PERSONALITY

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AGENDA

- What is personality?
- Can we automatically detect personality?
- Does big data help improve predictions?

Think about someone you know well.

Write down how you would describe this person to others. Use as many words/phrases as necessary to fully describe the person.

HAVE YOU EVER…

Asked ChatGPT to assess how your text or email sounds?

CHATGPT

Something to do later…

Run an email you recently sent where you were concerned with how you came across.

- Ask ChatGPT to tell you what it thinks, it may offer terms such as:
  - Warm
  - Clear
  - Professional
  - Competent
  - Assertive
- Then run it through a second time but with some context – a bit of background information about the situation and person you are sending it to.
  - How does this change the output?

CHATGPT, LLMS & PERSONALITY

Matz et al. (2024). The Potential of Generative AI for Personalized Persuasion at Scale

- LLMs like ChatGPT are effective at tailoring messages to be more persuasive based on recipient

Piastra & Catellani (2025). On the Emergent Capabilities of ChatGPT 4 to Estimate Personality Traits

- Used written text; Found moderate to significant abilities to predict personality

WHAT IS PERSONALITY?

This is about who you are – your characteristic style of behaving, thinking, and feeling.

How can we assess differences in personality?

- 4 main approaches in psychology:
  - Trait
  - Psychodynamic
  - Humanistic
  - Social-Cognitive

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TRAIT APPROACH

Personality = a combination of traits

Assumes:

- People differ from each other in (relatively) stable ways.
- Traits are consistent ways of behaving and therefore can predict future actions.

Attempts to find a taxonomy (classification scheme) for core traits that define personality.

DIMENSIONS OF PERSONALITY

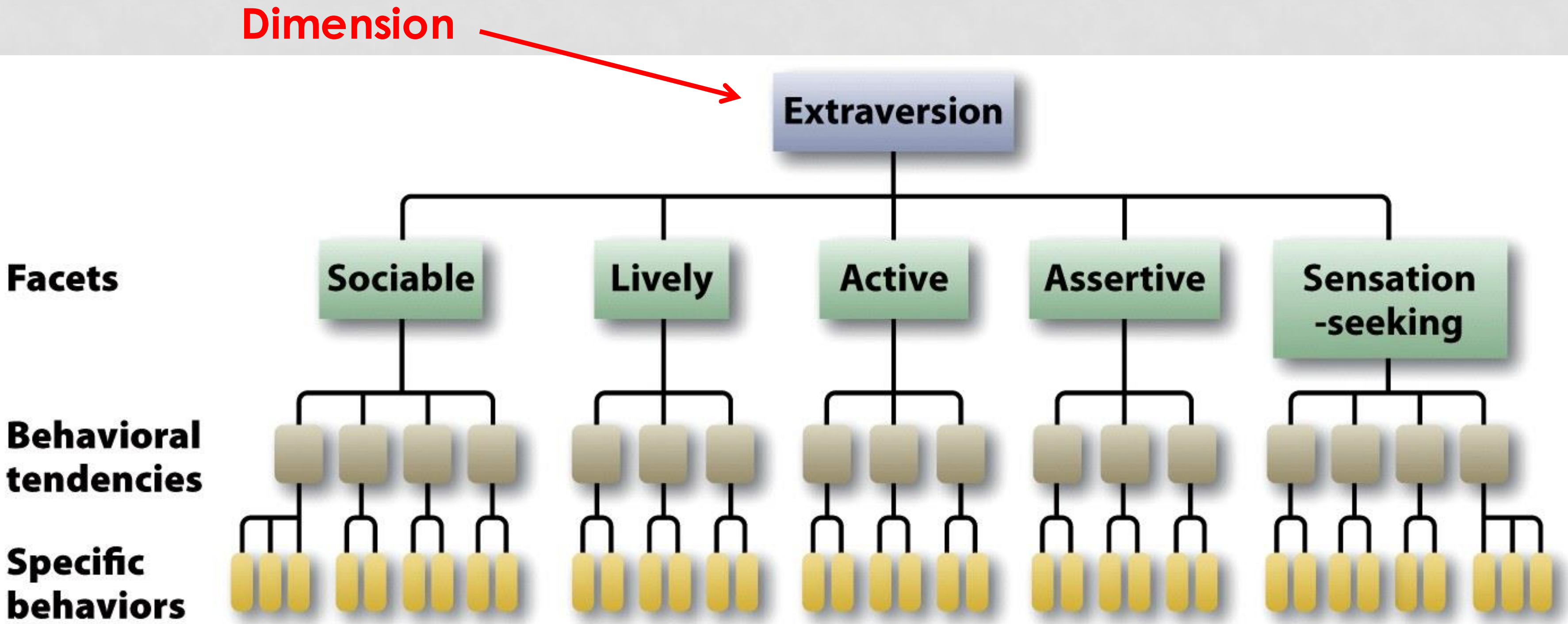
Traits are grouped into ***dimensions of personality***

- Thus, personality is thought of as a combination of separate dimensions (as opposed to types).

How were the dimensions determined?

- 18,000 words for potential traits (Allport & Odbert, 1936)
- Goal: sorted words into underlying groups/dimensions
- Used both self-report and informant data to measure personality.

DETERMINING CORE TRAITS



Psychology, 8/e Figure 15.2

THE BIG FIVE

- **O**penness to experience
- **C**onscientiousness
- **E**xtraversion
- **A**greeableness
- **N**euroticism

Table 12.2	The Big Five Factor Model
Conscientiousness	organized · · · disorganized careful · · · careless self-disciplined · · · weak-willed
Agreeableness	softhearted · · · ruthless trusting · · · suspicious helpful · · · uncooperative
Neuroticism	worried · · · calm insecure · · · secure self-pitying · · · self-satisfied
Openness to experience	imaginative · · · down-to-earth variety · · · routine independent · · · conforming
Extraversion	social · · · retiring fun loving · · · sober affectionate · · · reserved

Source: McCrae & Costa, 1999, 1990.

QUESTIONS ABOUT THE BIG FIVE

How stable are the traits?

- Change over development
- Stable in adulthood

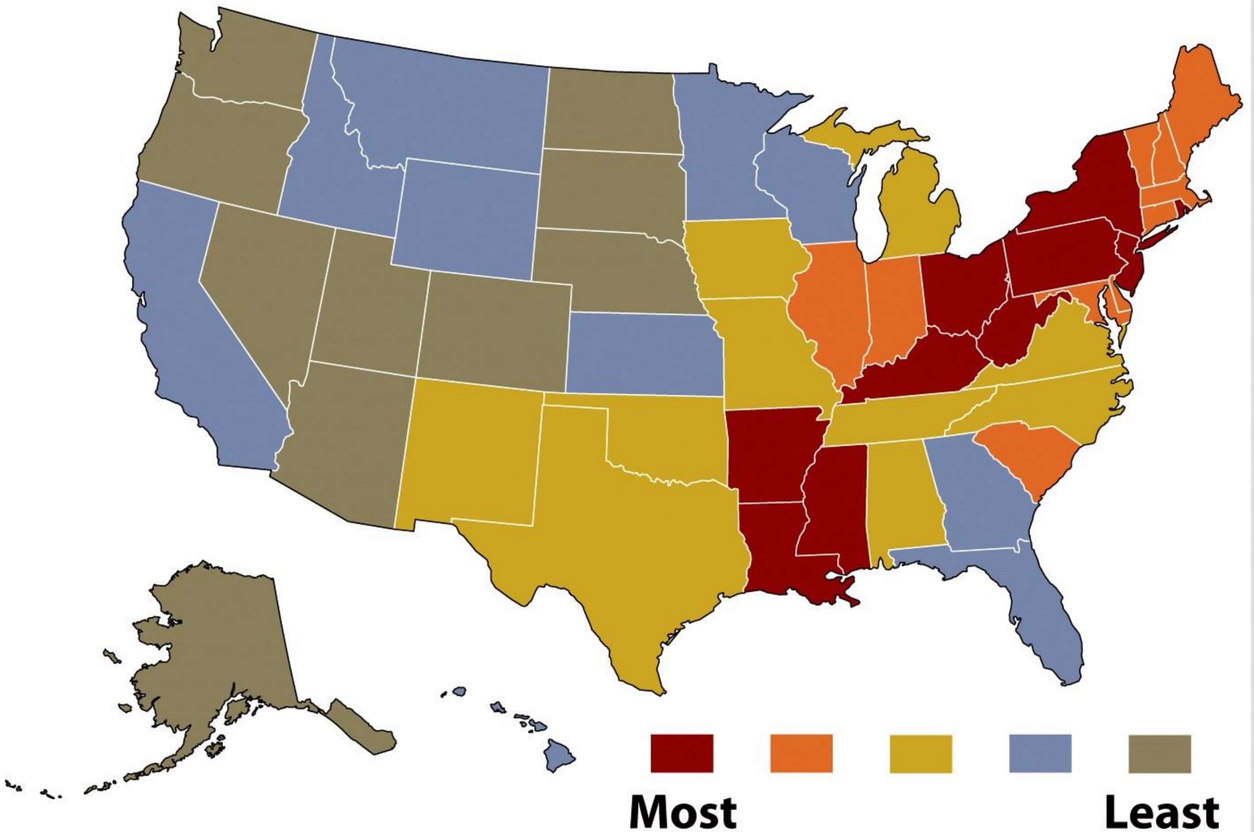
How heritable are they?

- ~50% for each trait (.40 to .55 heritability)
  - Influence of temperament?
  - Other factors, ie, in extraversion

How about other cultures?

- Traditionally traits are thought to be common across cultures
- But research has shown cultural differences in personality

WHERE ARE THE MORE "NEUROTIC" PLACES TO LIVE?



Psychology, 8/e Figure 15.9

ARE TRAITS TRULY CONSTANT?

Personality paradox: people often behave less consistently than expected

- **Person-Situation Controversy** (e.g., Mischel 1968; 1984; 2004)
  - Part of the explanation for this paradox is the power of the situation

Counter-argument:

- Trait theorists argue that behaviors from a situation may be different, but average behavior remains the same
- Therefore, traits matter

One solution? ***Consistency of behavior as a trait***

- Interaction between personality and situations
  - Situations interact with individual differences
- Some people are more consistent in their behaviors—the Self-Monitoring Scale
  - *Higher self monitoring = higher emotional intelligence

TRAITS VS STATES

Personality traits = consistent; stable

Personality states = transient; variable

States are linked to traits but range based on other factors

- Ie, extraverted behavior vs extraversion
- Ie, anger vs hot-headed

Both personality traits & states have tremendous predictive power!

Where do emotions play a role?

- This gets tricky as emotions are transient and often called a state!
- Focus of research is on how *personality impacts emotions*

ASSESSING TRAITS

How can we assess differences in personality?

- **Personality inventories:** questionnaires (often with true-false or agree-disagree items) designed to gauge a wide range of feelings and behaviors assessing several traits at once
  - **Clinical setting:** Minnesota Multiphasic Personality Inventory (MMPI)
  - **Research:** NEO-FFI & TIPI (require clinical license)
  - **Open source:** International Personality Item Pool (IPIP)

NEO-FFI

- Short questionnaire to assess the big 5 traits
- Widely used in research
- 60 items (12/trait)
- Likert scale
  - SD (strongly disagree) — SA (strongly agree)
  - 0 - 4
- Example questions:
  - When I’m under a great deal of stress, sometimes I feel like I’m going into pieces.
  - I usually prefer to do things alone.

TIPI

- Newer, even shorter questionnaire to assess the big 5 traits
- Starting to be used in research
- 10 items (2/trait)
- Likert scale
  - 1 - 7
  - 1 = Disagree strongly; 7 = Agree strongly

TEN-ITEM PERSONALITY INVENTORY-(TIPI)

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

1 = Disagree strongly
2 = Disagree moderately
3 = Disagree a little
4 = Neither agree nor disagree
5 = Agree a little
6 = Agree moderately
7 = Agree strongly

I see myself as:

1. _____ Extraverted, enthusiastic.

2. _____ Critical, quarrelsome.

3. _____ Dependable, self-disciplined.

4. _____ Anxious, easily upset.

5. _____ Open to new experiences, complex.

6. _____ Reserved, quiet.

7. _____ Sympathetic, warm.

8. _____ Disorganized, careless.

9. _____ Calm, emotionally stable.

10. _____ Conventional, uncreative.

TIPI scale scoring ("R" denotes reverse-scored items): Extraversion: 1, 6R; Agreeableness: 2R, 7; Conscientiousness; 3, 8R; Emotional Stability: 4R, 9; Openness to Experiences: 5, 10R.

IPIP

- International Personality Item Pool
- Public and open source of personality inventory items
- Ie, For testing for the 5 factors, IPIP-NEO has a 300 items and a 120 item version

ASSESSING PERSONALITY STATES

Traditionally scores gathered using daily diary or experience sampling

- But no gold-standard measurement to date
- Although recent research has shown advancements using using digital traces from wearable devices, smartphone sensor data, etc

AUTOMATIC PERSONALITY DETECTION

Automatic Personality Detection (APD)

Research has examined a multitude of cues for determining traits:

- Written language
- Nonverbal vocal behaviors
- Spoken/conversational language

And from a multitude of sources:

- Facebook, Twitter, blogs, general language use

AUTOMATIC PERSONALITY DETECTION, CONT'D

Most recent work focuses on a combination of ***features and type of classification model to improve predictions*** (ie, Azucar, Marengo & Settanni, 2017)

- Ie, word embedding; deep learning models such as BERT
- Ie, stylistic features

Useful for:

- Marketing
- Adaptive/personalized systems
- Detecting deception/sarcasm/irony
- Predicting task/job success

What else?

DETECTION WITH WRITTEN LANGUAGE

Written language use → personality

Pennebaker and King (1999), Linguistic styles: Language use as an individual difference

- Stream-of-conscious essays
- Big 5 personality assessment
- Lexical features (LIWC)
- Findings, ie.,
  - Agreeableness
    - more positive emotion words
    - fewer negative emotion words
    - fewer articles
    - more first-person

Table 6

LIWC Factors and Simple Correlations With Five-Factor Scores

LIWC factor	Five-factor dimension				
	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness
Immediacy	**.10***	**.04**	**−.16****	**.07***	**−.02**
First-person singular	.13**	.04	−.13**	.07*	.01
Articles	−.09*	−.09*	.13**	−.15**	−.04
Words of more than 6 letters	−.03	−.04	.16**	−.03	.06
Present tense	.06	.01	−.15**	.04	.00
Discrepancies	.05	−.03	−.01	−.02	−.07*
Making Distinctions	**.05**	**−.14****	**.06**	**−.05**	**−.13****
Exclusive	.00	−.08*	.10*	−.06	−.08*
Tentativity	.06	−.14**	.11**	−.02	−.06
Negations	.05	−.12**	.00	−.04	−.15**
Inclusive	−.01	.07*	.01	.03	.06
The Social Past	**.04**	**.00**	**.08***	**−.02**	**−.04**
Past tense	.03	.04	−.03	.06	−.06
Social	−.01	.12**	.02	.00	.02
Positive emotion	−.13**	.15**	−.06	.07*	.07*
Rationalization	**−.06**	**.02**	**−.03**	**.07**	**.04**
Insight	.03	−.02	.07*	.05	−.01
Causation	.03	−.08*	−.08*	.00	−.07*
Negative emotion	.16**	−.08*	.05	−.07*	−.15**

DETECTION WITH SPOKEN LANGUAGE

Can we assess personality from what is said and/or how it is said?

E.g., Mairesse & Walker (2006)

- Can personality be recognized automatically in conversation?
- Data (previously collected by Mehl & Pennebaker):
  - Daily life conversations, collected and transcribed
  - Personality ratings from 5-7 independent observers
- Features/analyses:
  - 5-7 judges of personality
  - LIWC (linguistic features)
  - MRC psycholinguistic database
  - Utterance type (ie, commands, back-channels)
  - Praat (pitch, intensity, speech rate)

RESULTS

Feature set	All	LIWC	MRC	Type	Pros
Set size	117	88	14	4	11
Extraversion	0.35•	0.36•	0.45	0.55	**0.26**•
Emot. stability	0.40	0.41	**0.39**•	0.43	0.45
Agreeableness	**0.31**•	0.32•	0.44	0.45	0.54
Conscientious.	**0.33**•	0.36•	0.41•	0.44	0.55
Intellect	0.38•	**0.37**•	0.41	0.49	0.44

• statistically significant improvement over the random ordering baseline (two-tailed paired t-test, $p < 0.05$)

RESULTS: SPECIFIC FEATURES

#	Extraversion with prosody	α	Emotional stability with MRC	α	Agreeableness with all	α	Conscientiousness with all	α	Intellect with LIWC	α
1	Word-per-sec $\geq$ 0.73	1.43	Nlet $\geq$ 3.28	0.53	Nphon $\geq$ 2.66	0.56	Occup $\geq$ 1.21	0.37	Colon $\geq$ 0.03	0.49
2	Pitch-mean $\geq$ 194.61	0.41	T-L-freq $\geq$ 28416	0.25	Tentat $\geq$ 2.83	0.50	Insight $\geq$ 2.15	0.36	Insight $\geq$ 1.75	0.37
3	Voiced $\geq$ 647.35	0.41	Meanc $\geq$ 384.17	0.24	Colon $\geq$ 0.03	0.41	Posfeel $\geq$ 0.30	0.30	Job $\geq$ 0.29	0.33
4	Word-per-sec $\geq$ 2.22	0.36	AOA $\geq$ 277.36	0.24	Posemo $\geq$ 2.67	0.32	Int-stddev $\geq$ 7.83	0.29	Music $\geq$ 0.18	0.32
5	Voiced $\geq$ 442.95	0.31	K-F-nsamp $\geq$ 322	0.22	Voiced $\geq$ 584	0.32	Nlet $\geq$ 3.29	0.27	Optim $\geq$ 0.19	0.24
6	Pitch-max $\geq$ 599.88	0.30	Meanp $\geq$ 654.57	0.19	Relig $\geq$ 0.43	0.27	Comm $\geq$ 1.20	0.26	Inhib $\geq$ 0.15	0.24
7	Pitch-mean $\geq$ 238.99	0.26	Conc $\geq$ 313.55	0.17	Insight $\geq$ 2.09	0.25	Nphon $\geq$ 2.66	0.25	Tentat $\geq$ 2.23	0.22
8	Int-stddev $\geq$ 6.96	0.24	K-F-ncats $\geq$ 14.08	0.15	Prompt $\geq$ 0.06	0.25	Nphon $\geq$ 2.67	0.22	Posemo $\geq$ 2.67	0.19
9	Int-max $\geq$ 85.87	0.24	Nlet $\geq$ 3.28	0.14	Comma $\geq$ 4.60	0.23	Nphon $\geq$ 2.76	0.20	Future $\geq$ 0.87	0.17
10	Voiced $\geq$ 132.35	0.23	Nphon $\geq$ 2.64	0.13	Money $\geq$ 0.38	0.20	K-F-nsamp $\geq$ 329	0.19	Certain $\geq$ 0.92	0.17
11	Pitch-max $\geq$ 636.35	-0.05	Fam $\geq$ 601.98	-0.19	Fam $\geq$ 601.61	-0.16	Swear $\geq$ 0.20	-0.18	Affect $\geq$ 5.07	-0.16
12	Pitch-slope $\geq$ 312.67	-0.06	Nphon $\geq$ 2.71	-0.19	Swear $\geq$ 0.41	-0.18	WPS $\geq$ 6.25	-0.19	Achieve $\geq$ 0.62	-0.17
13	Int-min $\geq$ 54.30	-0.06	AOA $\geq$ 308.39	-0.23	Anger $\geq$ 0.92	-0.19	Pitch-mean $\geq$ 229	-0.20	Othref $\geq$ 7.67	-0.17
14	Word-per-sec $\geq$ 1.69	-0.06	Brown-freq $\geq$ 1884	-0.25	Time $\geq$ 3.71	-0.20	Othref $\geq$ 7.64	-0.20	I $\geq$ 7.11	-0.19
15	Pitch-stddev $\geq$ 115.49	-0.06	Fam $\geq$ 601.07	-0.25	Negate $\geq$ 3.52	-0.20	Humans $\geq$ 0.83	-0.21	WPS $\geq$ 5.60	-0.20
16	Pitch-max $\geq$ 637.27	-0.06	K-F-nsamp $\geq$ 329	-0.26	Fillers $\geq$ 0.54	-0.22	Swear $\geq$ 0.93	-0.21	Social $\geq$ 10.56	-0.20
17	Pitch-slope $\geq$ 260.51	-0.12	Imag $\geq$ 333.50	-0.27	Time $\geq$ 3.69	-0.23	Swear $\geq$ 0.17	-0.24	You $\geq$ 3.57	-0.21
18	Pitch-stddev $\geq$ 118.10	-0.15	Meanp $\geq$ 642.81	-0.28	Swear $\geq$ 0.61	-0.27	Relig $\geq$ 0.32	-0.27	Incl $\geq$ 4.30	-0.33
19	Int-stddev $\geq$ 6.30	-0.18	K-F-ncats $\geq$ 14.32	-0.35	Swear $\geq$ 0.45	-0.27	Swear $\geq$ 0.65	-0.31	Physcal $\geq$ 1.79	-0.33
20	Pitch-stddev $\geq$ 119.73	-0.47	Nsyl $\geq$ 1.17	-0.63	WPS $\geq$ 6.13	-0.45	Int-max $\geq$ 86.84	-0.50	Family $\geq$ 0.08	-0.39

COMPUTER VS HUMAN JUDGMENTS

Computer models from meta-data are found to be more accurate than human judgments (even better than close friends!)

E.g., Youyou, Kosinski & Stillwell (2015)

- Assessed accuracy of personality judgments by humans vs computers
- 3 different criteria:
  - Self-other agreement
  - Interjudge agreement
  - External validity
- And compared it to scores on the IPIP

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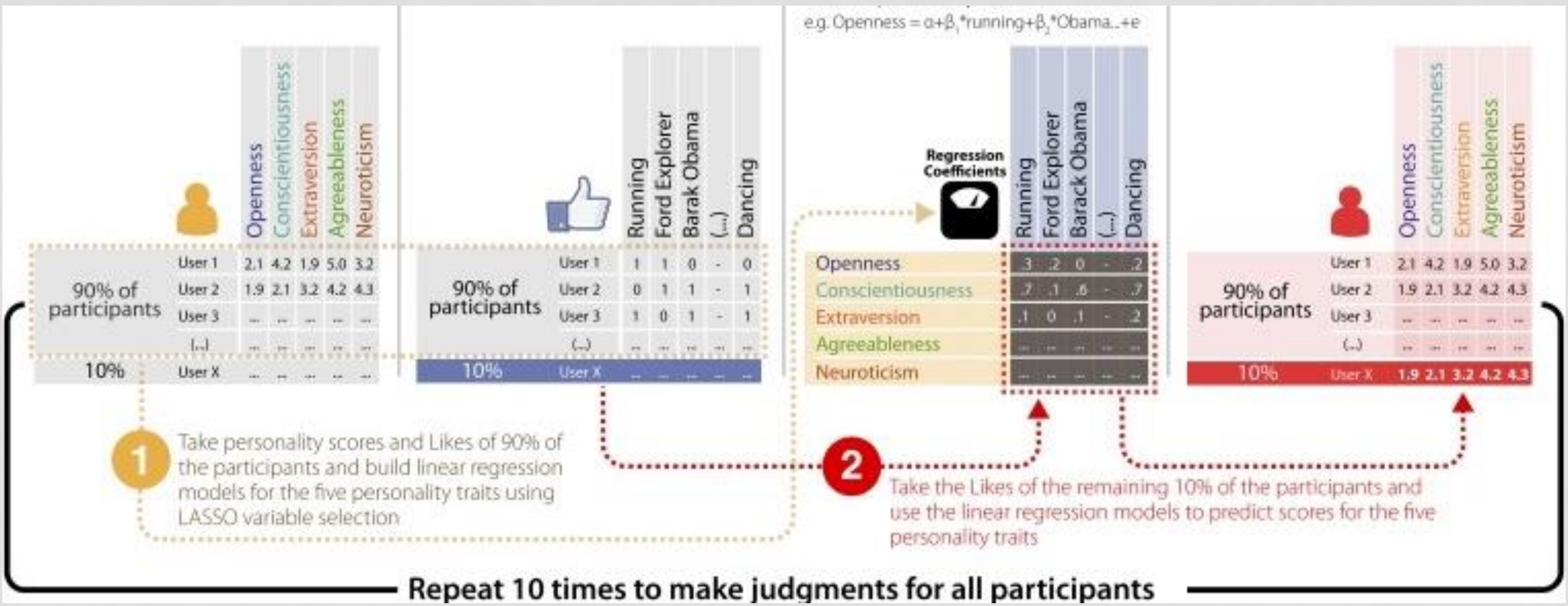
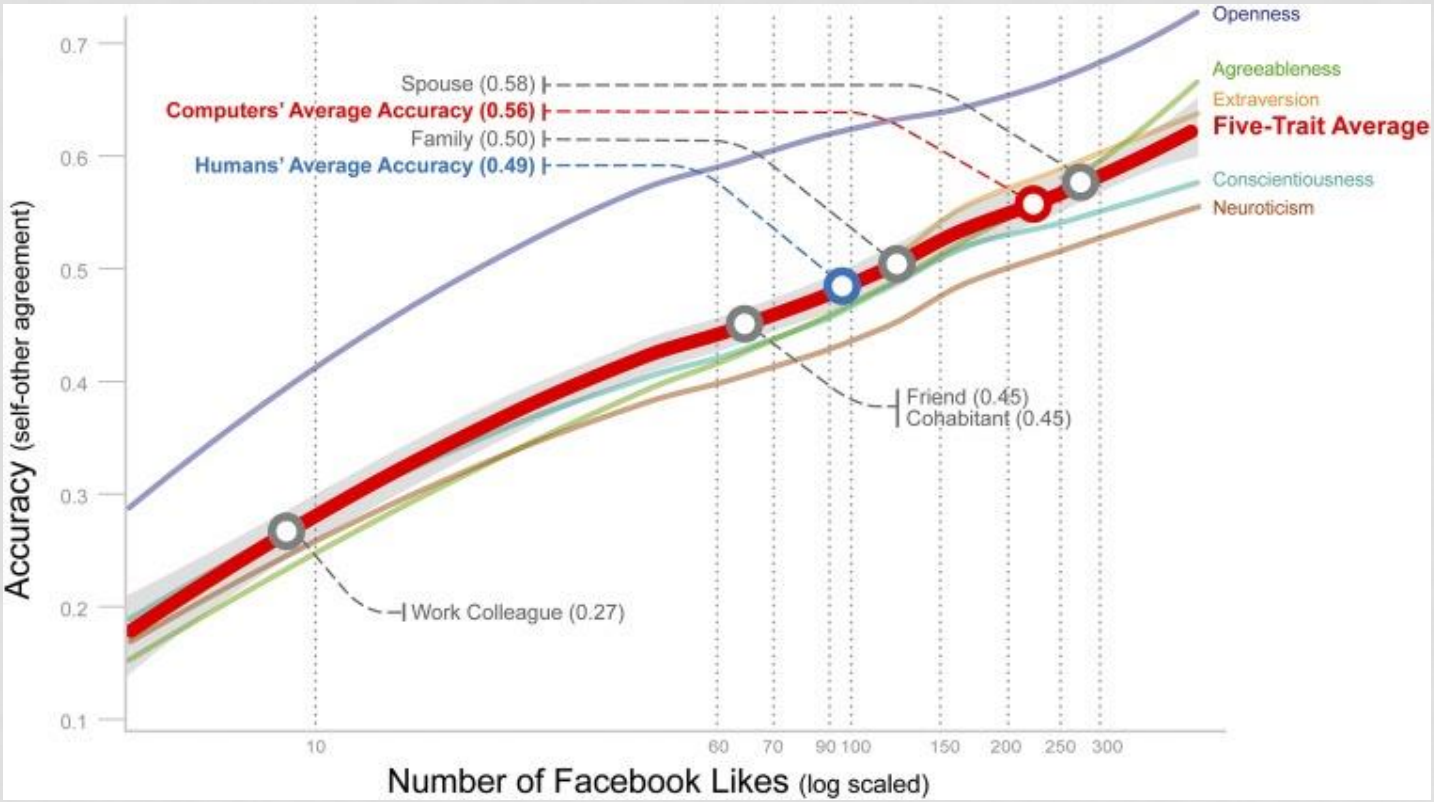


e.g. Openness = α+β₁*running+β₂*Obama...+e
Openness
Conscientiousness
Extraversion
Agreeableness
Neuroticism
90% of participants
User 1 2.1 4.2 1.9 5.0 3.2
User 2 1.9 2.1 3.2 4.2 4.3
User 3
(...)
10%
User X
Running
Ford Explorer
Barak Obama
(...)
Dancing
User 1 1 1 0 - 0
User 2 0 1 1 - 1
User 3 1 0 1 - 1
Regression Coefficients
Barack Obama
.3 .2 0 - .2
.7 .1 .6 - .7
.1 0 .1 - .2
User X 1.9 2.1 3.2 4.2 4.3
1
Take personality scores and Likes of 90% of the participants and build linear regression models for the five personality traits using LASSO variable selection
2
Take the Likes of the remaining 10% of the participants and use the linear regression models to predict scores for the five personality traits
Repeat 10 times to make judgments for all participants



Openness
Agreeableness
Extraversion
Five-Trait Average
Conscientiousness
Neuroticism
Spouse (0.58)
Computers' Average Accuracy (0.56)
Family (0.50)
Humans' Average Accuracy (0.49)
Friend (0.45)
Cohabitant (0.45)
Work Colleague (0.27)
Accuracy (self-other agreement)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
10
60
70
90 100
150
200
250
300
Number of Facebook Likes (log scaled)

COMPUTER VS HUMAN JUDGMENTS

3 different criteria:

- Self-other agreement
- **Interjudge agreement**
- **External validity**

And compared it to scores on the IPIP

Why?

- More information → increased accuracy
- Statistical modeling → fewer biases

META-ANALYSIS: DIGITAL DATA

Azucar, Marengo & Settanni (2017). Predicting the Big 5 Personality Traits from Digital Footprints on Social Media: A Meta-Analysis

- **Digital footprints → personality traits?**
- **Goals:**
  - 1) Determine average predictive power of digital footprints on each factor
  - 2) Assess impact of different types of data on accuracy
- **Overall findings:**
  - Digital footprints are able to predict personality
  - Better when data from multiple sources, but different sources for different traits
- Sources:
  - Private vs public platforms
  - Demographics
  - User activity stats
  - Language/text vs pictures

APPLICATIONS

Marketing (ie Matz & Netzer, 2017)

- Big data to predict psychological traits and states, and then target marketing
  - Traits help understand consumers' general tendency to think
  - States help understand how they feel in a particular context

Job recruiting (ie Koutsoumpis et al, 2024; Grunenberg et al, 2024)

- Sbert and other deep learning models are starting to predict personality on very small amounts of written or spoken data

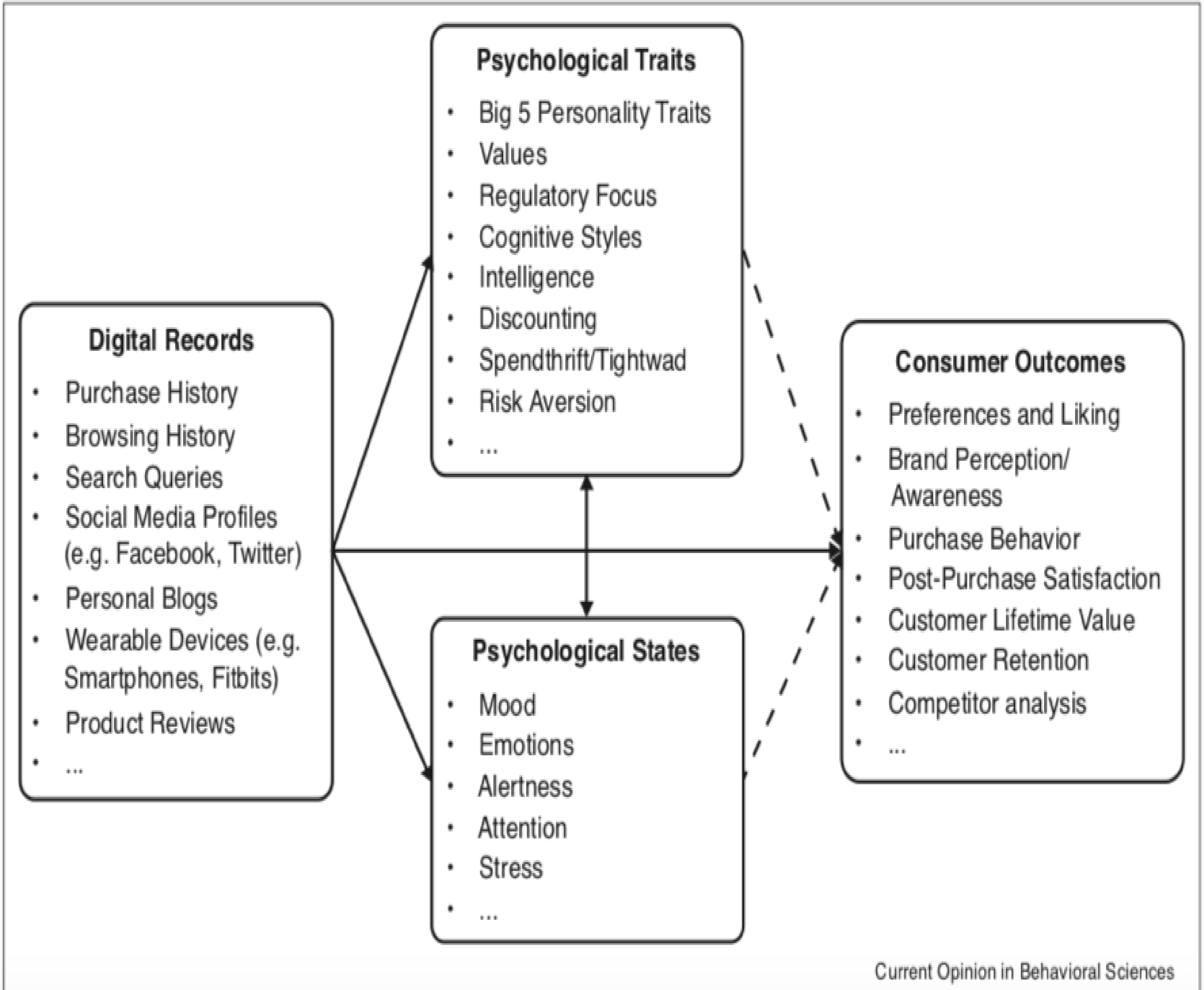
PRACTICAL APPLICATION: MARKETING

Matz, S.C. & Netzer, O. (2017)

Big data → psychological traits & states → marketing strategy

Research question: Can big data help predict psychological traits and states and thus help marketing strategy?

Hypothesis: Now that vast amount of consumer information is available, consumers' general tendency to think (traits) and how they feel in a particular context (states) can be inferred and thus targeted marketing can improve.


Psychological Traits
Big 5 Personality Traits
Values
Regulatory Focus
Cognitive Styles
Intelligence
Discounting
Spendthrift/Tightwad
Risk Aversion
...
Digital Records
Purchase History
Browsing History
Search Queries
Social Media Profiles (e.g. Facebook, Twitter)
Personal Blogs
Wearable Devices (e.g. Smartphones, Fitbits)
Product Reviews
...
Consumer Outcomes
Preferences and Liking
Brand Perception/ Awareness
Purchase Behavior
Post-Purchase Satisfaction
Customer Lifetime Value
Customer Retention
Competitor analysis
...
Psychological States
Mood
Emotions
Alertness
Attention
Stress
...
Current Opinion in Behavioral Sciences

PERSONALITY AND SOCIAL MEDIA

Recent work focuses on personality detection from:

- Blogs, Twitter, Facebook
- Instagram, Snapchat
- Browser history, transactional data, wearable devices

Must consider:

- **Source of data:** purpose of platform; purpose of user
- **Ethics:** consent; user-expectations

Ie, Cambridge Analytica