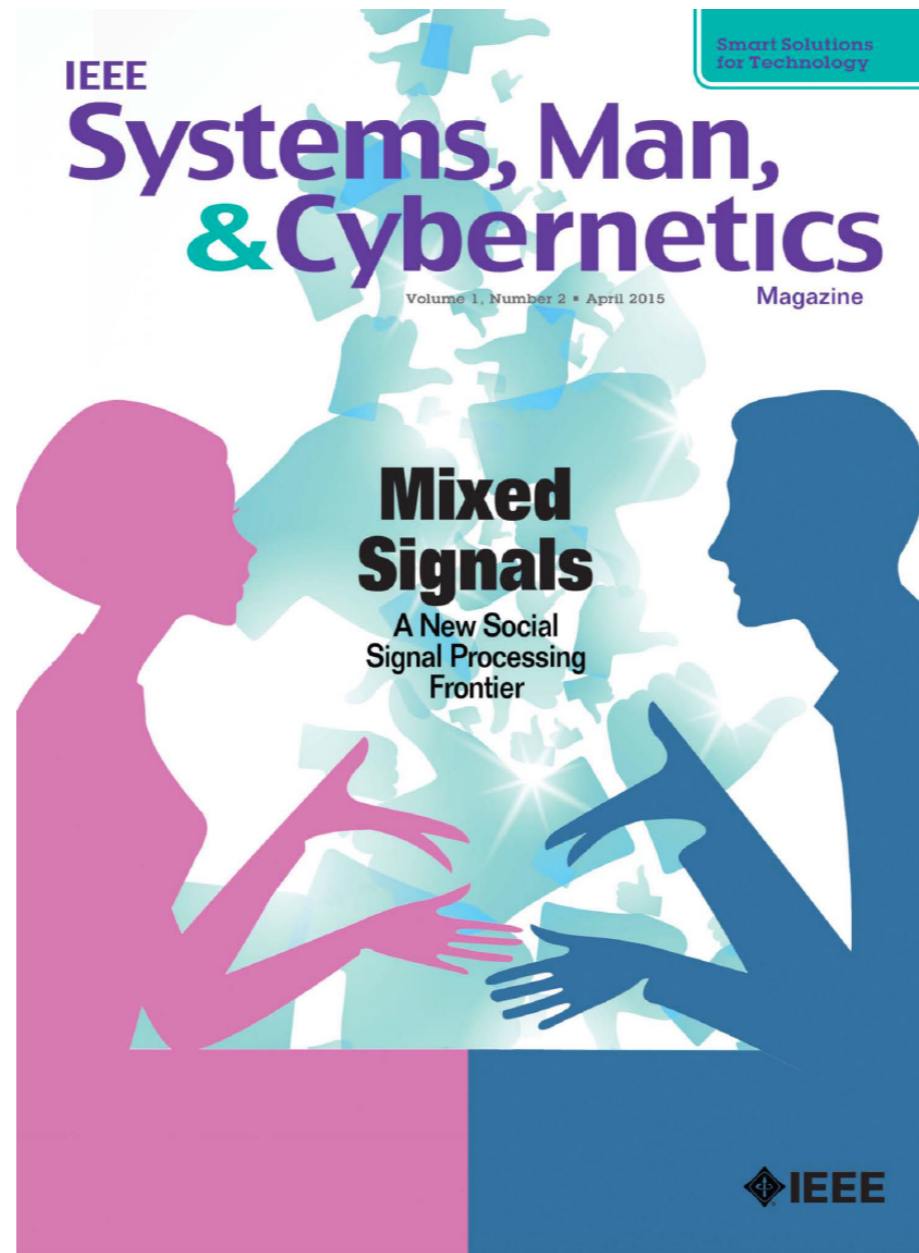
Richmond and McCroskey, "Nonverbal Behaviors in Interpersonal Relations", Allyn and Bacon, 1995



University
of Glasgow



New Social Signals?



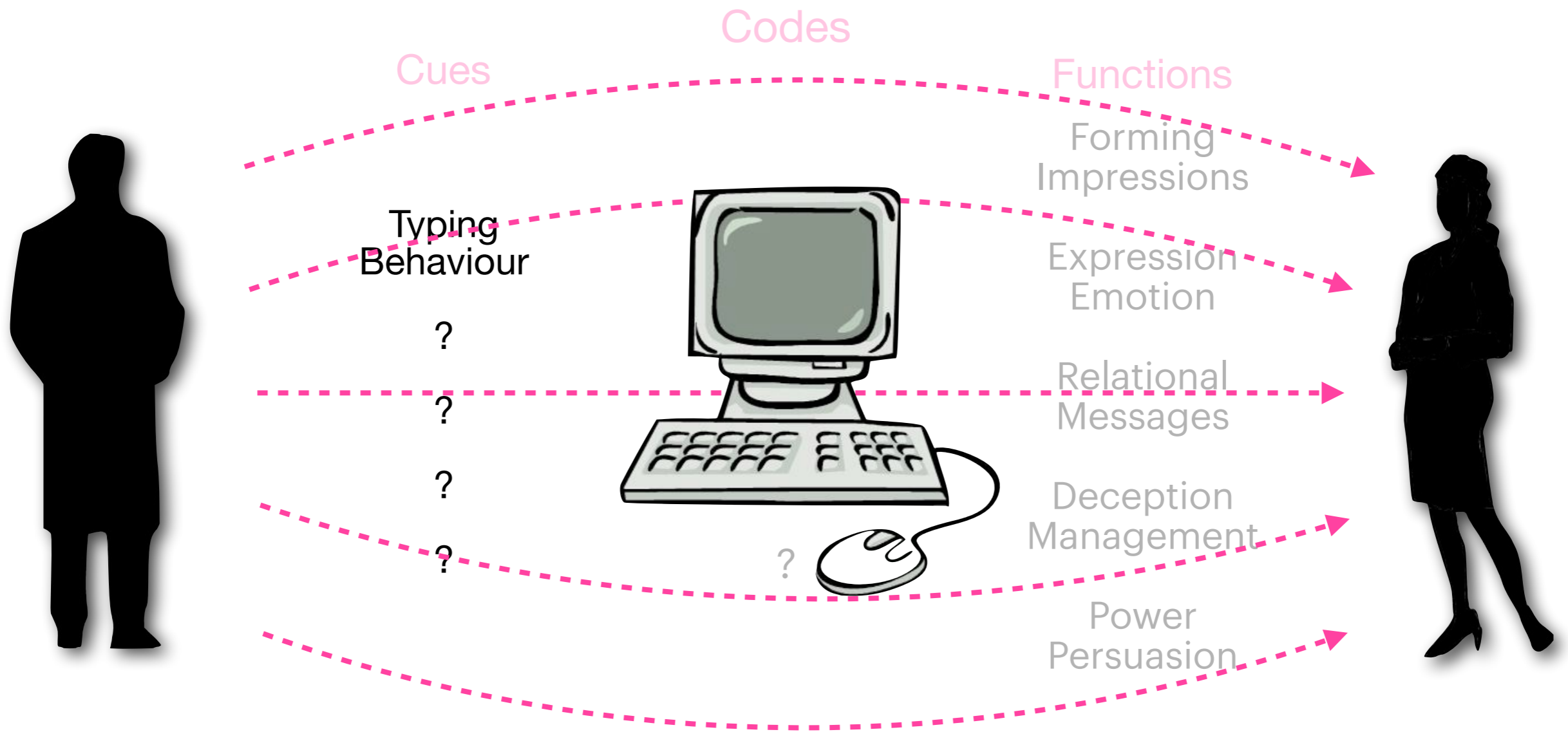
Vinciarelli and Pentland, "New Social Signals in a New Interaction World: The Next Frontier of Social Signal Processing", IEEE SMC Magazine 1(2):10-17, 2015



University
of Glasgow

Outline

- Body Language Without a Body
- Example: Typing Behaviour
- Example: Favs and Personality
- Conclusions

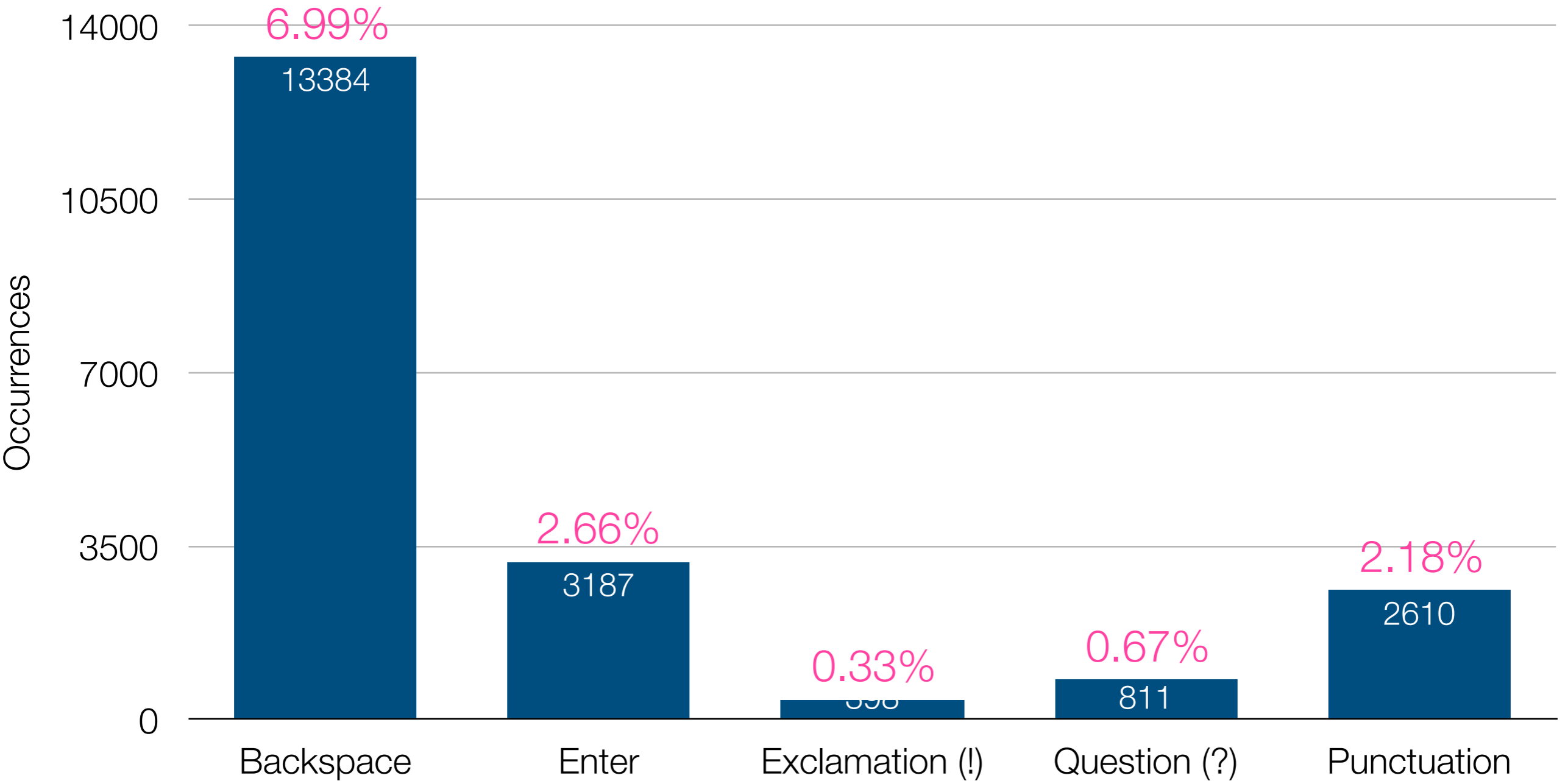


Participants

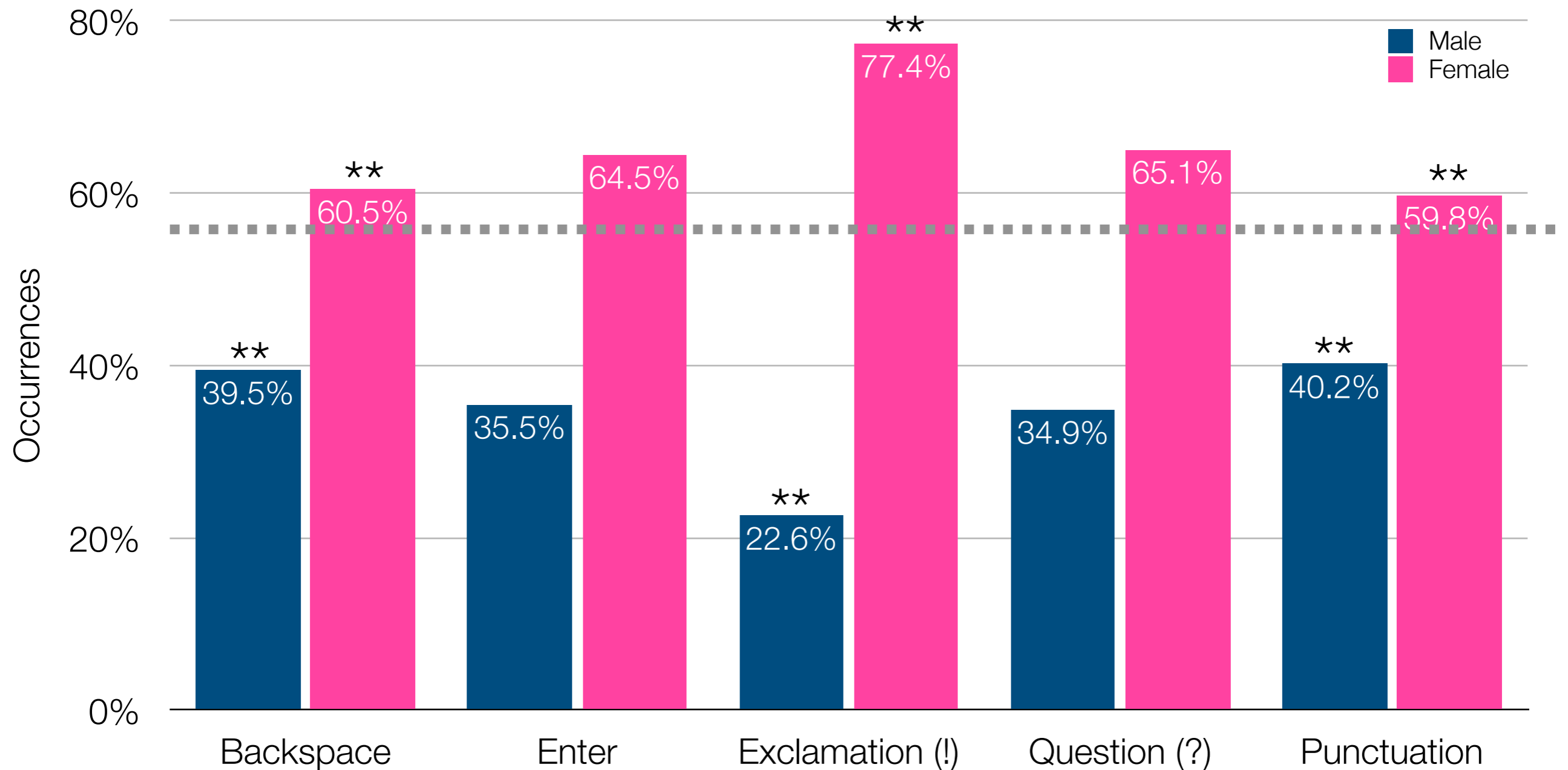
Number of Chats	30
Number of Participants	60
Total Length	191,411
Average Length	3,980.4
Females / Males	35 / 25
Callers / Receivers	30 / 30
Annotated Cues	20,390

- Dyadic Conversations captured through a text based online platform equipped with a **key-logging** function (same scenario as the conversations);

Cue Occurrences



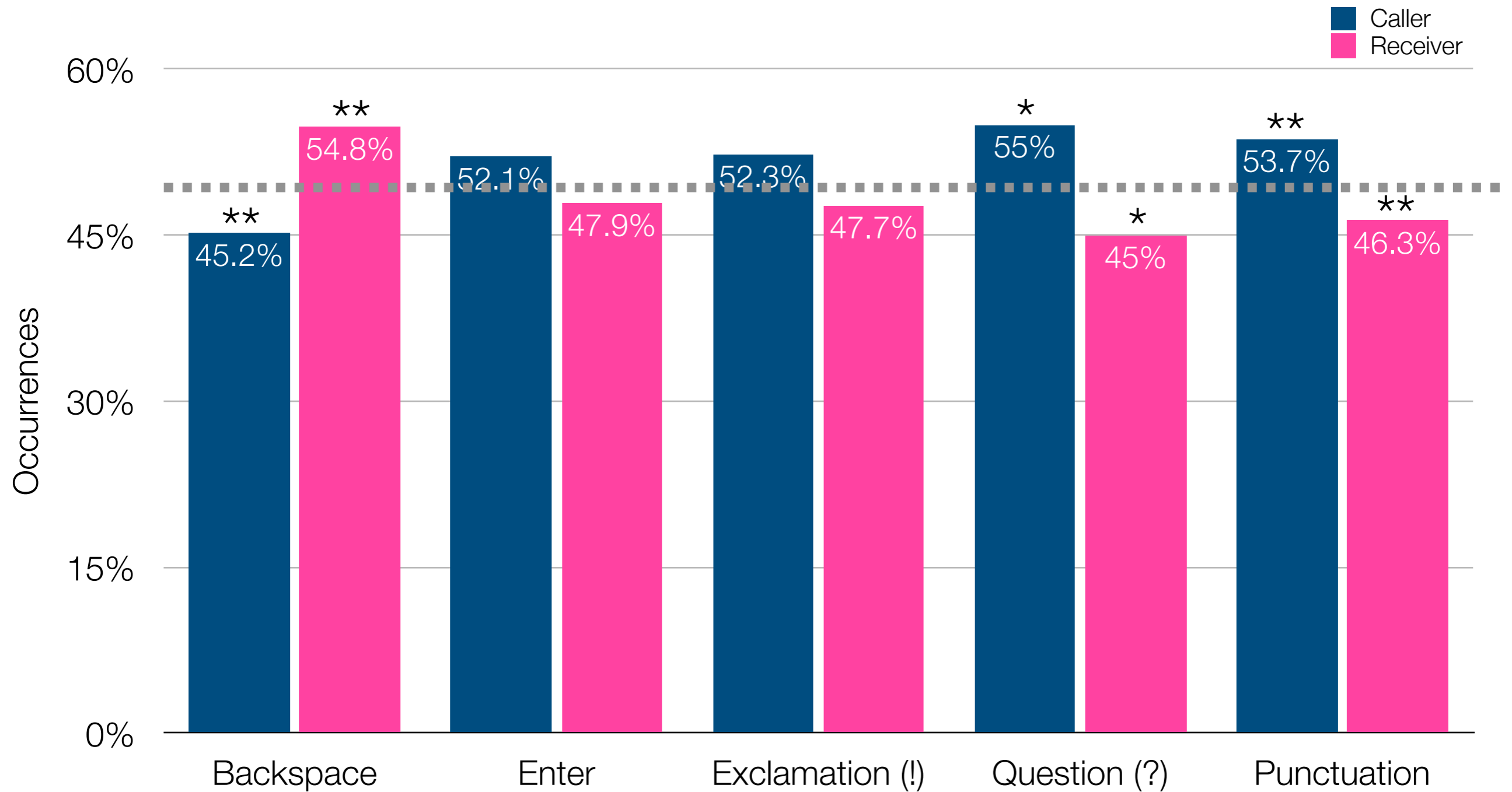
Gender Differences



Gender Differences

- Female participants tend to use the backspace more frequently than expected, they tend to **avoid misspellings** or to **hesitate more** than expected;
- Female participants tend to use exclamation marks more frequently than expected, meaning that they tend to **use emotions more** than expected;
- Female participants tend to use punctuation more frequently than expected, meaning that they tend to be **closer to written** than to spoken expression.

Role Differences



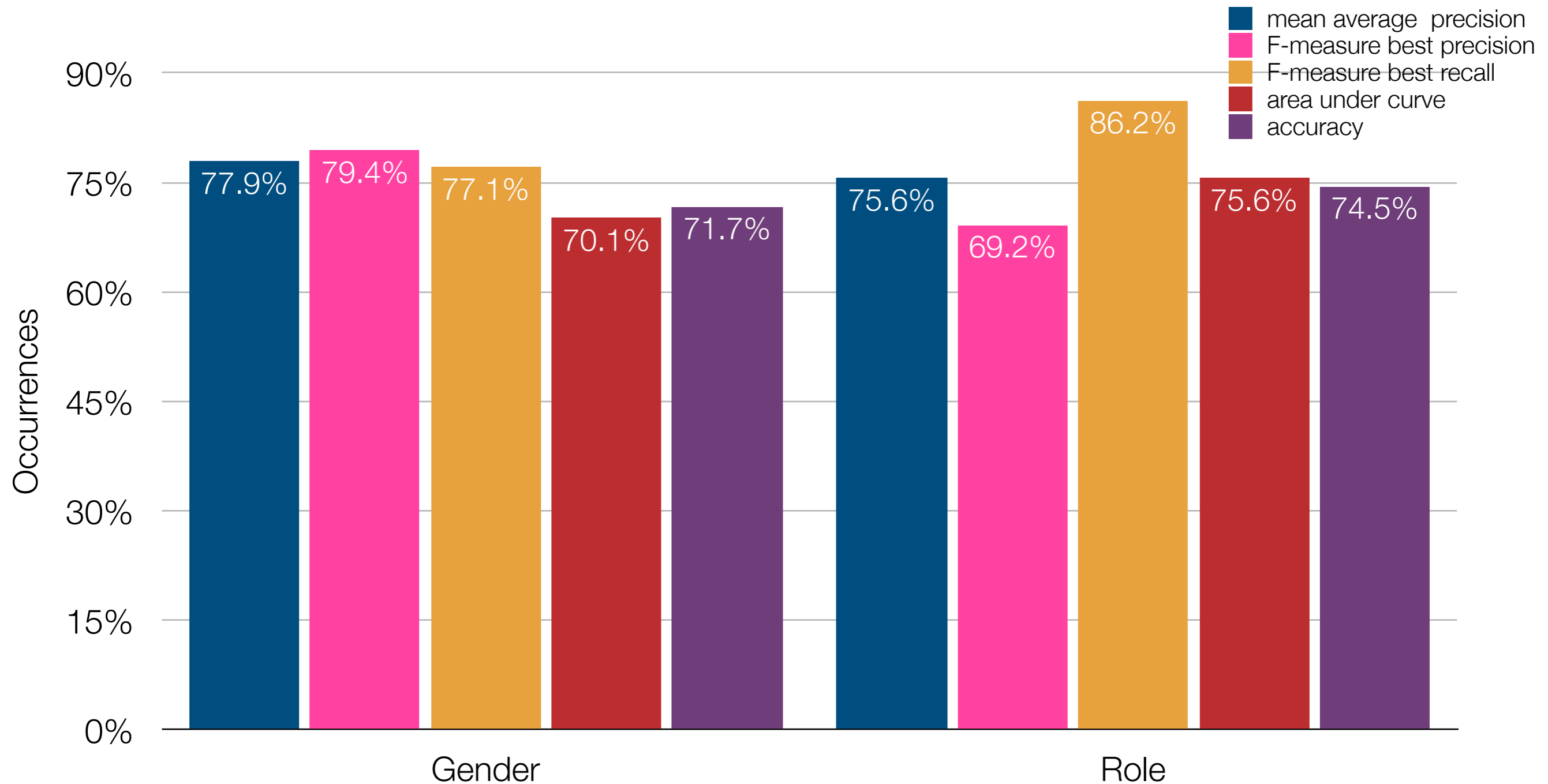
Role Differences

- Receivers tend to use the backspace more frequently than expected, they tend to **avoid misspellings** or to **hesitate more** than expected;
- Callers tend to use question marks more frequently than expected, meaning that they tend to **ask questions more** than expected;
- Callers tend to use punctuation more frequently than expected, meaning that they tend to be **closer to written** than to spoken expression.

Features

Feature	Description
Backspace	Density of “Backspace” keys
Exclamation	Density of “!” key
Emoticons	Density of key sequences corresponding to emoticons
Uppercase Tokens	Density of tokens written in uppercase letters
Uppercase Keys	Density of keys corresponding to uppercase letters
Points	Density of keys corresponding to “.”
Question	Density of keys corresponding to “?”
Non-Alphanumeric	Density of keys that do not correspond to letters
Point Distance	Average distance between consecutive “.” keys
Length (Keys)	Total number N of keys in the chunk
Length (Tokens)	Total number of tokens in the chunk
Inter-Key Speed	$\Delta t = t_N - t_1$, with t_k time at which key k is pressed
Backspace Time	Total time spent in pressing the “Backspace” key
Speed	Number of keys pressed per unit of time
Median Time	Median of time between two keys pressed consecutively

Role Differences

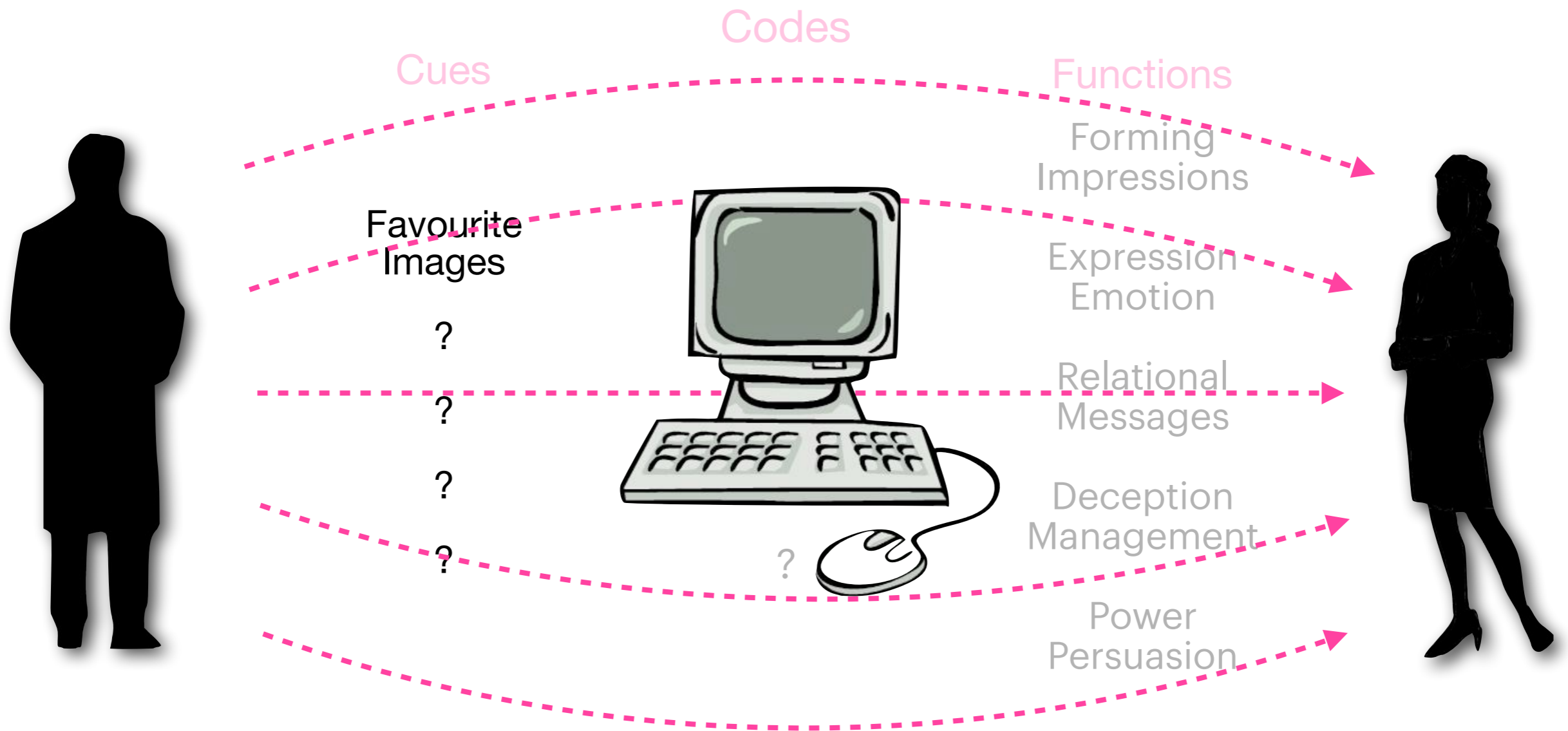


Role Differences

- While having only words available to communicate, people still use **more than 13% of the keys in nonverbal typing cues**;
- Nonverbal features show some **statistically significant differences**, at least in terms of two major dimensions like **gender and role**;
- The differences are sufficiently consistent to allow the **automatic prediction of role and gender** without using what people type, only **how they type** it.

Outline

- Body Language Without a Body
- Example: Typing Behaviour
- Example: Favs and Personality
- Conclusions



Personality

“The **Big Five Personality Factors** appear to provide a set of highly replicable dimensions that parsimoniously and comprehensively **describe most phenotypic individual differences.**”

The Big-Five

- **Extraversion**: tendency to be active, assertive, energetic, outgoing, etc.;
- **Agreeableness**: tendency to be appreciative, forgiving, generous, kind, sympathetic, trusting, etc.;
- **Conscientiousness**: tendency to be efficient, organised, planful, reliable, responsible, thorough, etc.;
- **Neuroticism**: tendency to be anxious, self-pitying, tense, touchy, unstable, worrying, etc.;
- **Openness**: tendency to be artistic, curious, imaginative, insightful, etc.

This robot is reserved	E	-
This robot is generally trusting	A	+
This robot tends to be lazy	C	-
This robot is relaxed, handles stress well	N	-
This robot has few artistic interests	O	-
This robot is outgoing, sociable	E	+
This robot tends to find faults with others	N	+
This robot does a thorough job	C	+
This robot gets nervous easily	A	-
This robot has an active imagination	O	+

Corpus Collection

BFI-10
1st Person

A table with 10 rows and 10 columns of Likert scales. Each cell contains a 5-point scale from '1 (not at all)' to '5 (very much)'. The rows correspond to the 10 BFI-10 subscales: 1. Warm, 2. Compassionate, 3. Trusting, 4. Vulnerable, 5. Non-defensive, 6. Open to experience, 7. Assertive, 8. Empathic, 9. Warm, 10. Compassionate.

BFI-10
1st Person

A table with 10 rows and 10 columns of Likert scales. Each cell contains a 5-point scale from '1 (not at all)' to '5 (very much)'. The rows correspond to the 10 BFI-10 subscales: 1. Warm, 2. Compassionate, 3. Trusting, 4. Vulnerable, 5. Non-defensive, 6. Open to experience, 7. Assertive, 8. Empathic, 9. Warm, 10. Compassionate.

Self-Assessment



Flickr

A table with 10 rows and 10 columns of Likert scales. Each cell contains a 5-point scale from '1 (not at all)' to '5 (very much)'. The rows correspond to the 10 BFI-10 subscales: 1. Warm, 2. Compassionate, 3. Trusting, 4. Vulnerable, 5. Non-defensive, 6. Open to experience, 7. Assertive, 8. Empathic, 9. Warm, 10. Compassionate.



BFI-10
3rd Person

Assessment

The PsychoFlickr Corpus

Number of Galleries	300
Number of Pictures	60,000
Number of Participants	300
Gender Balance	71.3% Male / 28.7% Female
Category Balance	100% Pro Users
Participants	11 (UK) + 11 (Asia)
Total Items	44,000

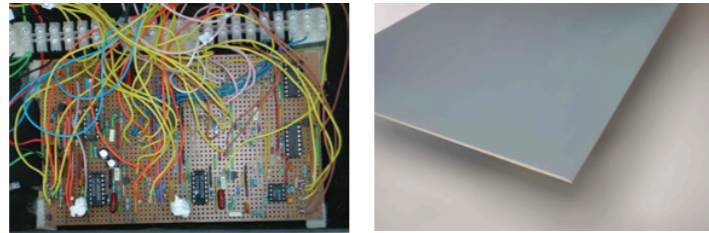
- Dyadic Conversations captured through a text based online platform equipped with a **key-logging** function (same scenario as the conversations);

Aesthetic Preferences



Texture

Entropy



high (= 4.66)

low (= 0.31)

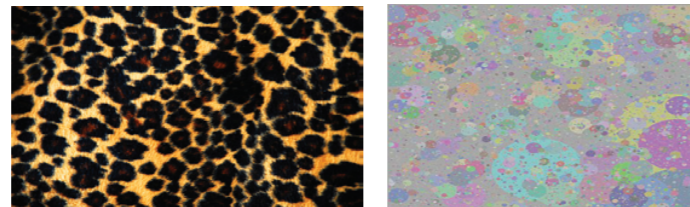
Tamura coarseness



high (= 4.06)

low (= 2.93)

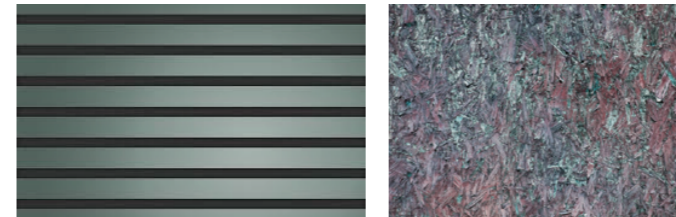
Tamura contrast



high (= 0.0598)

low (= 0.0027)

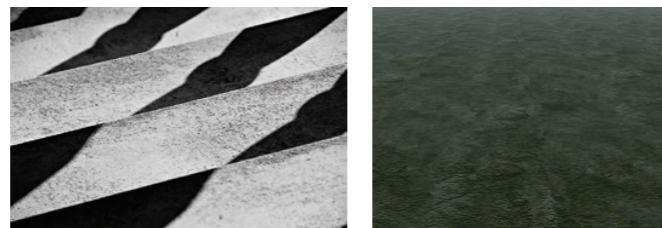
Tamura directionality



high (= 0.5)

low (= 0.25)

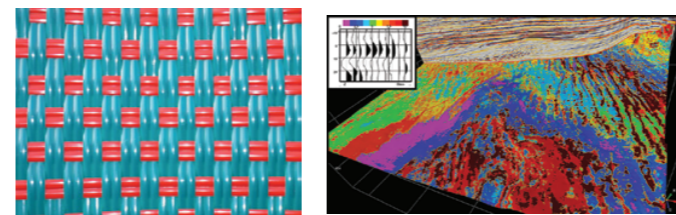
GLCM contrast (on the V channel)



high (= 1)

low (= 0.75)

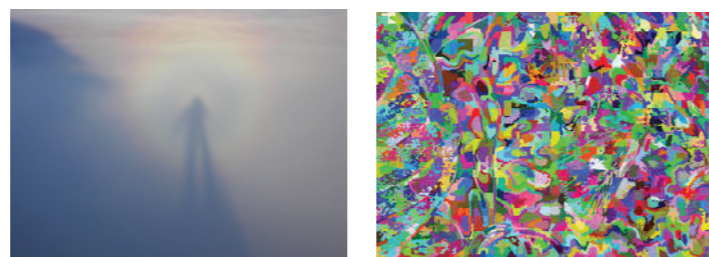
GLCM correlation (on the H channel)



high (= 0.9646)

low (= 0.7646)

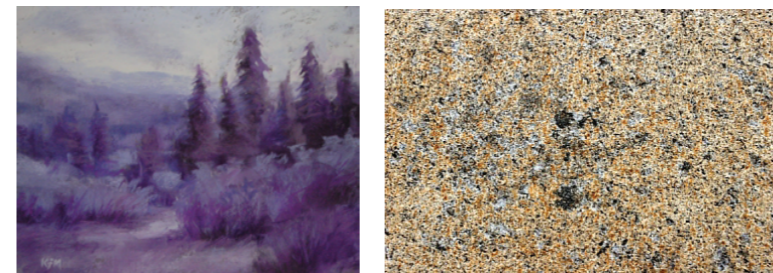
GLCM energy (on the S channel)



high (= 0.99)

low (= 0.58)

GLCM homogeneity (on the H channel)



high (= 0.95)

low (= 0.47)

Composition

Canny



original

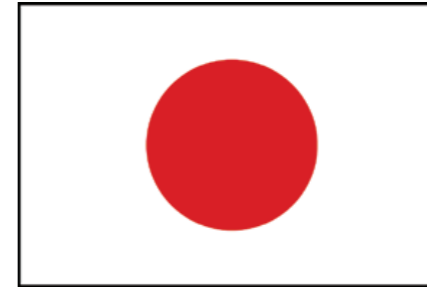


processed

Level of detail



high (number of segments = 528
norm. average extension = 0.002)



low (number of segments = 2
norm. average extension = 0.5)

Low depth of field indicator



strong (= 2,1.3, 2)



weak (= 1.1, 0.9, 0.9)

Composition

Use of light



high (= 0.79)



low (= 0.14)

Average saturation



high (= 0.89)



low (= 0.17)

Valence



high (= 0.72)



low (= 0.18)

Dominance

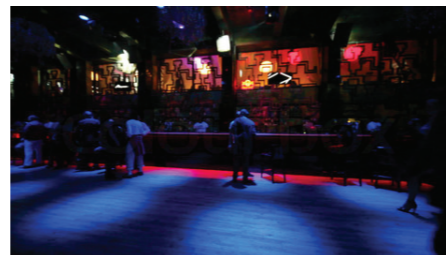


high (= -0.03)



low (= -0.50)

Arousal



high (= 0.36)



low (= -0.22)

Color diversity



high (= 1/8.16)



low (= 1/16.7)

Hue circular variance

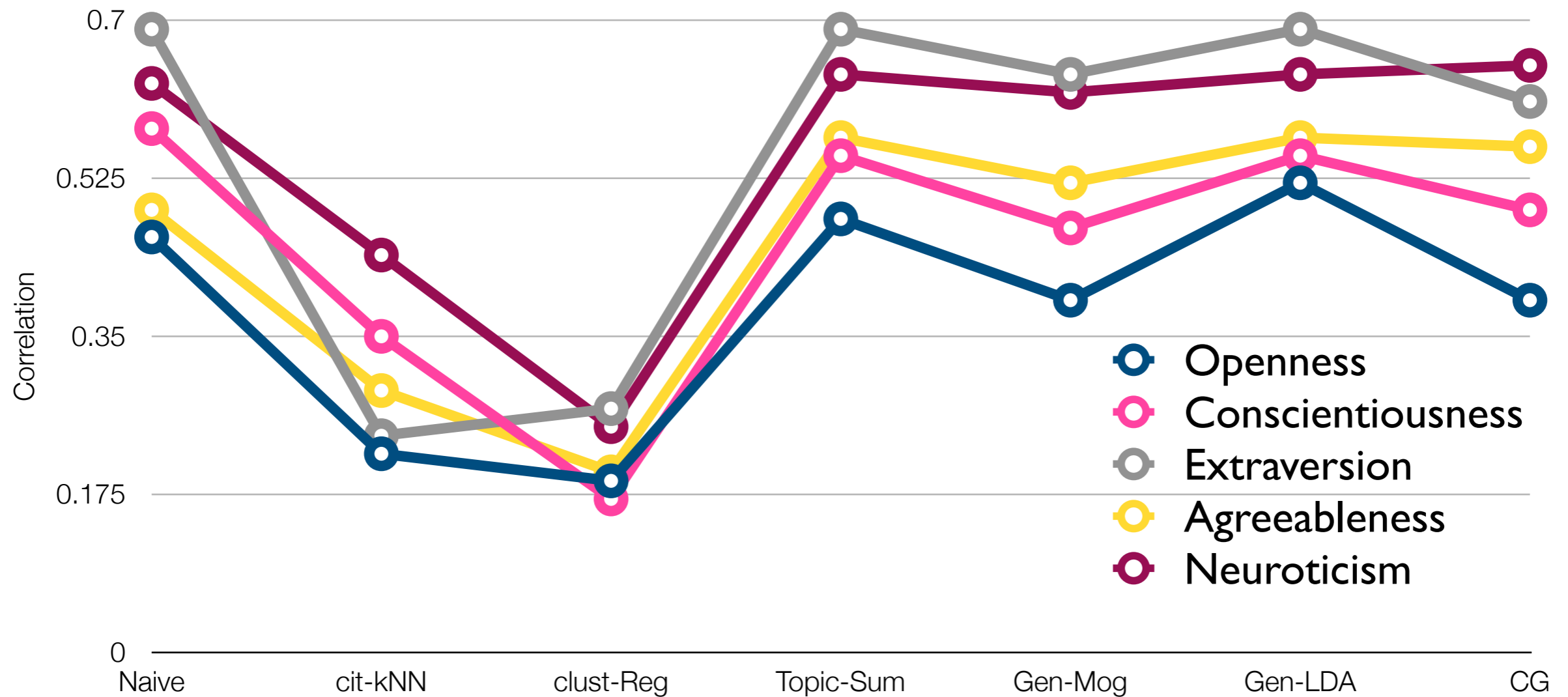


high (= 0.84)

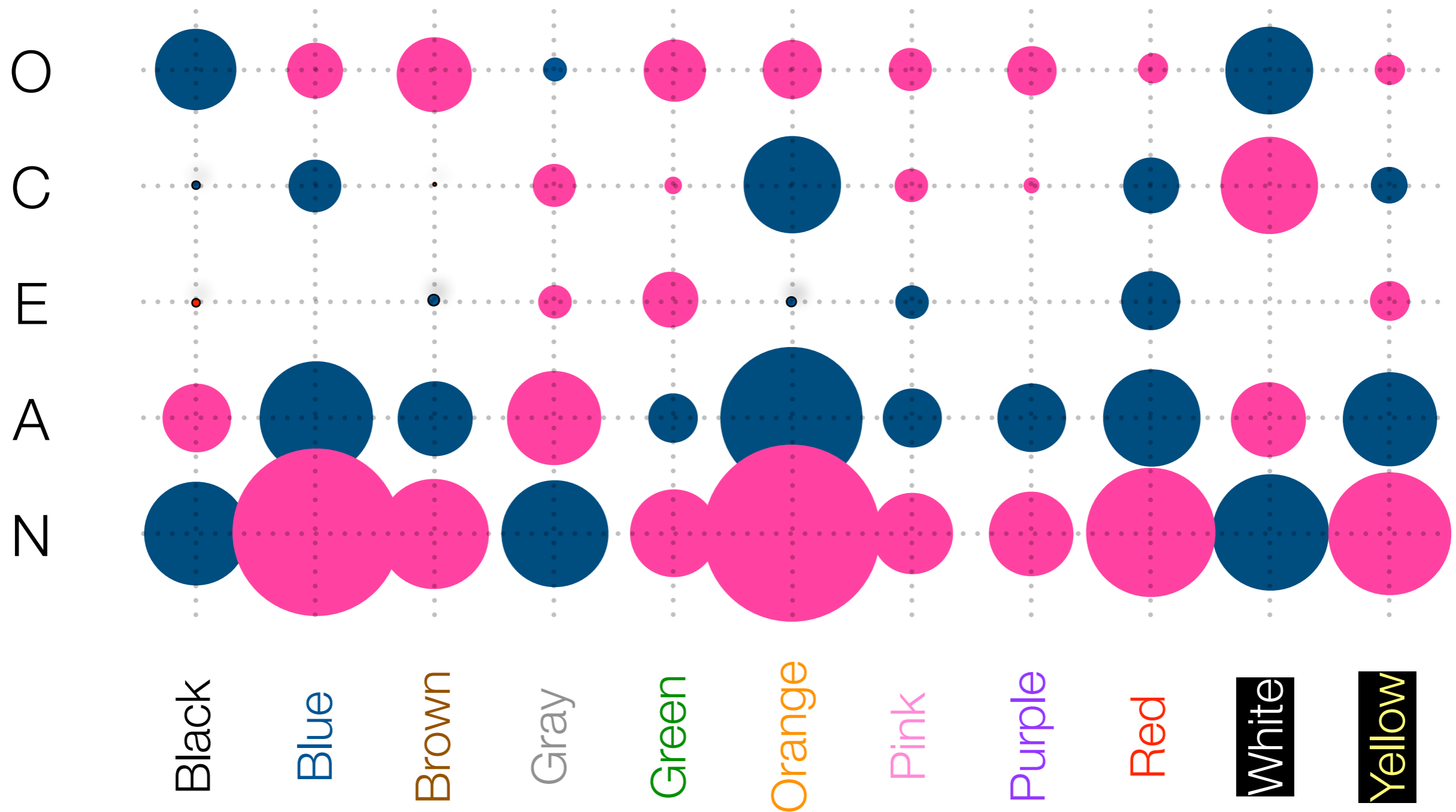


low (= 0.04)

Trait Prediction



Correlation Colour Trait

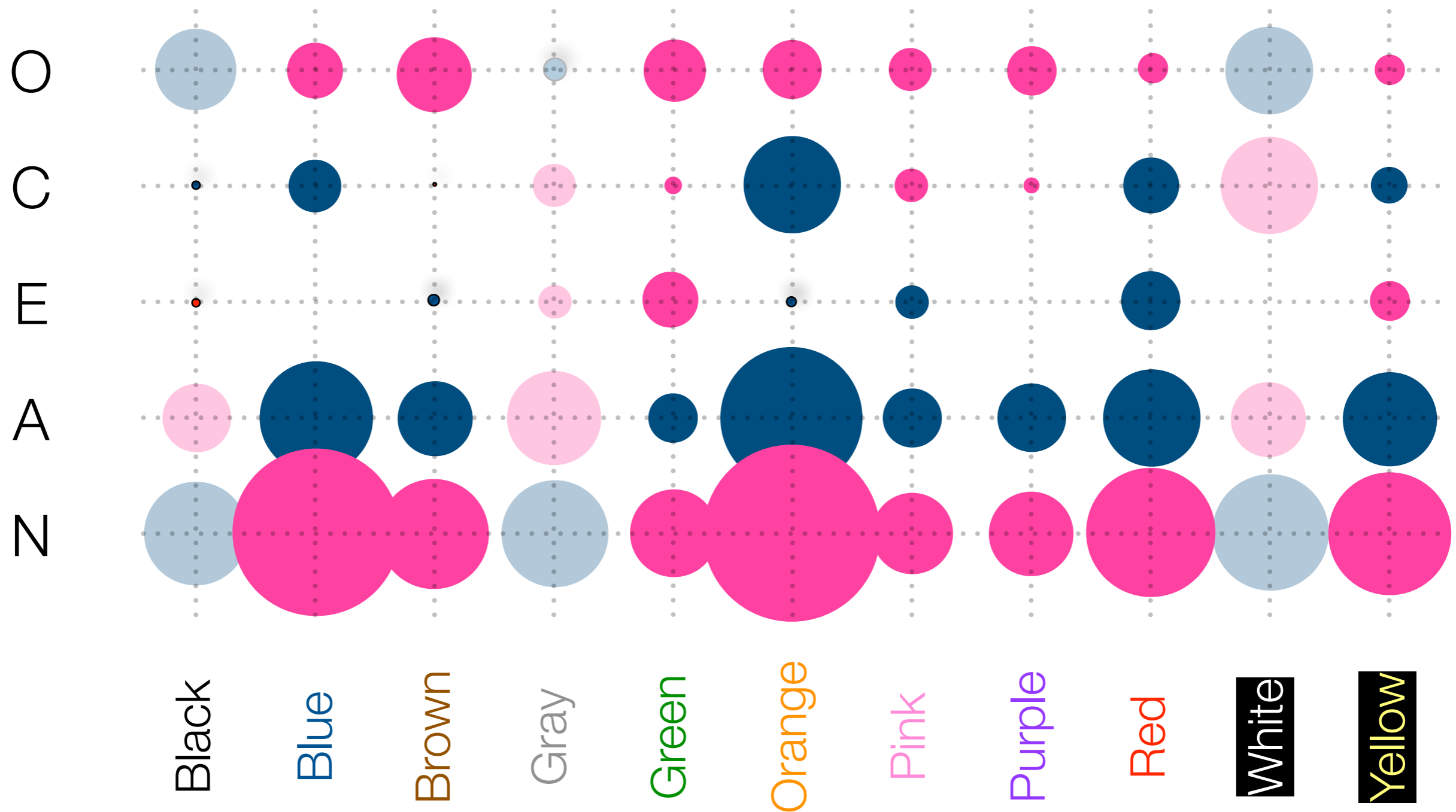


Segalin, Perina, Cristani and Vinciarelli, "The Pictures we Like are our Image",
 IEEE Transactions on Affective Computing 8(2):268-285, 2017



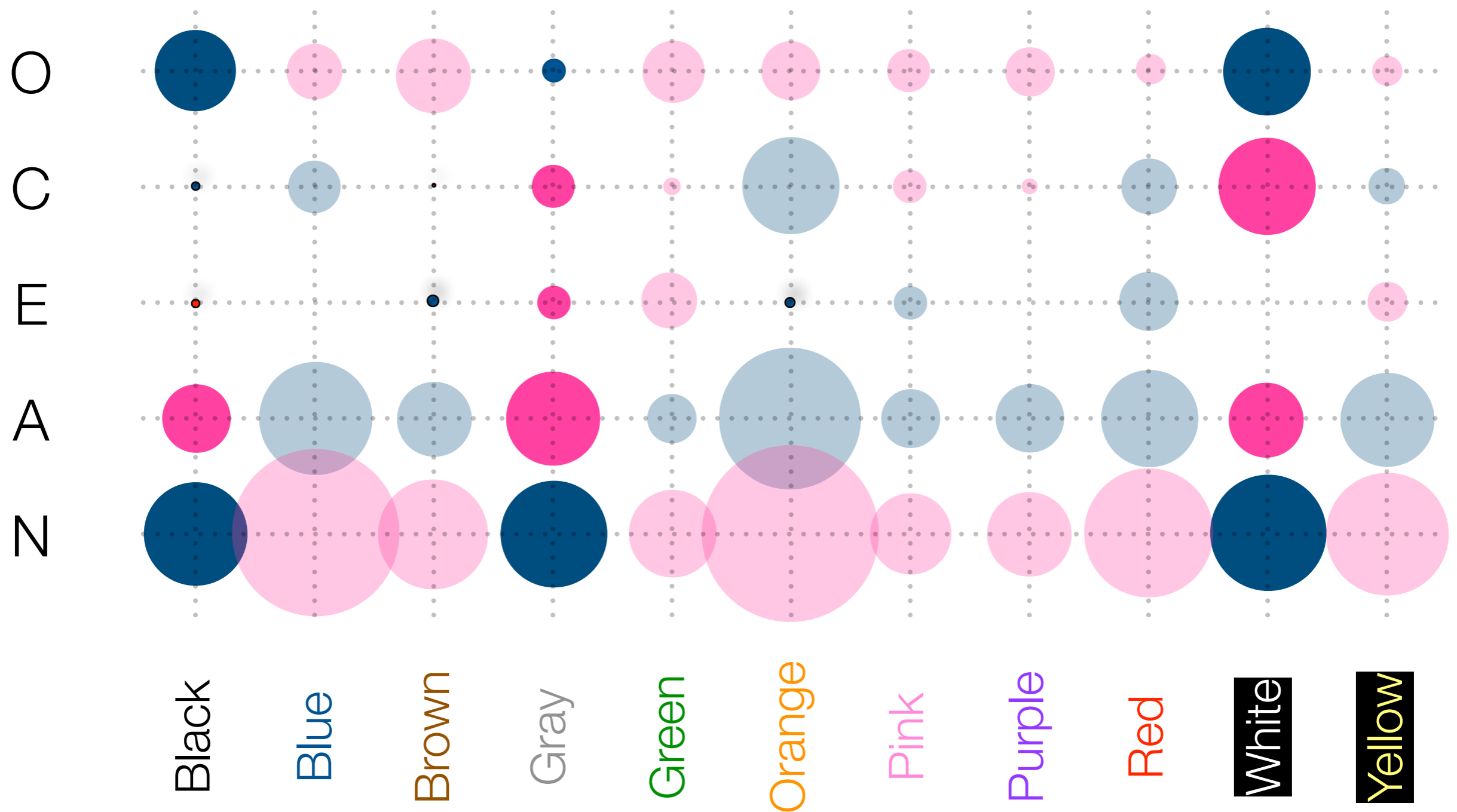
University
of Glasgow

Correlation Colour Trait



Segalin, Perina, Cristani and Vinciarelli, "The Pictures we Like are our Image",
 IEEE Transactions on Affective Computing 8(2):268-285, 2017

Correlation Colour Trait



Segalin, Perina, Cristani and Vinciarelli, "The Pictures we Like are our Image",
 IEEE Transactions on Affective Computing 8(2):268-285, 2017

Images as Social Signals

- While not corresponding to any previous form of communication, favourite pictures appear to act as social signals;
- There are significant correlations between low-level visual features and personality traits;
- The correlation is sufficient to allow the automatic prediction of traits based on low-level visual features.
- Extraversion and Neuroticism are the two best predicted traits, the correlation accounts for close to 50% of the variance in the raters' judgments.

Outline

- Body Language Without a Body
- Example: Typing Behaviour
- Example: Favs and Personality
- Conclusions

Conclusions

- Social signals are the **physical and machine detectable evidence** of both social and psychological phenomena;
- Automatic detection and interpretation of social signals make **machines socially intelligent**;
- The model seems to apply not only to natural cues, but also to **artificial ones generated in new interaction contexts**;
- One possible reason is that the **new, digital signals** we use to communicate **still pass through a brain designed for face-to-face interactions**.

Thank You!