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毛义T尺T井I口口 (VIII)

@NinaStrohminge



Big data is just personality psychology without the theory

The power of personality in predicting and explaining important life outcomes

Prof. Uku Vainik
Institute of Psychology & Institute of Genomics,
University of Tartu, Estonia
Montreal Neurological Institute, McGill University, Canada

XXV Baltic Actuarial Summer Seminar
30.06.2025, Mäeotsa

Dawes, R. M., Faust, D., & Meehl, P. E. (1989) Clinical versus actuarial judgment. *Science*, 243:1668-1674. Including Kleinmuntz, B. (1990) Letter: Clinical and actuarial judgment. Response by Faust, Meehl, & Dawes. *Science*, 247:146-147.

#138

Clinical Versus Actuarial Judgment

ROBYN M. DAWES, DAVID FAUST, PAUL E. MEEHL

Professionals are frequently consulted to diagnose and predict human behavior; optimal treatment and planning often hinge on the consultant's judgmental accuracy. The consultant may rely on one of two contrasting approaches to decision-making—the clinical and actuarial methods. Research comparing these two approaches shows the actuarial method to be superior. Factors underlying the greater accuracy of actuarial methods, sources of resistance to the scientific findings, and the benefits of increased reliance on actuarial approaches are discussed.

Psychology in actuarial science?

Q: I am a soon to be entering my last year of college with a double major in statistics and psychology. /.../ I was wondering if there is any field of actuarial science where it could be useful to have a psychology background?

A1: I think there's opportunity for crossover between actuarial work and psychology, but I have doubts about it happening early in your career /.../ but if you want to use it later in your career you could probably find a role to do so.

A1.1: I agree with this as well. I have a degree in psyche and I have no clue how you'd realistically apply it.

A2: Look up the work of Kahneman and Tversky /.../ there are many interesting findings about the way humans make predictions.

A2: I initially double majored in psych and econ until dropping the psych major for a minor. Imo, the one psych class i strongly suggest to any college student is industrial/organizational psych if available. **Everything else that i took was useless as an actuary**

The utility & genomics of personality

- What is personality
- Personality & life outcomes
- Personality measurement & more outcomes
- Genomics of personality & causal inference
- Personality & job choice



Personality & wellbeing

Front: René Mõttus

Middle: Liisi Ausmees

Sam Henry

Anu Realo

Kadri Arumäe

Kerli Ilves

Kätlin Anni

Helo Liis Soodla

Maris Vainre

Back: Uku Vainik

Kenn Konstabel

Kirsti Akkermann +
many more



Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning

[Tal Yarkoni](#)  and [Jacob Westfall](#) [View all authors and affiliations](#)

[Volume 12, Issue 6](#) | <https://doi.org/10.1177/1745691617693393>

 Contents



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Abstract

Psychology has historically been concerned, first and foremost, with explaining the causal mechanisms that give rise to behavior. Randomized, tightly controlled experiments are enshrined as the gold standard of psychological research, and there are endless investigations of the various mediating and moderating variables that govern various behaviors. We argue that psychology's near-total focus on explaining the causes of behavior has led much of the field to be populated by research programs that provide intricate theories of psychological mechanism but that have little (or unknown) ability to predict future behaviors with any appreciable accuracy. We propose that principles and techniques from the field of machine learning can help psychology become a more predictive science. We review some of the fundamental concepts and tools of machine learning and point out examples where these concepts have been used to conduct interesting and important psychological research that focuses on predictive research questions. We suggest that an increased focus on prediction, rather than explanation, can ultimately lead us to greater understanding of behavior.

Humans vary in their behaviour



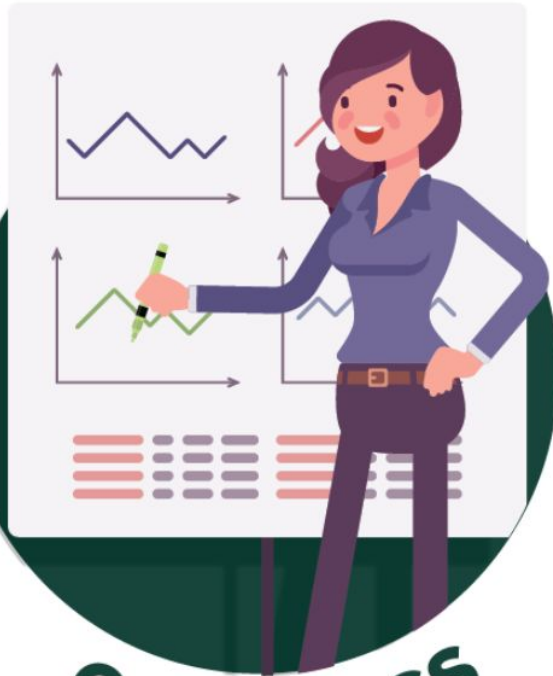
A

THE BIG FIVE



<https://www.audleytravel.com/us/inspiration/safaris/the-big-five>

1



High Five Tendencies

Imaginative
Curious
Experimental
Embraces challenges
Abstract thinker

Low Five Tendencies

Practical
Narrow interest range
Resists change
Conventional

<https://www.michiganstateuniversityonline.com/resources/leadership/lead-your-team-with-big-five-model/>

High Five Tendencies

Disciplined
Detail-oriented
Dutiful
Organized
Reliable

Low Five Tendencies

Spontaneous
Flexible
Procrastinates
Negligent
Unreliable



3



High Five Tendencies

Social
Enthusiastic
Assertive
Opinionated
Adventurous

Low Five Tendencies

Introverted
Self-sufficient
Passive
Reserved
Quiet

High Five Tendencies

Empathetic
Cooperative
Trustworthy
Good-natured
Straightforward

Low Five Tendencies

Independent
Uncooperative
Overly Critical
Dominant
Antagonistic



5



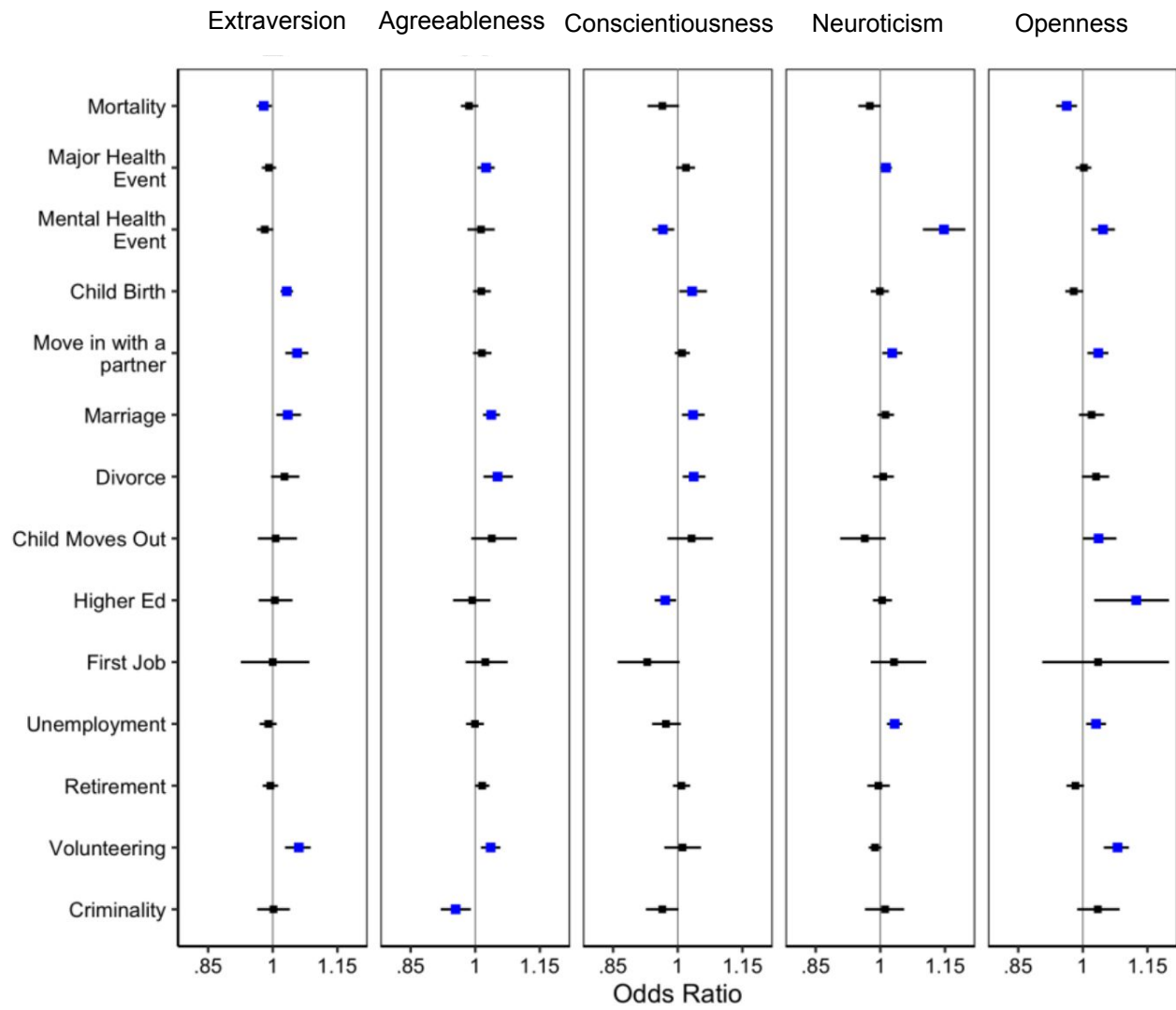
High Five Tendencies

Unstable
Anxious
Irritable
Self-conscious
Worrier

Low Five Tendencies

Composed
Calm
Even-tempered
Confident
Resilient

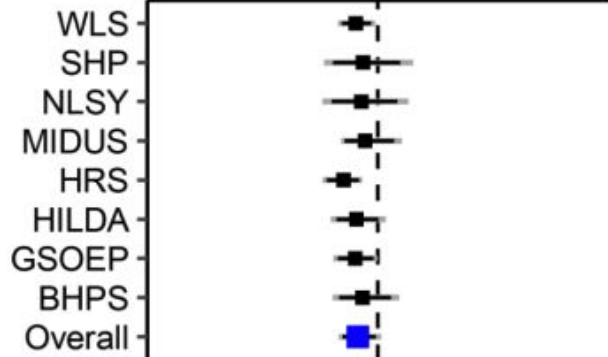
Personality & life events



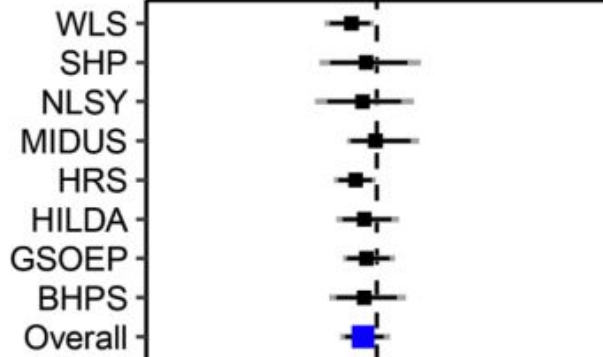
Beck & Jackson 2020
A Mega-Analysis of Personality
Prediction

Mortality

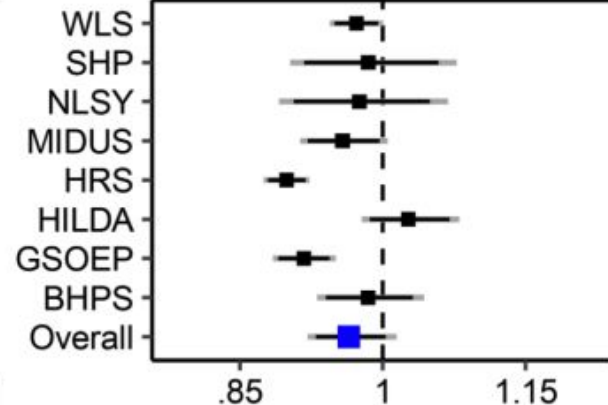
Extraversion



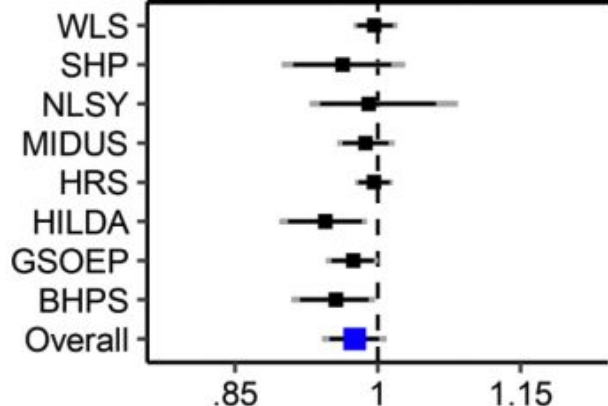
Agreeableness



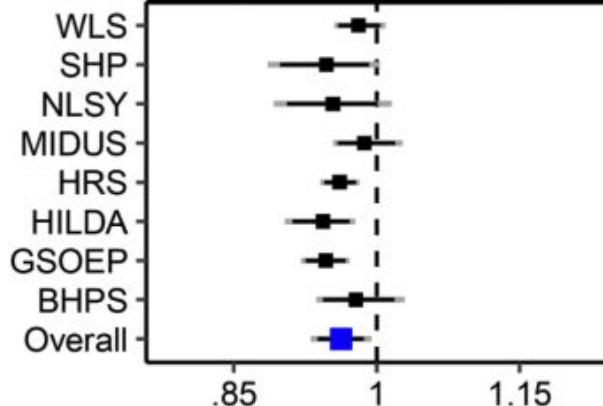
Conscientiousness



Neuroticism



Openness to Experience



Odds Ratio

Beck & Jackson 2020
A Mega-Analysis of
Personality Prediction
N~170 000

Cumulative value of small effects

- Personality is linked with many life events
- Effects are SMALL but robust
- They become consequential over time
- E.g. extraversion and shopping $r = 0.09$
 - One person - hard to tell. Full Christmas season → consequential

Evaluating Effect Size in Psychological Research: Sense and Nonsense

David C. Funder and Daniel J. Ozer
Department of Psychology, University of California, Riverside

Personality-tailored ads

A

High Extraversion



Dance like no one's watching
(but they totally are)

Low Extraversion



Beauty doesn't have to shout

Matz et al. (2017) Psychological
targeting as an effective approach
to digital mass persuasion

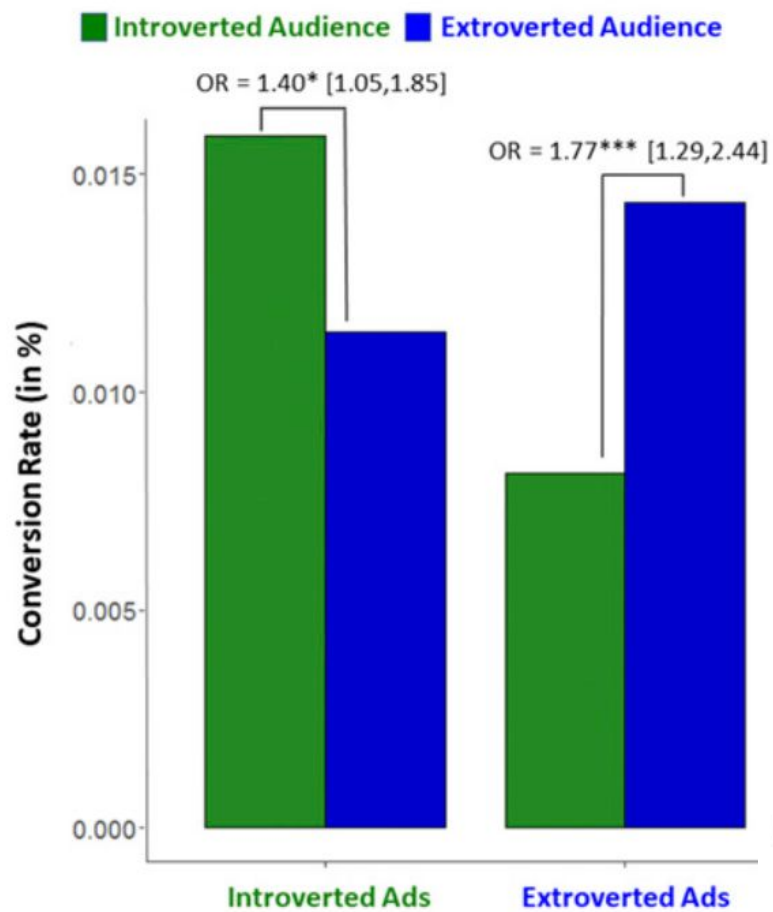
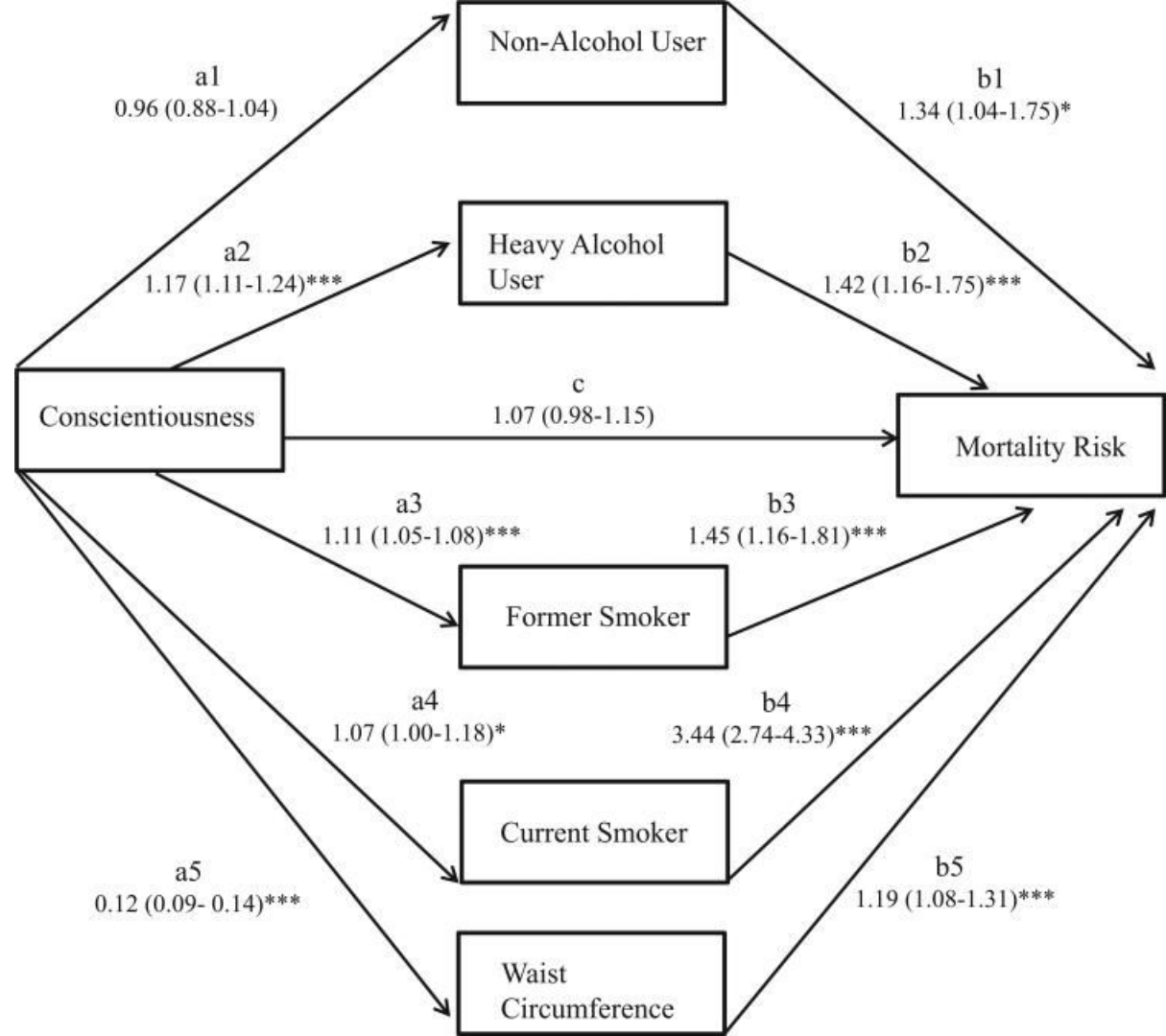
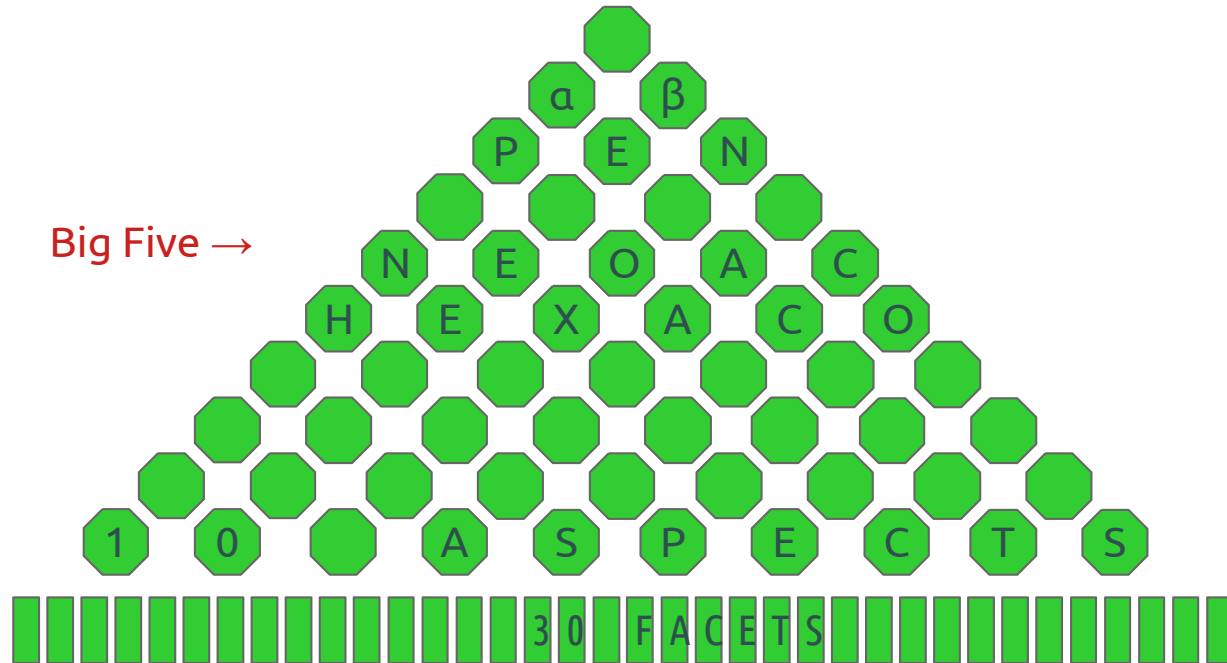


Fig. 2. Interaction effects of audience and ad personal

Does personality cause aging?



Turiano et al., (2015). Personality and the Leading Behavioral Contributors of Mortality



Courtesy of René Möttus

Neuroticism facets differentially predict mortality

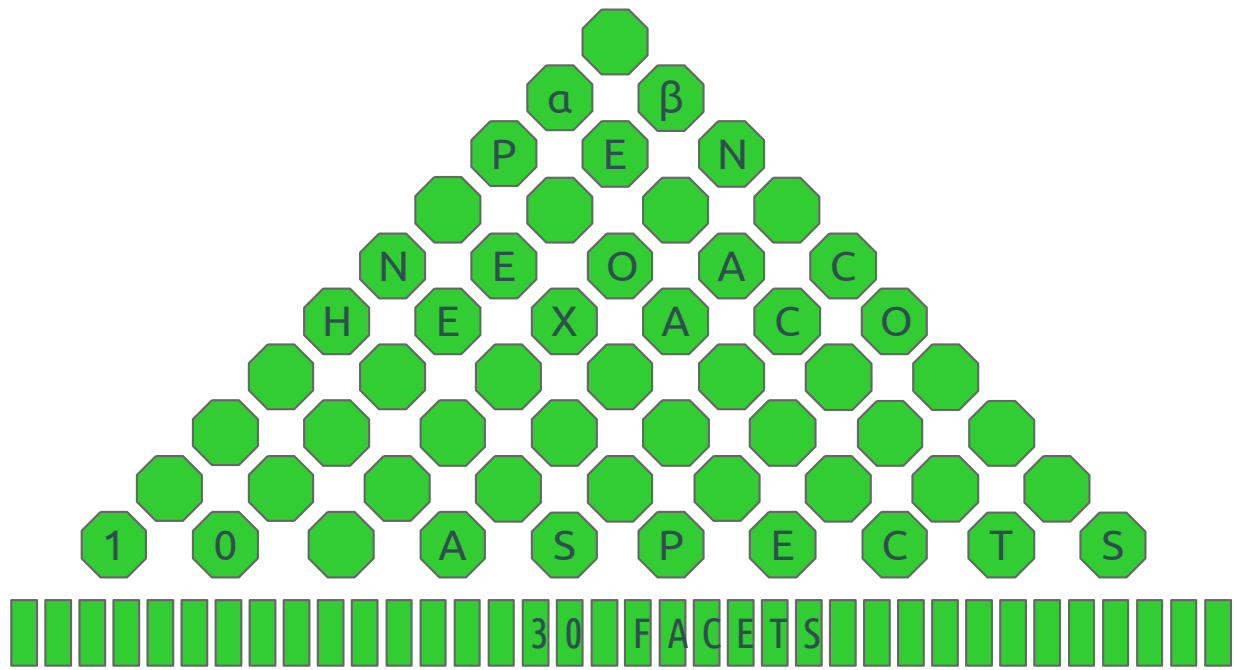
- Increased mortality:
 - vulnerability, cynicism, pessimistic, anxious, and depressive
- Decreased mortality:
 - Inadequacy, and worried-vulnerable

Butler et al., (2023). Neuroticism facets and mortality risk in adulthood: A systematic review and narrative synthesis

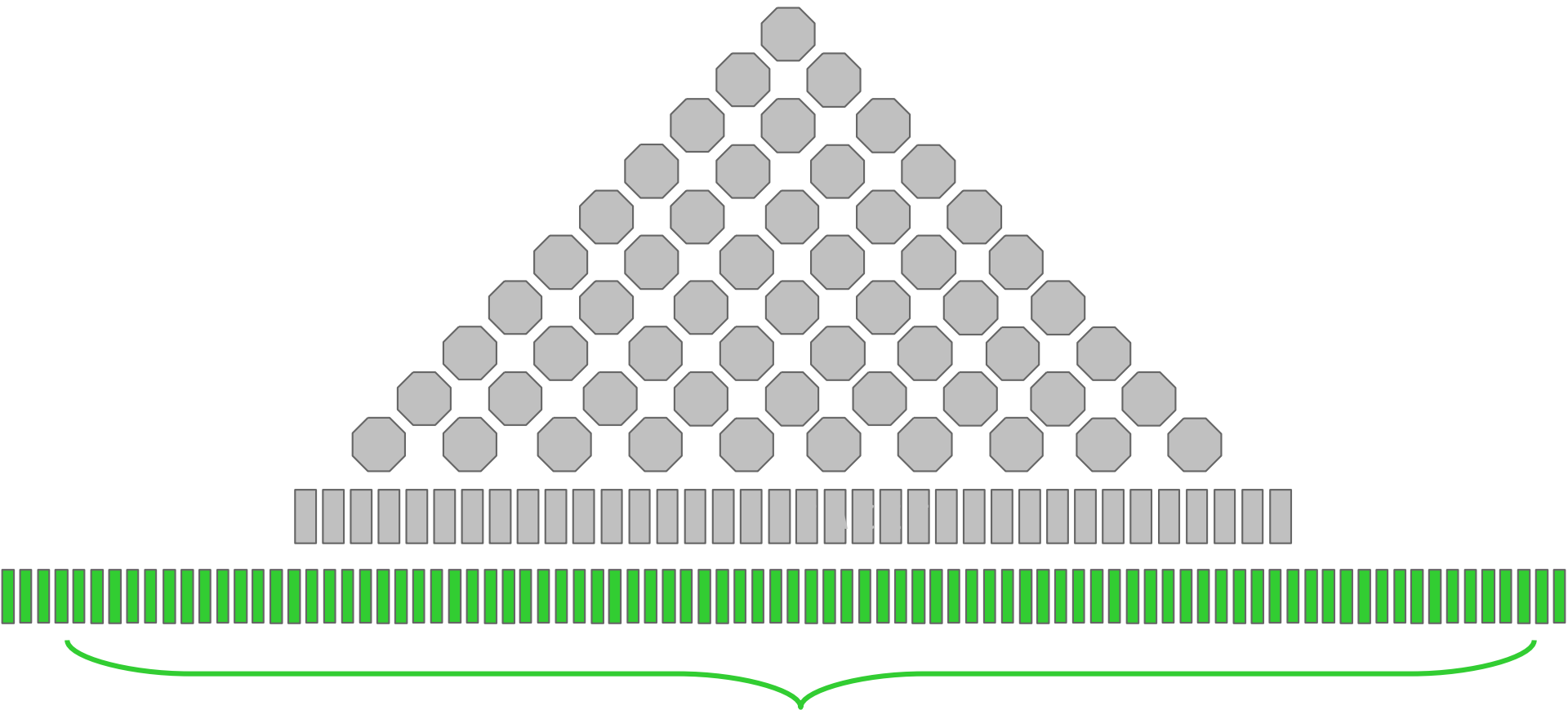
Personality & addictive behaviours



Vainik et al., (2020). Obesity has limited behavioural overlap with addiction and psychiatric phenotypes



???



Many items represent unique traits – **nuances**

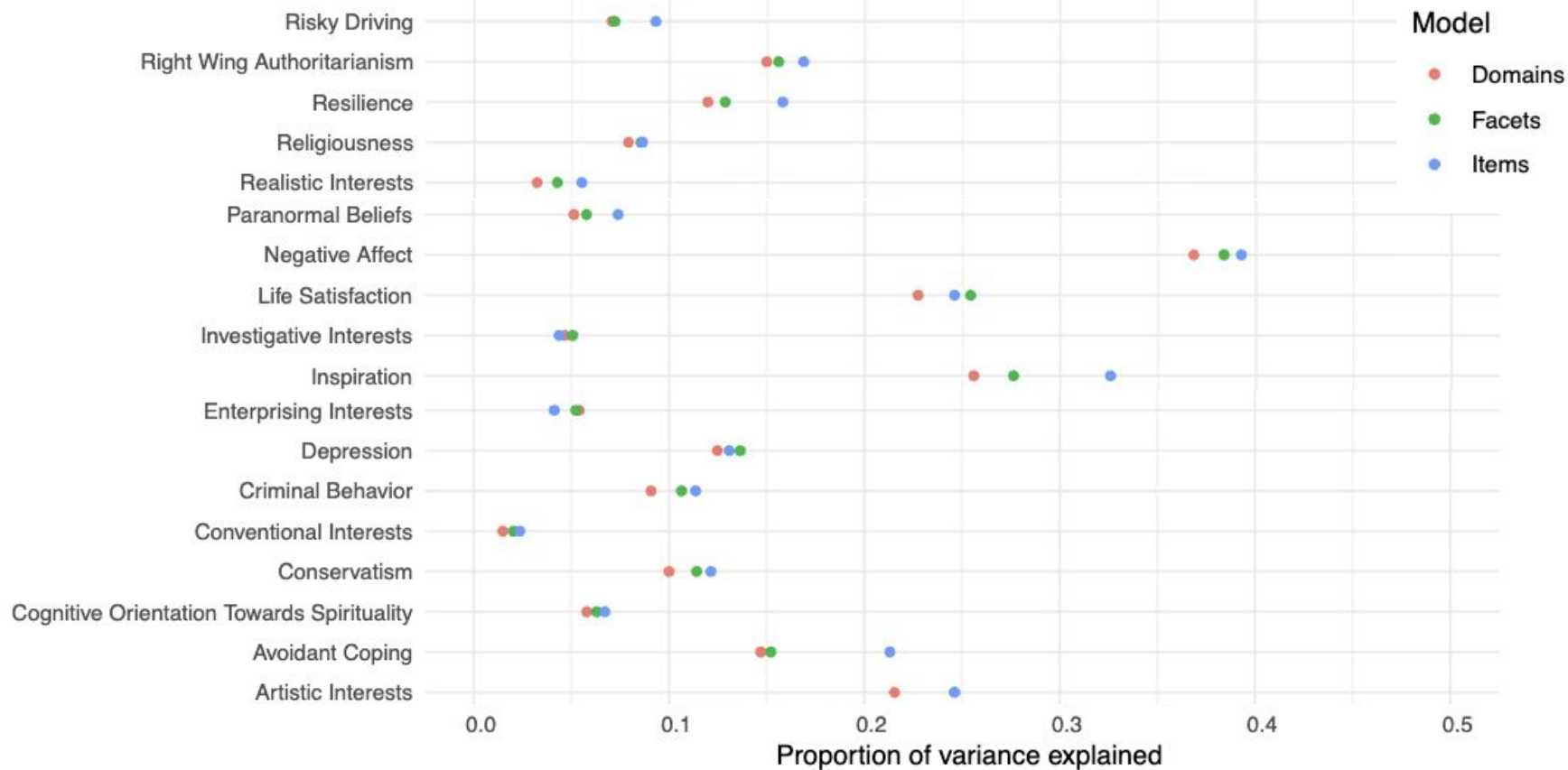
Courtesy of René Möttus

Increased R^2 with more detailed personality measurement

Phenotype	Big5 domain	Facet	Nuance
Body mass index	0.03	0.06	0.12
Internet use	0.13	0.17	0.24
Cannabis	0.11	0.14	0.18
Tobacco	0.13	0.19	0.25
Countryside/city	0.01	0.05	0.06

Päll (2024). Vainik et al. (2020) partial replication: Optimal level of personality evaluation in obesity and uncontrolled eating, and their behavioral overlap with addictions

Stewart et al., (2021) The finer details? The predictability of life outcomes from Big Five domains, facets, and nuances



The most comprehensive personality study in the world



Hundred nuances of personality (100 NP)

198 questions from International Personality Item Pool

Takes 15-25 minutes to complete

Compatible with Big Five and other legacy instruments

Item test-retest reliability $\sim .70$ (other tests $\sim .65$)

Item validity (cross-rater agreement) $\sim .36$ (other tests $\sim .30$)

Available in 10+ languages

Questions maximally independent

Henry & Möttus (2024). The 100 Nuances of Personality: Development of a Comprehensive, Non-Redundant Personality Item Pool

Behavioural measures at Estonian Biobank (EstBB)

200k genotyped participants, 20% of adult population
electronic health records, metabolomics, mental health.

2021-22: 100NP + optional SES, life events, attitudes

Smartphone and computer-proof

Instant feedback

Data collected & filtered:

Self-report 77,400 (3% excluded);

31,000 50% related

Other-report 21,986 (5% excluded)

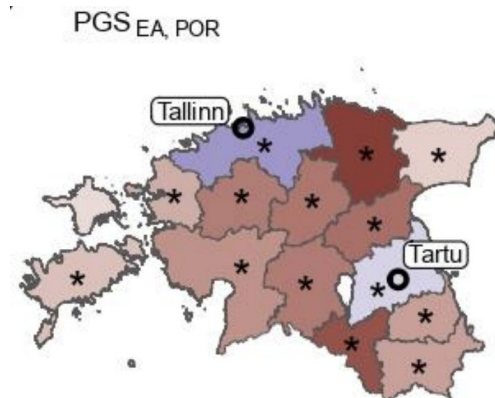
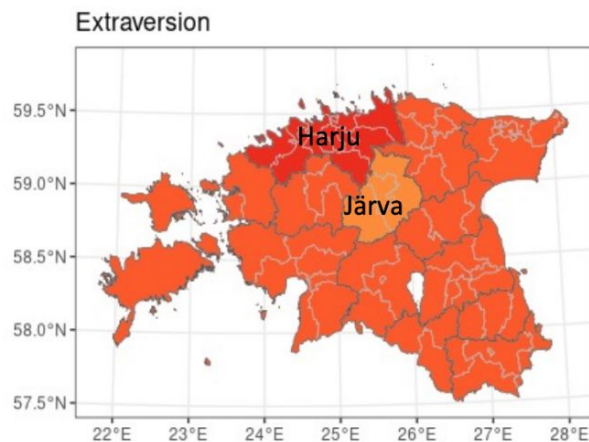
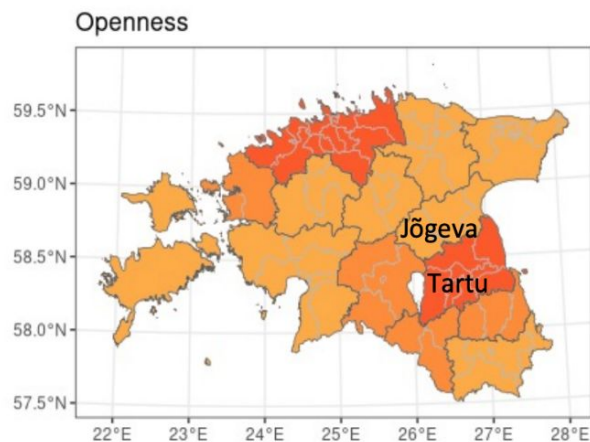
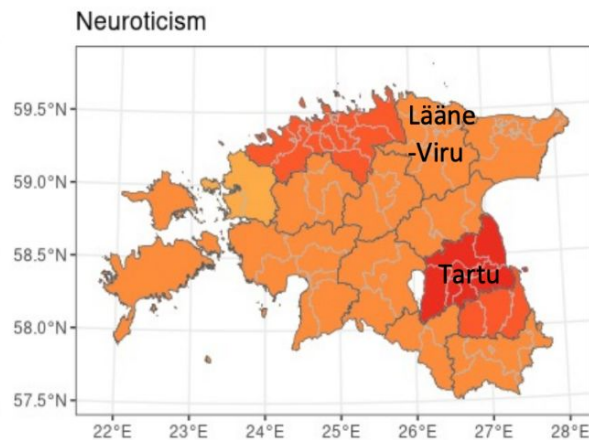
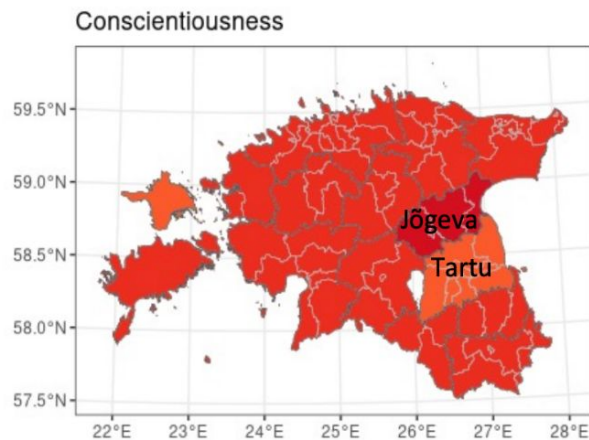
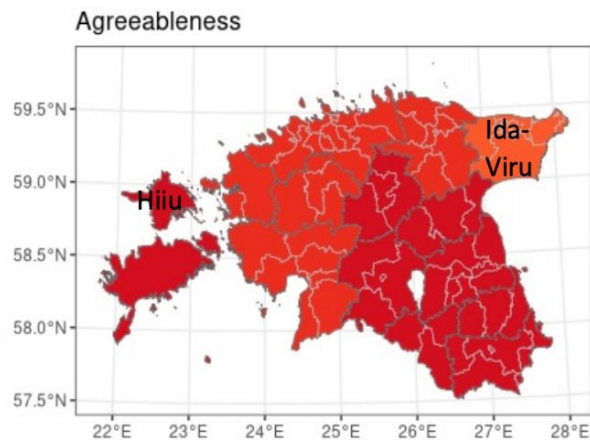
30% male, 5% Russian-speaking, 58% higher education

Upcoming cognition measurement with Test My Brain

3 times over 10 years



Things we have found



Xu et al., (2024). Does a Small Country Have Meaningful Regional Personality Differences? The Case of Estonia
 Kuznetsov et al., (2023). Assessing the impact of 20th century internal migrations on the genetic structure of

Personality and covid vaccination

Objective data from medical records

90% of sample vaccinated

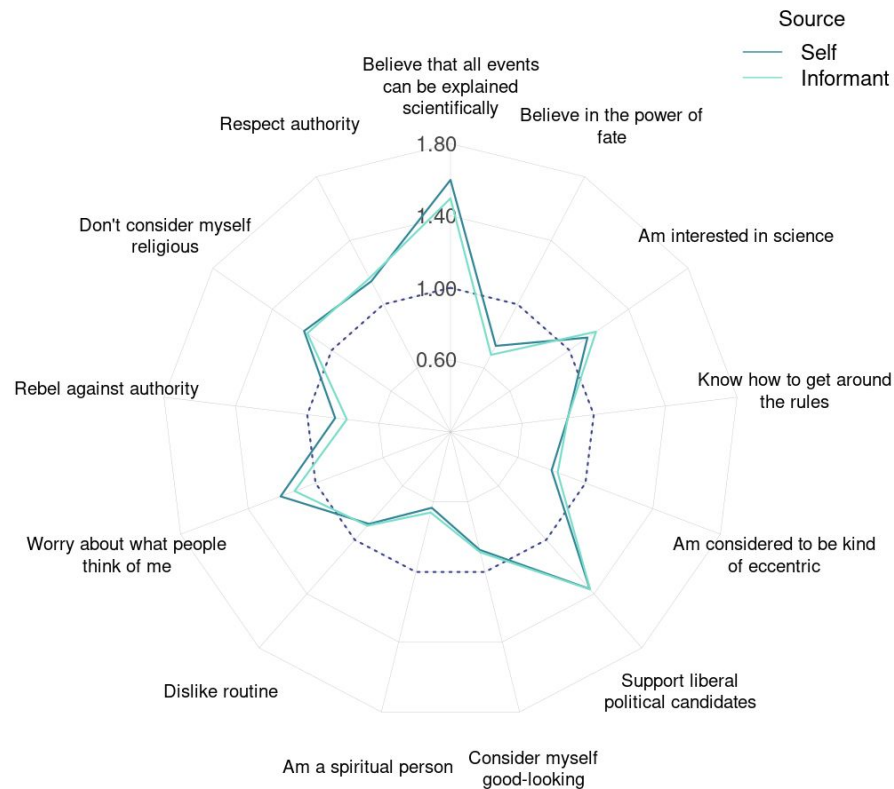
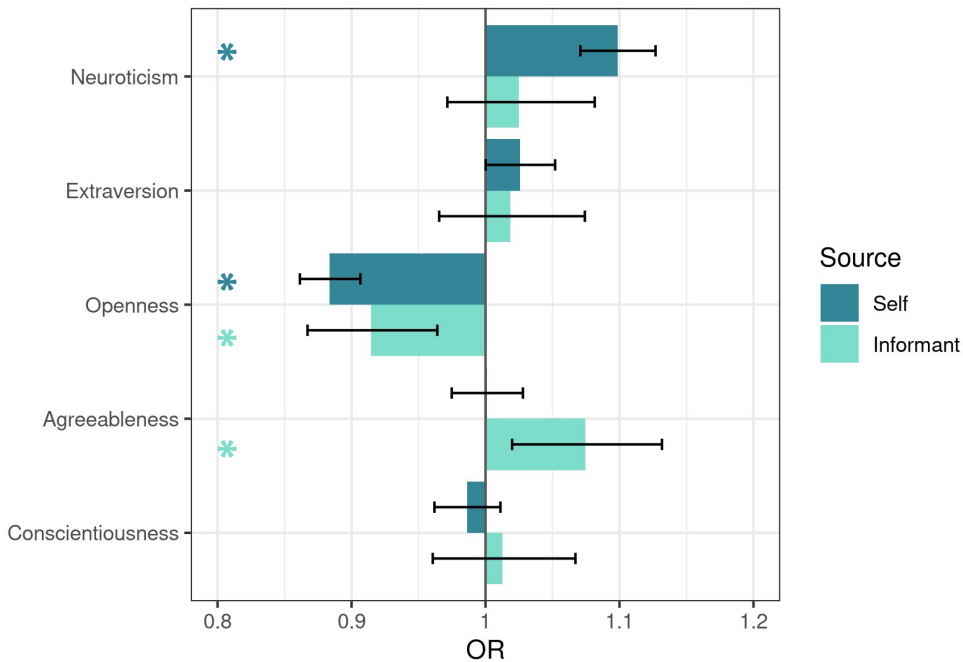
56,575 participants, 15,244 other-reports

33

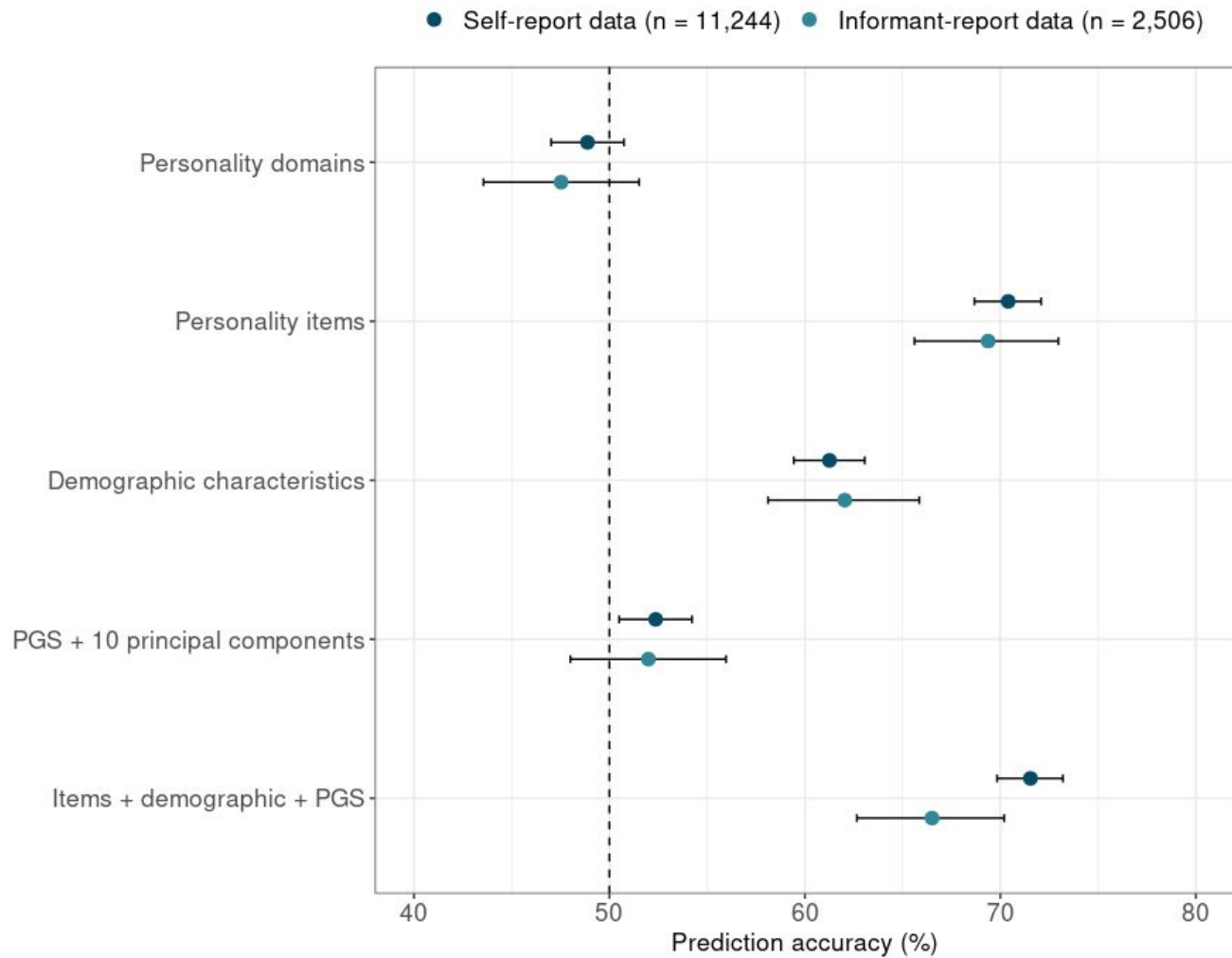
Arumäe et al., (2024). Self-and informant-reported personality traits and vaccination against COVID-19



Results: trait-level associations



Results: prediction



True correlations with life satisfaction

Among most desired life outcomes

Multidomain - satisfaction with work, relationships, etc

Known associations with personality

Limitations:

- single method

 - biased self-perception

 - characteristic response styles

- single measurement occasion

 - mood

 - recent events

Here we combine self & other reports

20,866 EST; 768 RUS; 600 ENG

36

Möttus et al., (2024). Most people's life satisfaction matches their personality traits: True correlations in multitrait, multirater, multisample data.



Getting rid of method effects

- Cross-rater, cross-variable correlations
 - Eg: LS-self \leftrightarrow extraversion informant
 - Variables valid co-variance, assuming at least some agreement
 - Not inflated by single-method effects
 - But deflated by random error, occasion, asymmetric information
- Cross-rater, same-variable correlations
 - Eg: LS self \leftrightarrow LS informant
 - Variables valid information (variance + any covariances)
 - Also deflated by random error, occasion, asymmetric information

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$$

True correlations

Ratio of valid variances co-variance
total valid variance

Occasion effects, asymmetrical information and error cancel out
Provide very high estimates for items with same
content

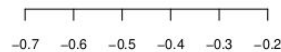
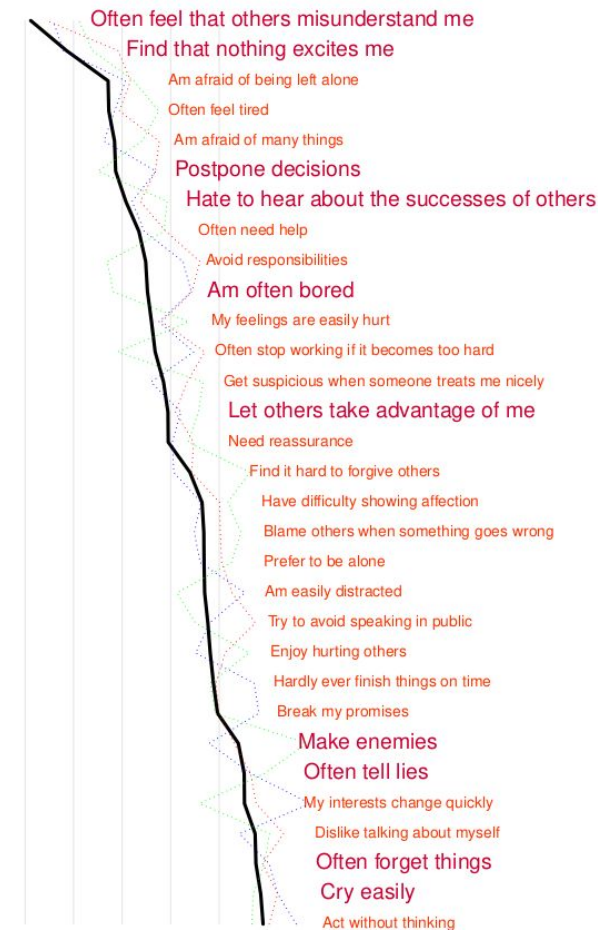
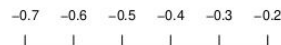
Item1	Item2
Break my promises	Keep my promises
Have no need for close friendships	Having good friends is important for me
Have strong sexual urges	Don't think much about sex
Am always worried about something	Rarely worry
Act without thinking	Make rash decisions
Keep things tidy	Leave a mess in my room
Am good at saving money	Spend more money than I should

- • • Am happy with my life
- • • Feel that my life lacks direction
- • • Have a dark outlook on the future

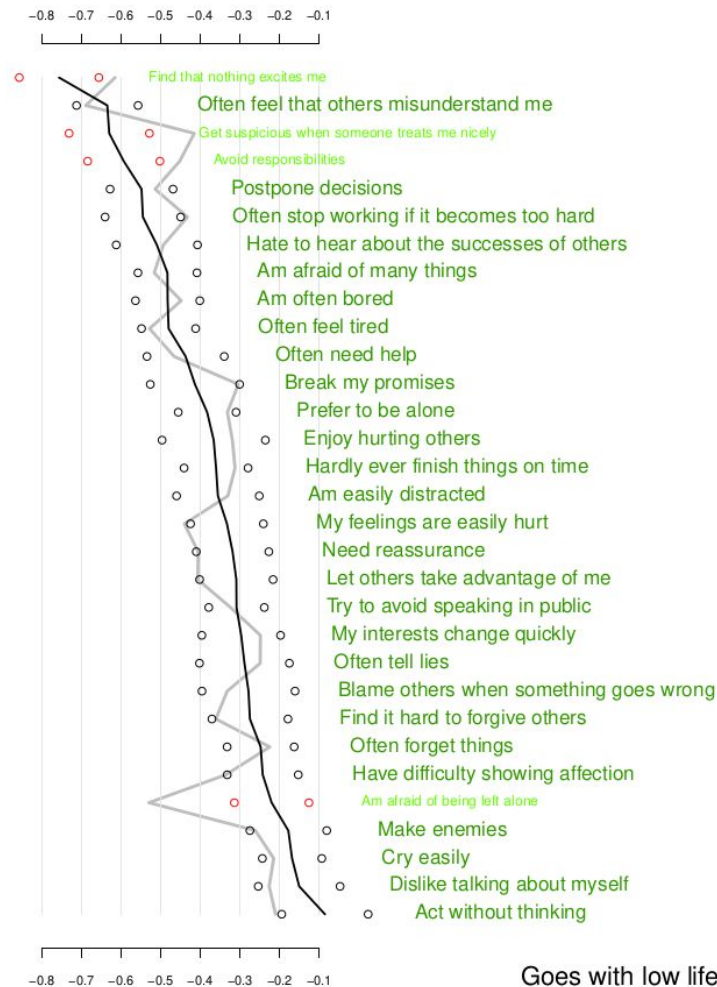
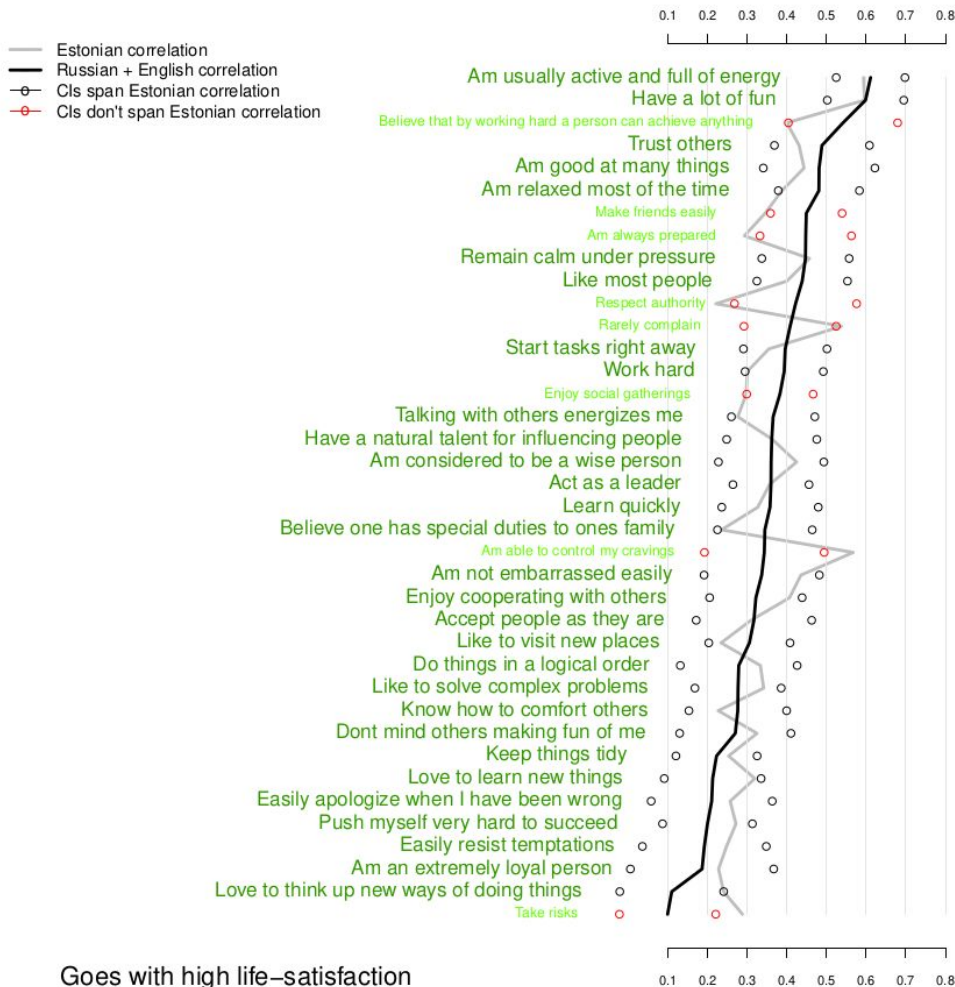
— Aggregate LS



Goes with high life-satisfaction



Goes with low life-satisfaction



Prediction

	Estonian-based data		Russian-based data		English-based data	
	r_{true}	SE	r_{true}	SE	r_{true}	SE
Five domains	.79	.008	.74	.046	.64	.049

“Often feel that others misunderstand me”

“Find that nothing excites me”

“Postpone decisions”

r_{true} with
mental
health

0.52

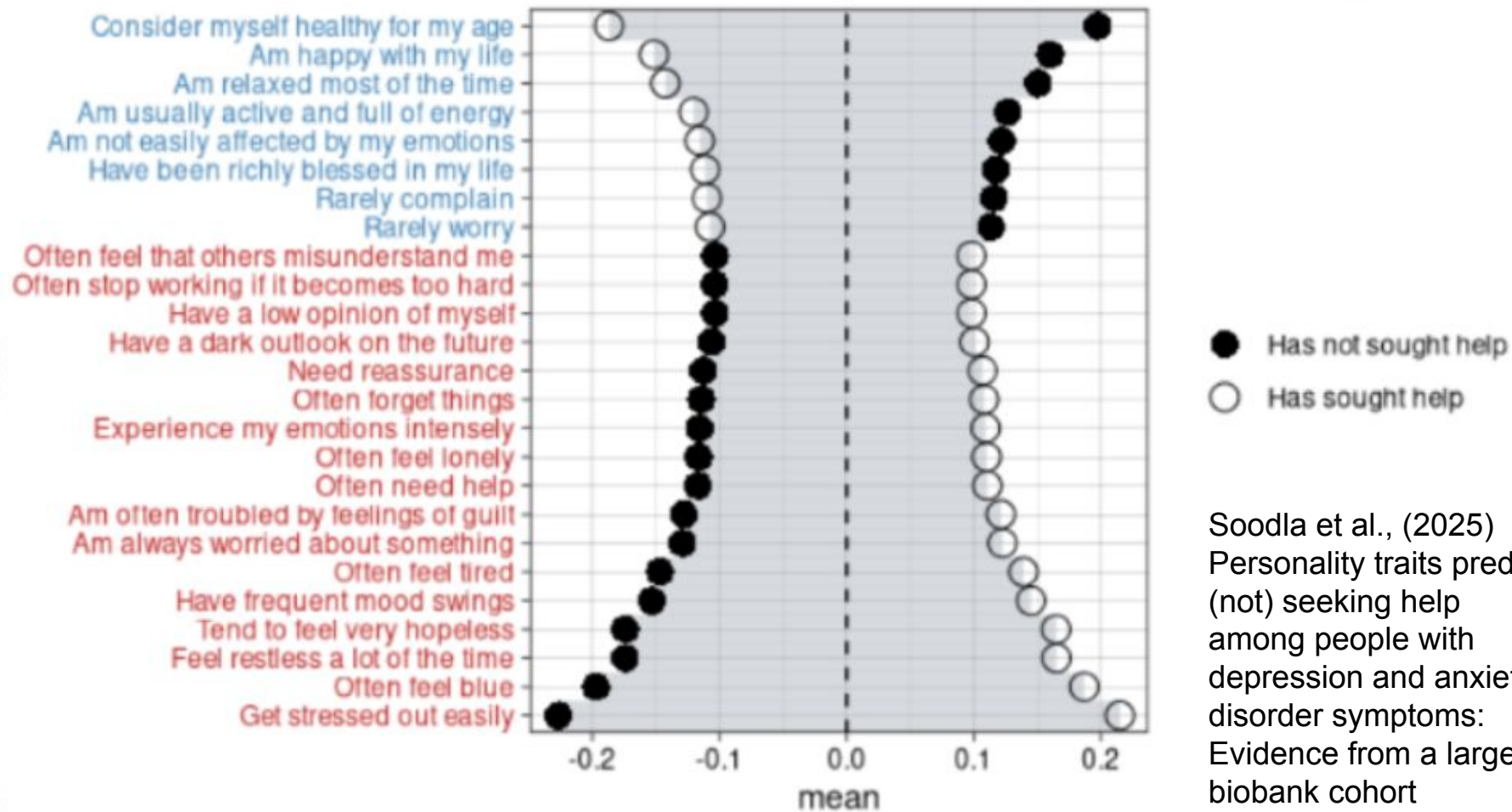
p-factor



Soodla et al., (2024). Accurately assessing the overlap of personality traits and psychopathology using multi-informant data: Two sides of the same coin?

a

Differences of objective help-seekers/non-help-seekers



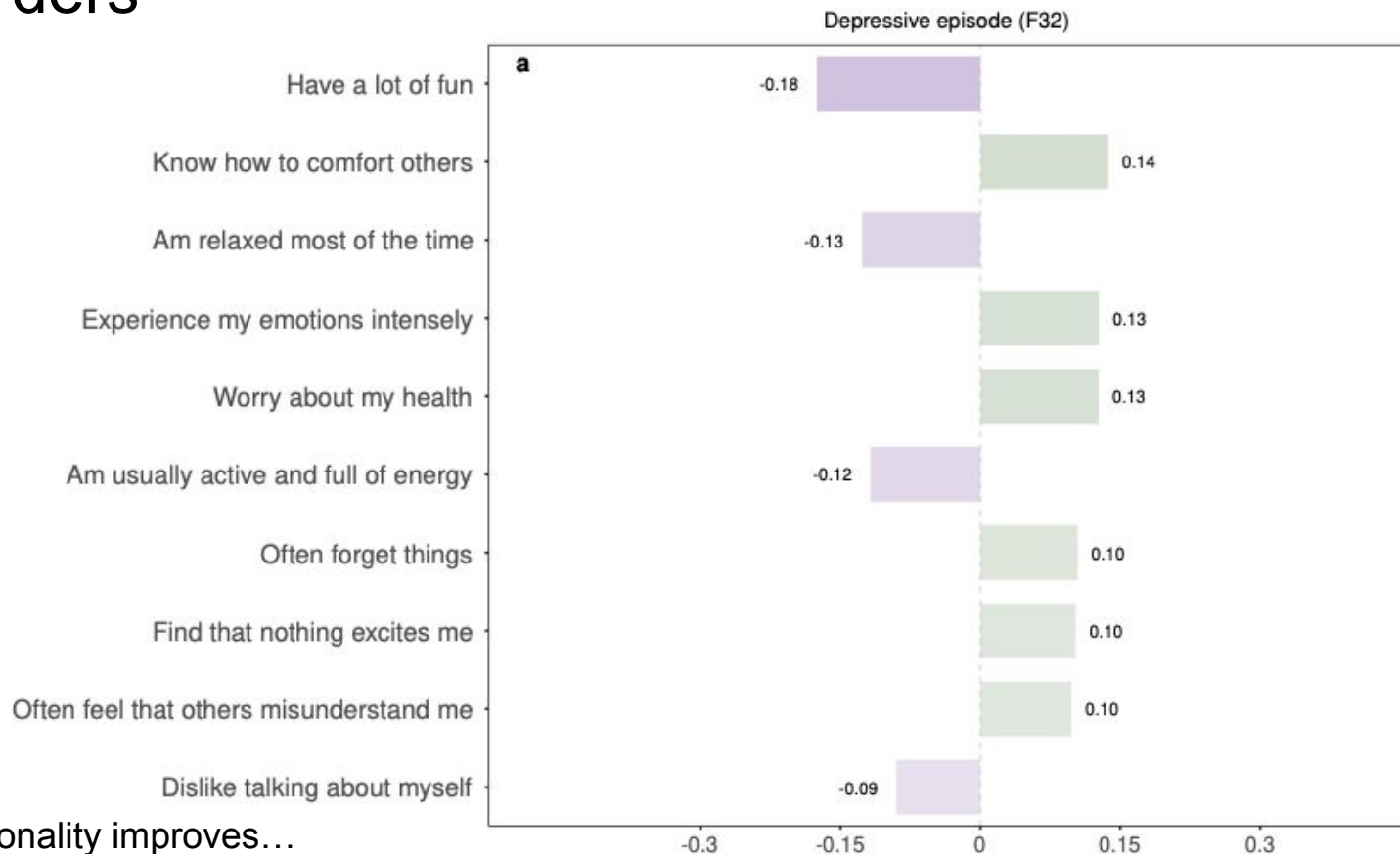
Soodla et al., (2025)
 Personality traits predict
 (not) seeking help
 among people with
 depression and anxiety
 disorder symptoms:
 Evidence from a large
 biobank cohort

Personality improves prediction of the onset of common mental disorders

Item-level
personality
model: mean
AUC=0.71

Demographic
factors: mean
AUC=0.59

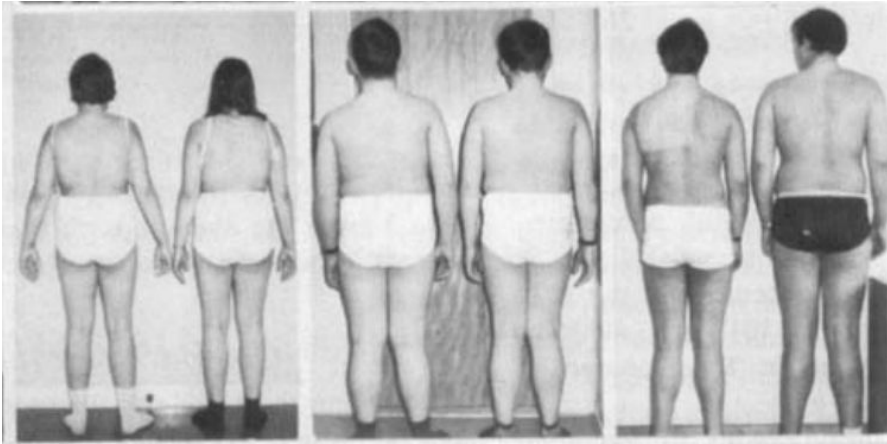
Depression:
AUC=0.8



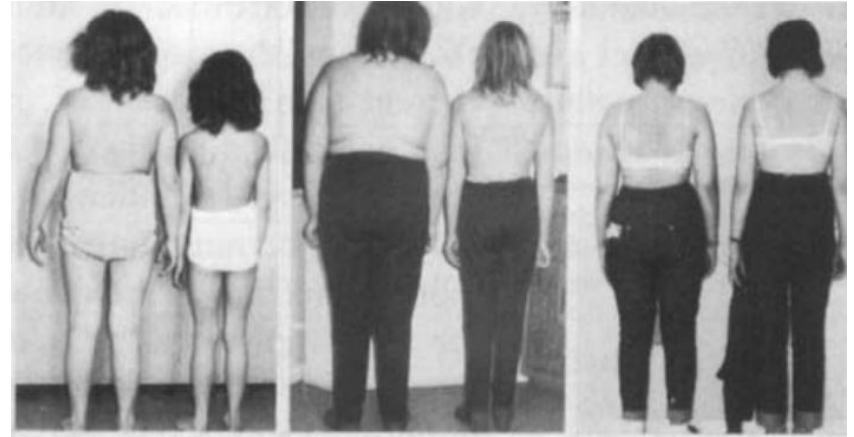


<https://vikerraadio.err.ee/1061406/kabi-ei-kuku>
<https://purepng.com/public/uploads/large/purepng.com-applef>

Heritability: genetic similarity → phenotypic similarity



Monozygotic twins:
100% shared genes



Dizygotic twins:
50% shared genes

How similar
are relatives'
personalities?



r_{true} parent-offspring personality

typical estimate $r = .11 - .15$

little more similar than strangers

→ narrow $h^2 \sim .22 - .28$

We applied r_{true} to self & other ratings of:

parent-offspring (N pairs = 522)

sibling-sibling pairs (N pairs = 388),

2nd degree relatives (N pairs = 475)

parent offspring $r_{\text{true}} \sim .30$

→ narrow $h^2 \sim .40$

parents and offspring are not strangers after all

but also not the same person

Molecular genetics of personality

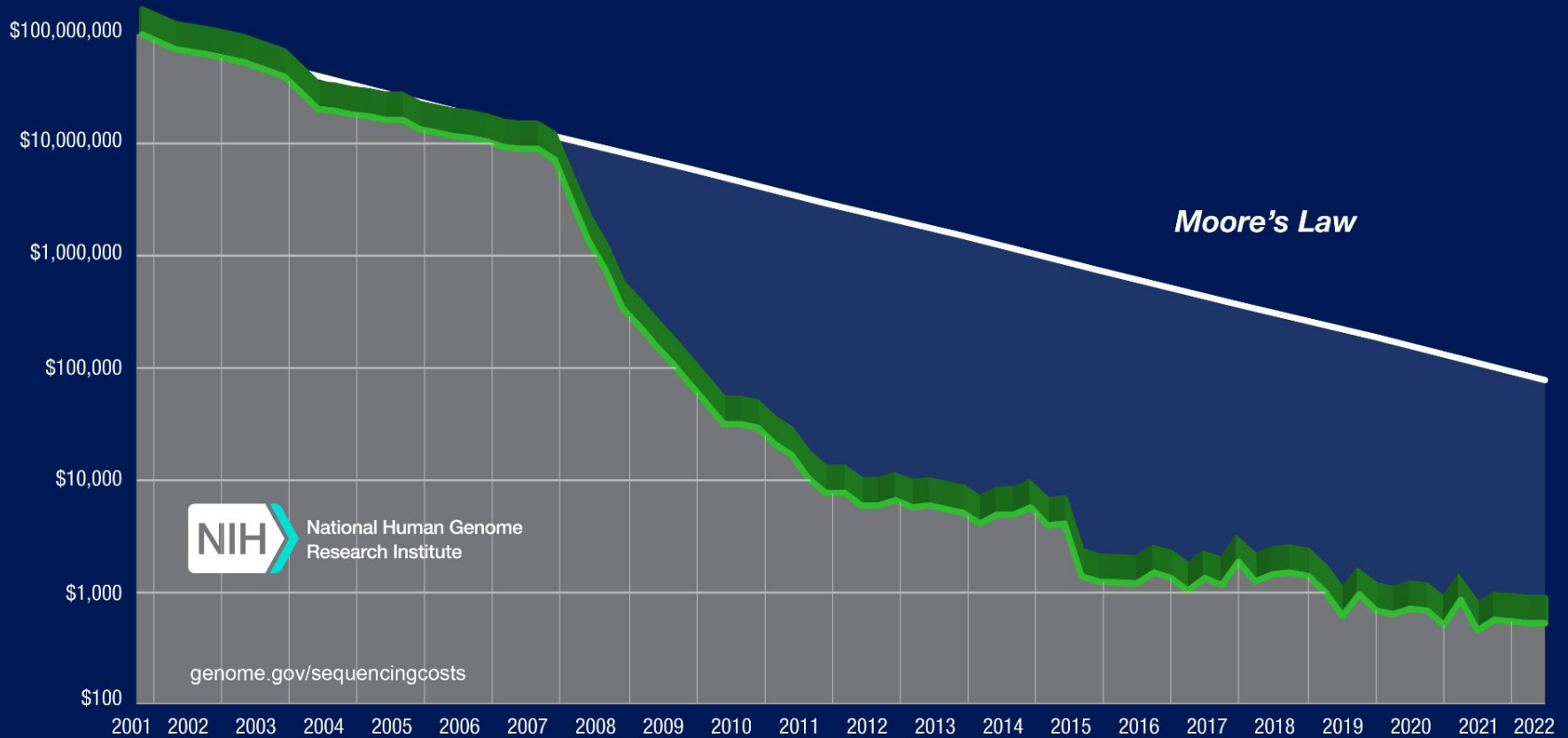
Genome-wide profiles

Genetic correlations

Polygenic scores

Causal inference

Cost per Human Genome

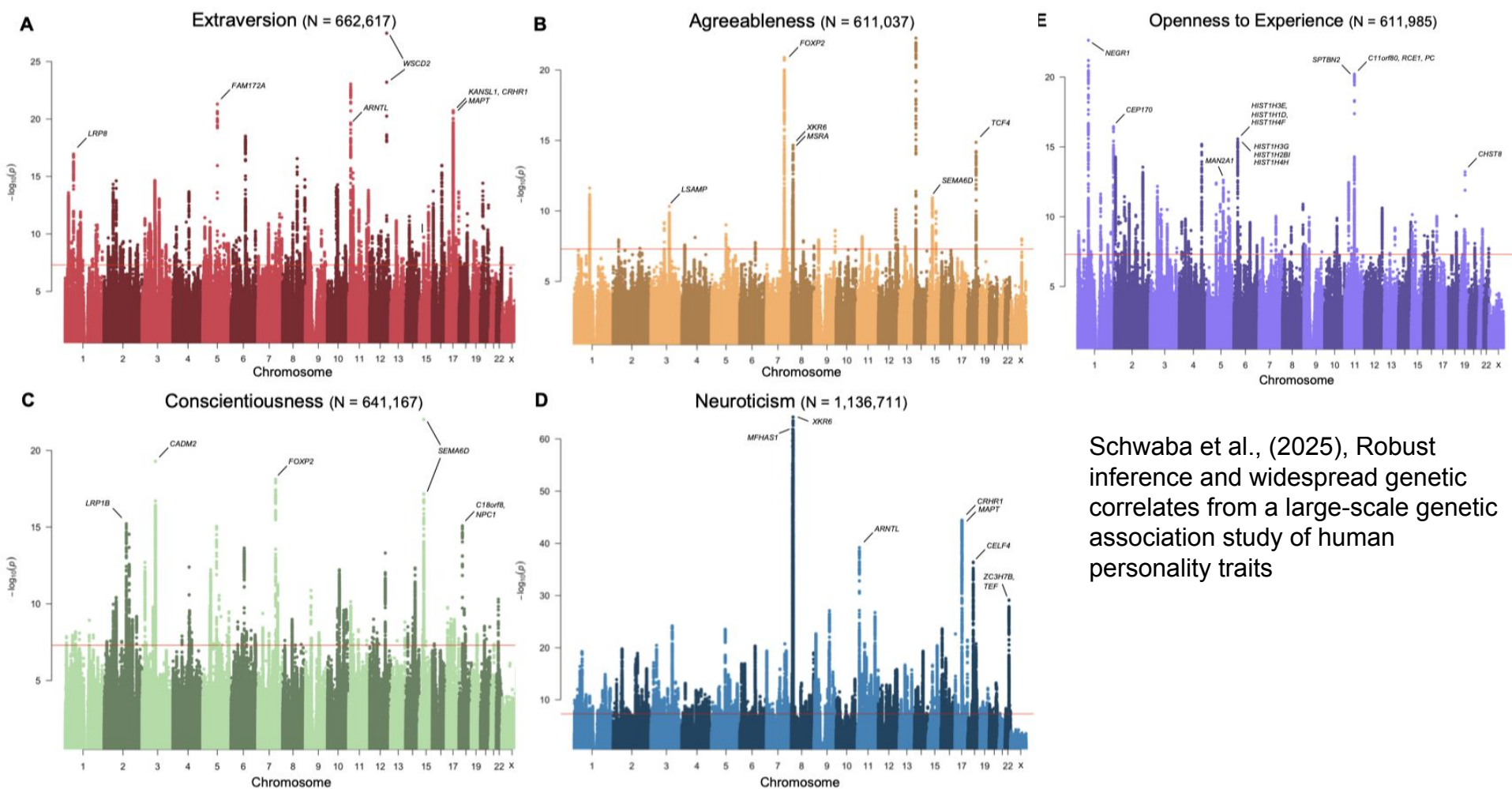


Many genes influence complex traits

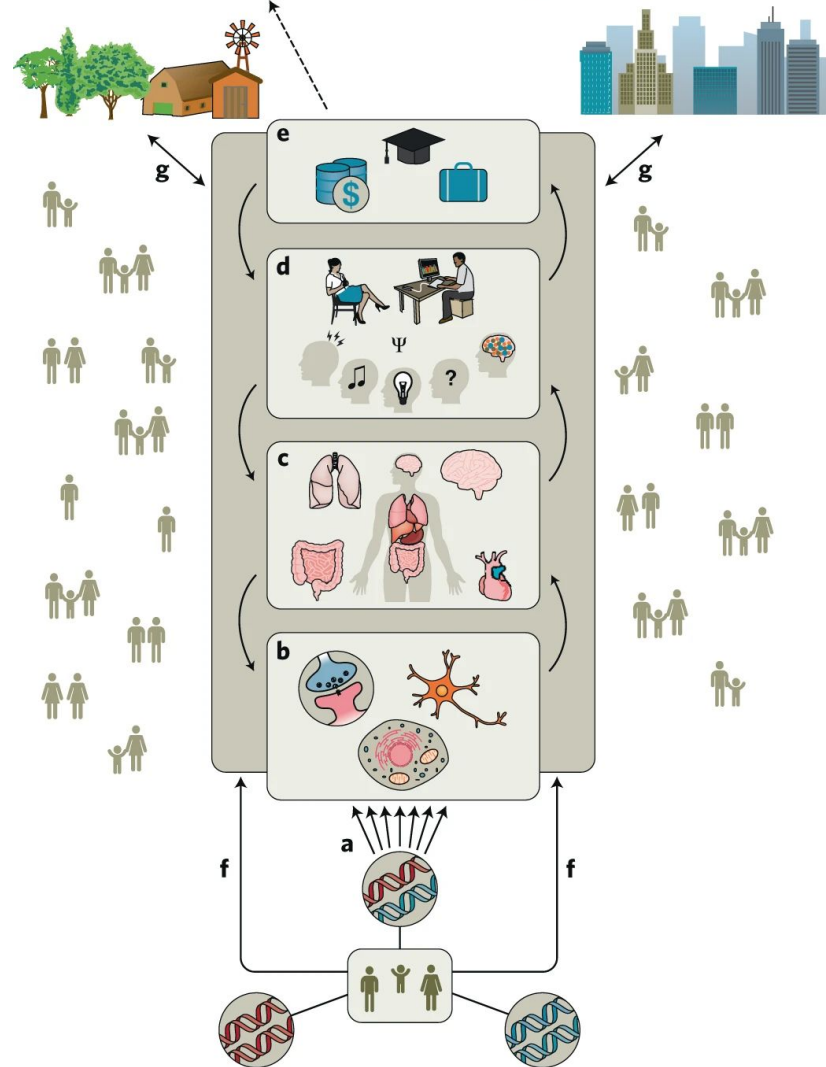
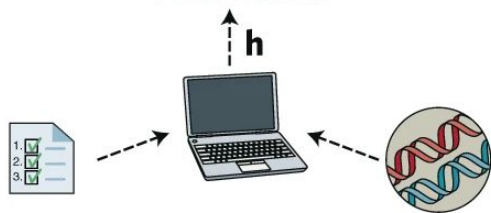
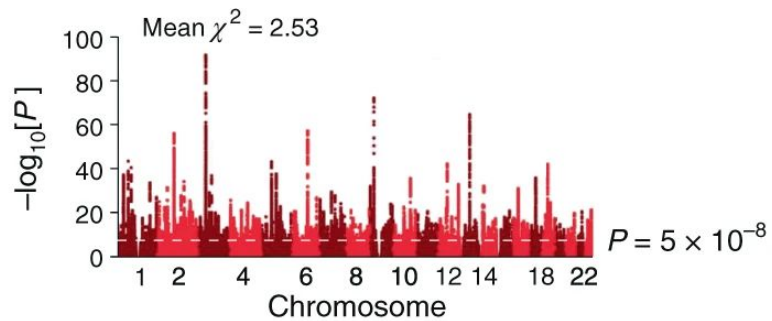
- Each gene has small effect (few mm regarding height)
- Effects tend to be additive
- Effects form a normal distribution
- We need 100k to millions of participants → collaboration



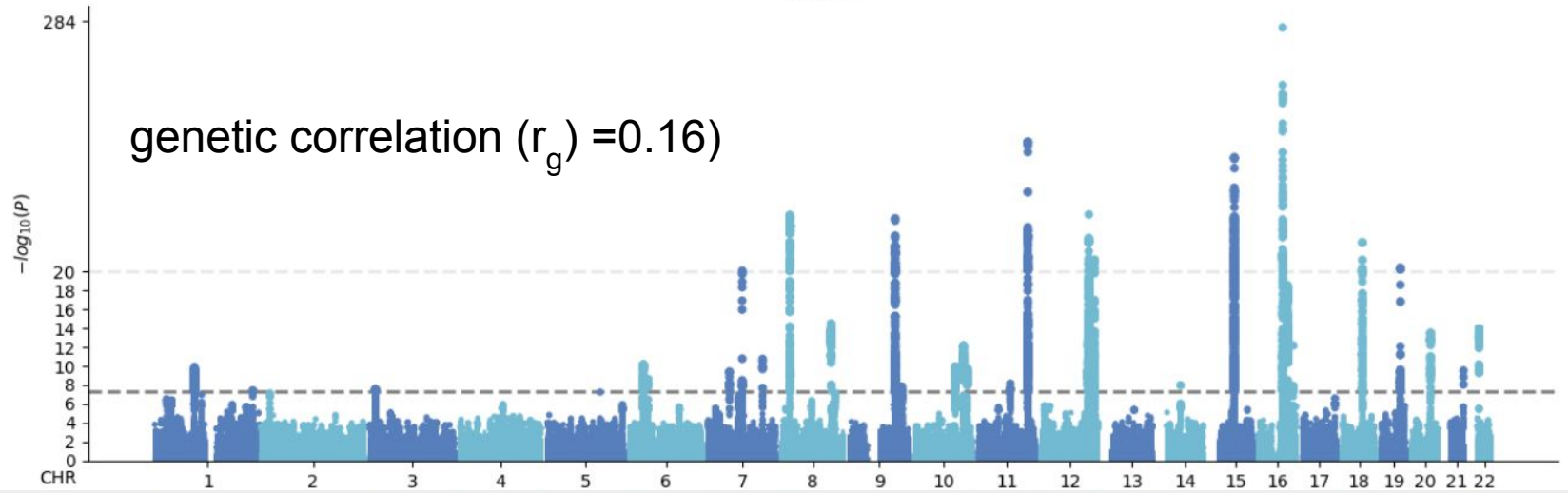
Height in inches



Schwaba et al., (2025), Robust inference and widespread genetic correlates from a large-scale genetic association study of human personality traits



HDL-C



Personality and health correlations

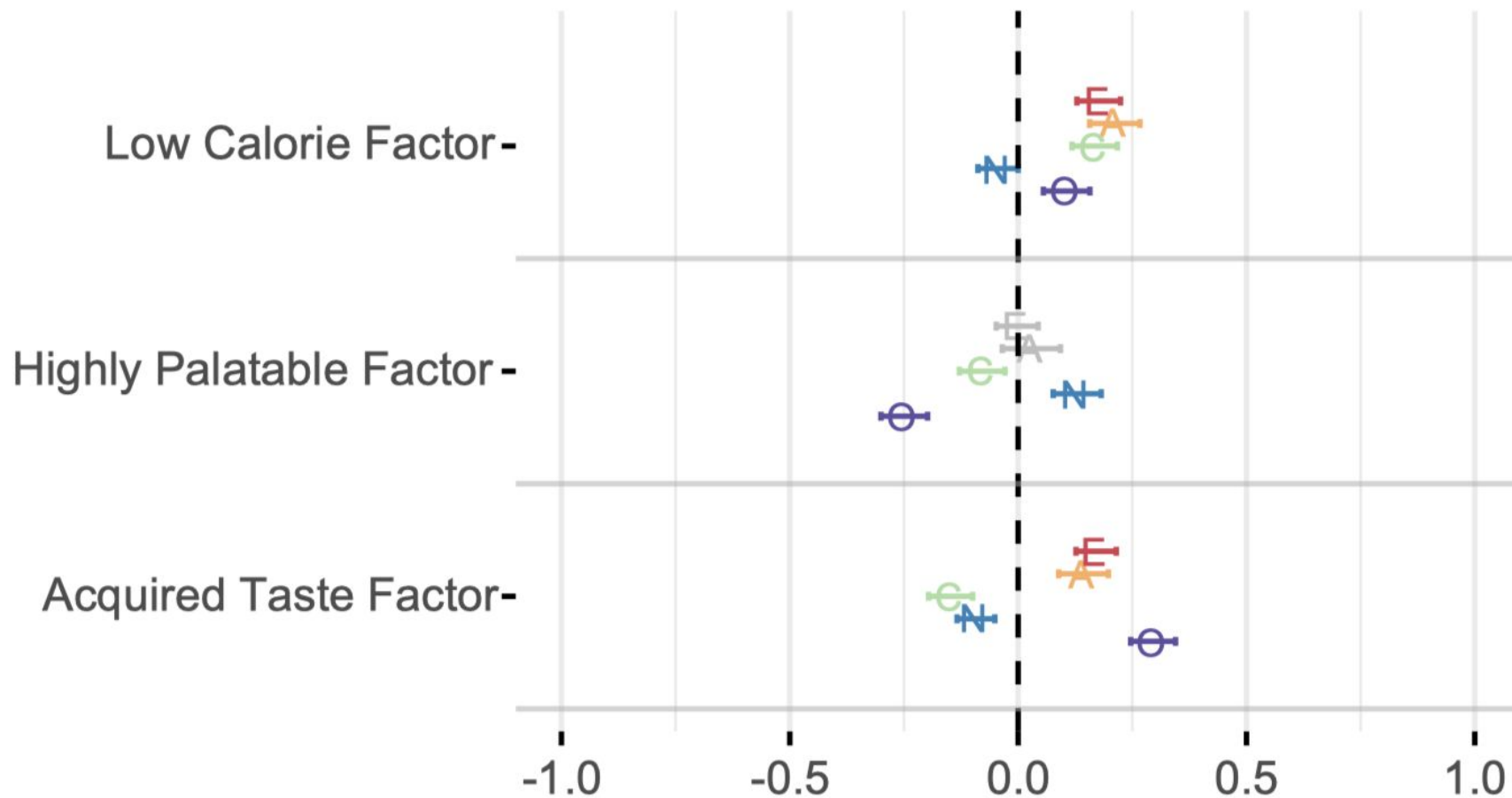
Physical Health

0.0 0.2 0.4 0.6 0.8 1.0

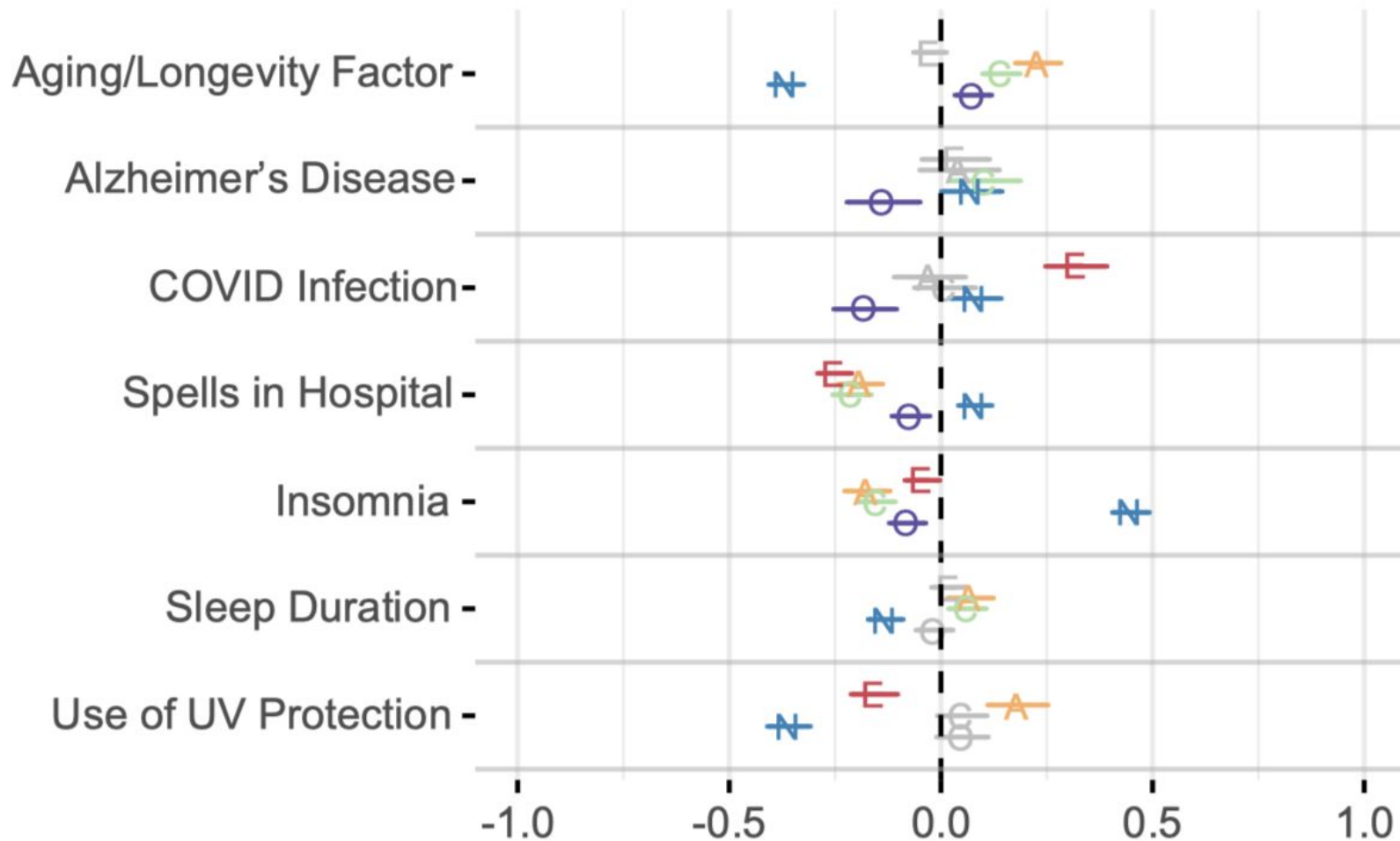


Schwaba et al., (2025), Robust inference and widespread genetic correlates from a large-scale genetic association study of human personality traits

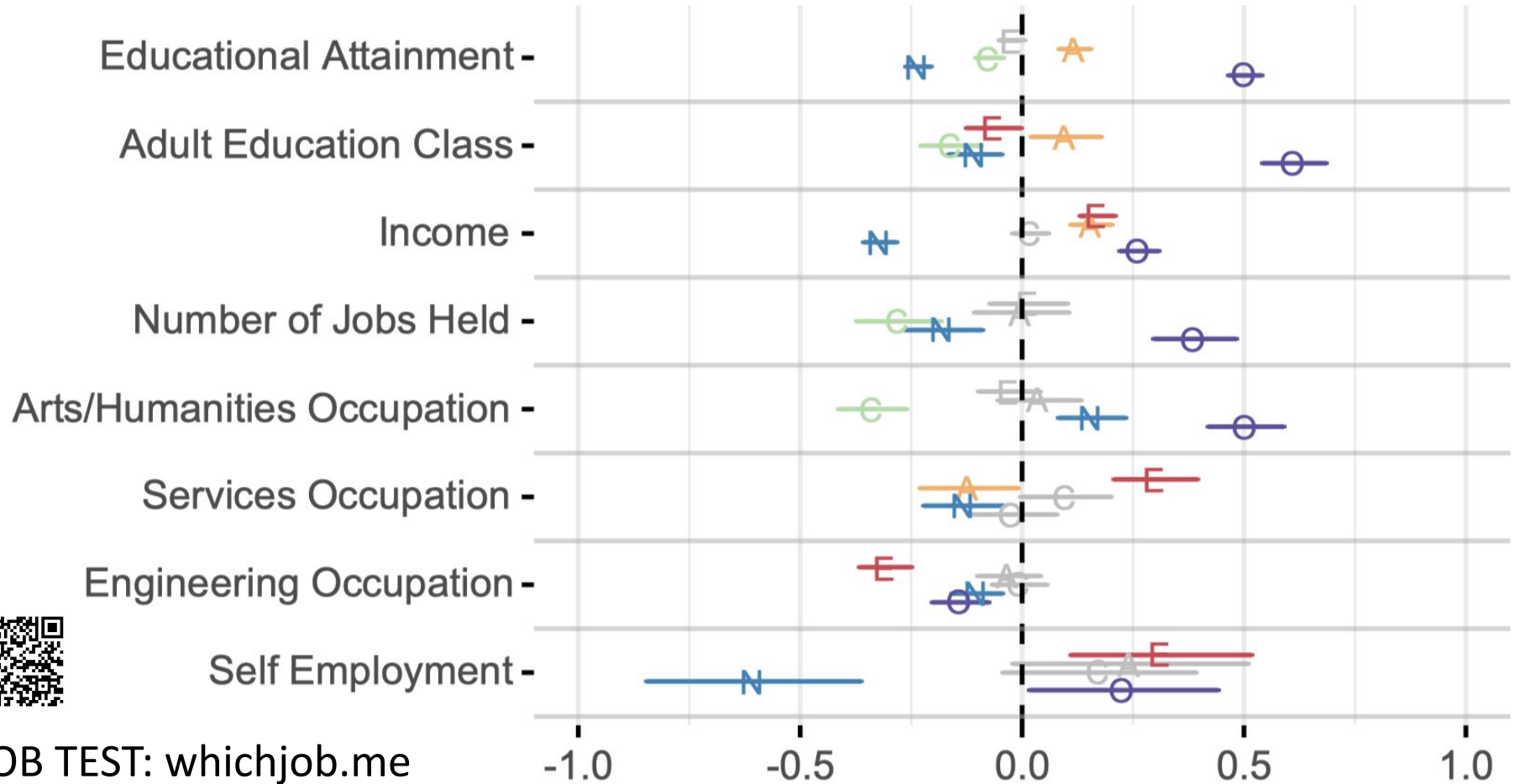
Diet



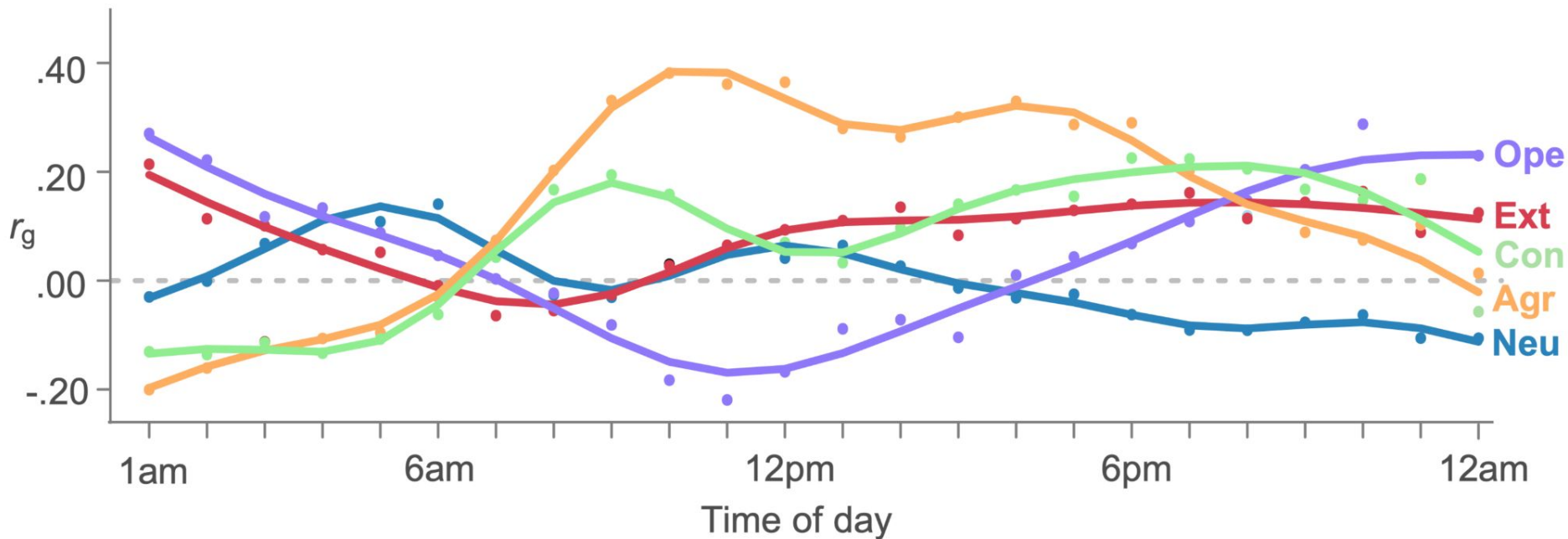
General Health



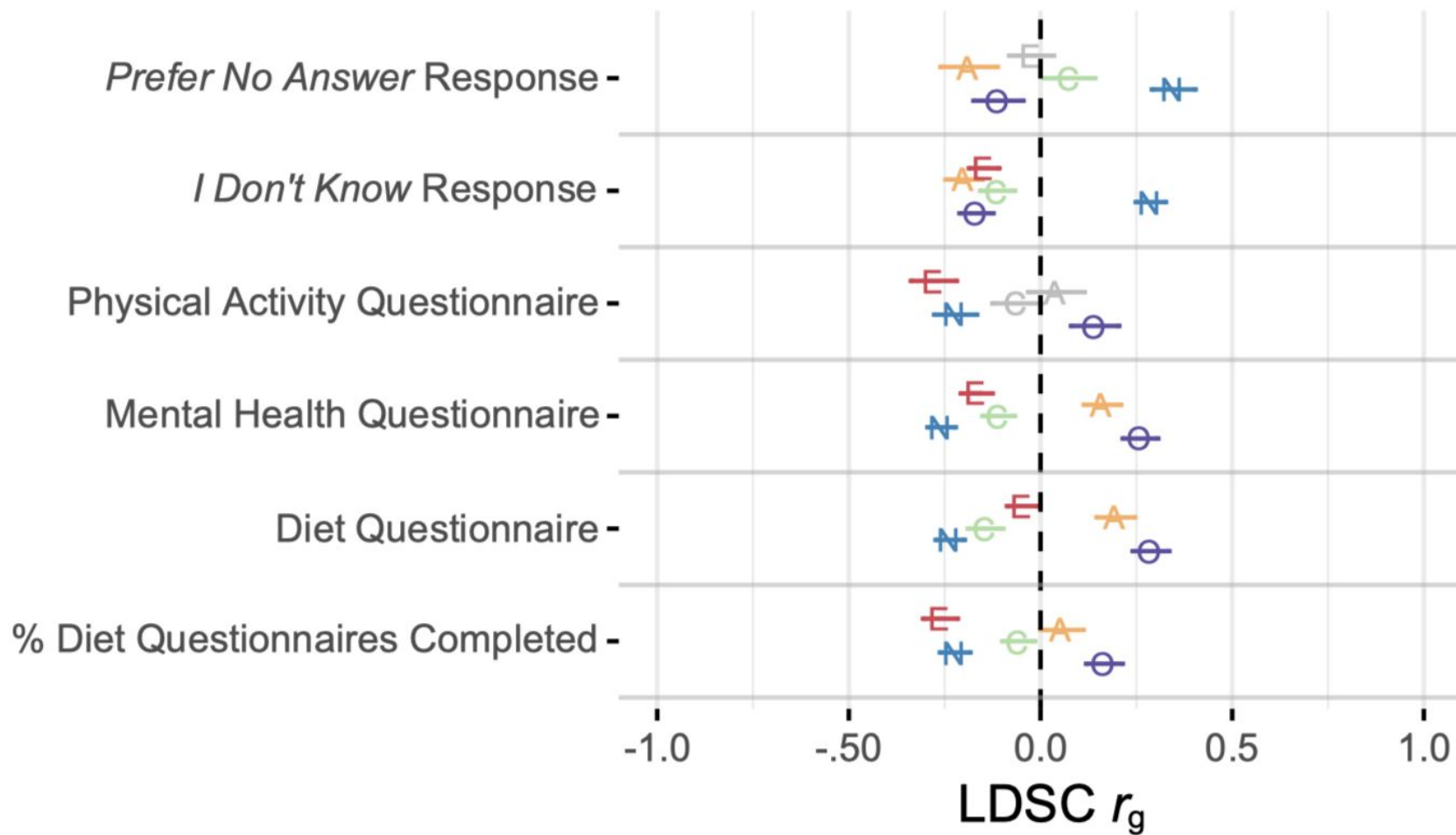
Education and Employment



D Genetic Correlations with Accelerometer in UK Biobank ($N_{\text{EUR}} \approx 95,000$)



Participation



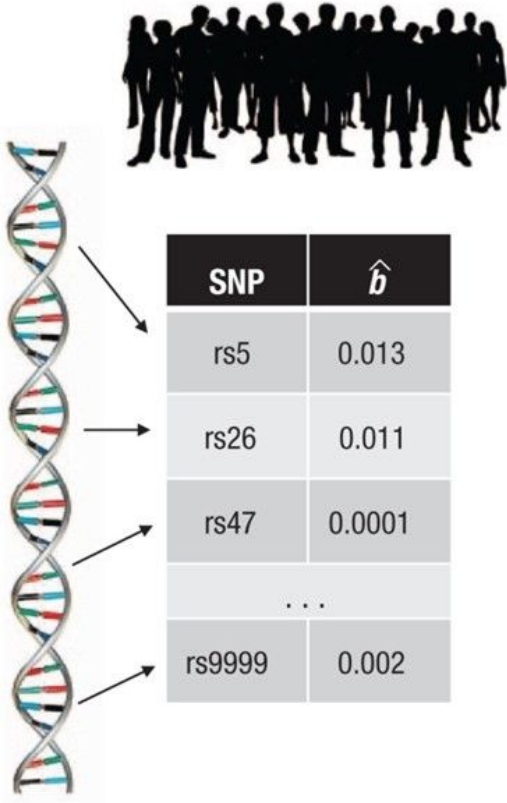
Polygenic scores - genetic potential

Genetic risk scores

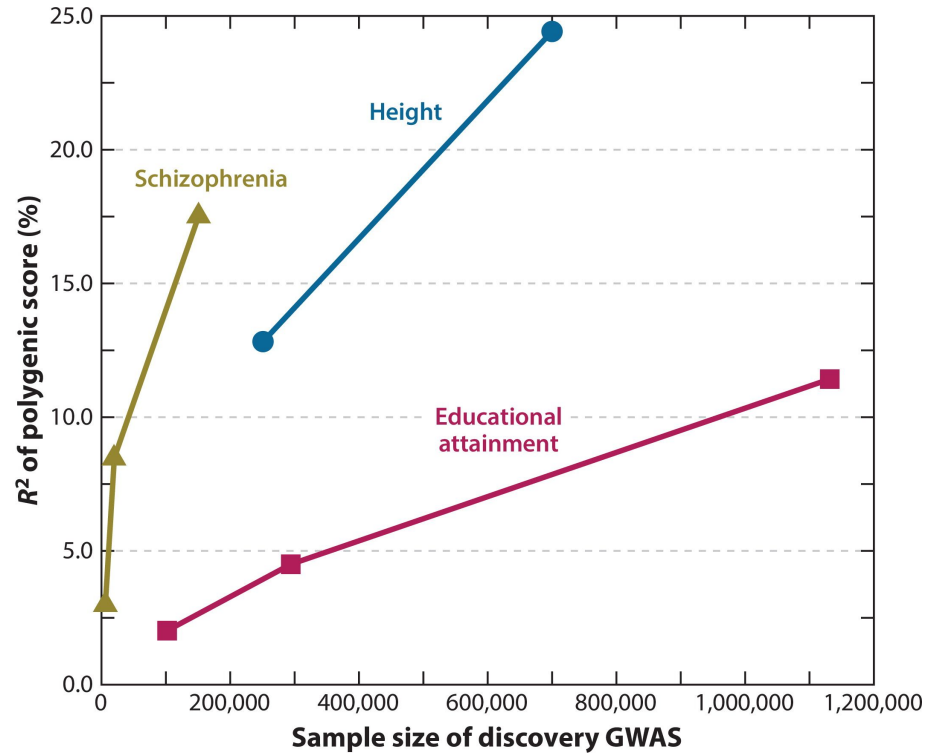
Polygenic indices

Discovery GWAS
 $N = 30K-1,000K$

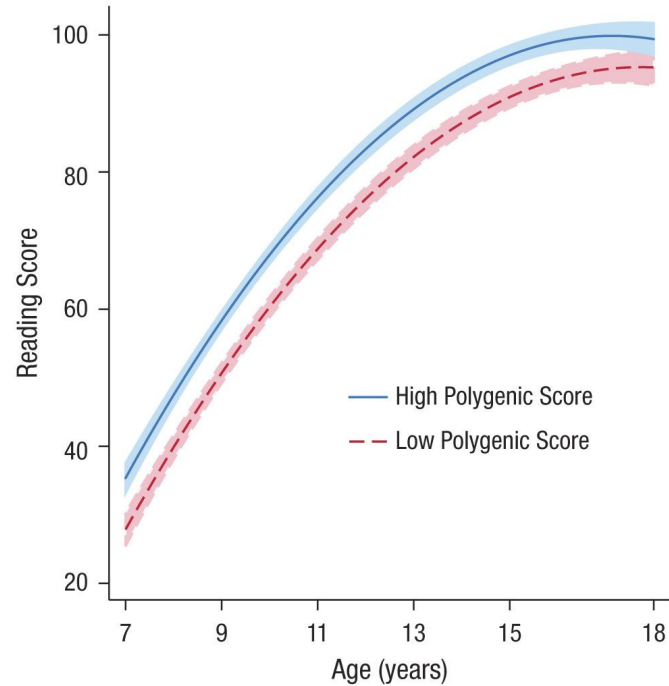
Polygenic Scoring
 $N = 300+$



Larger discovery sample → better prediction

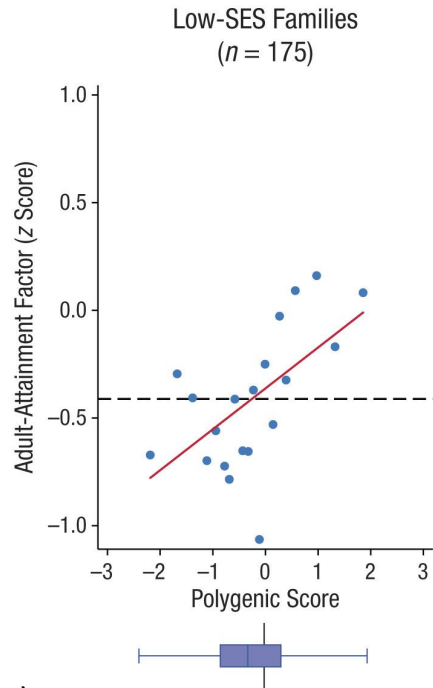


Education PGS and reading



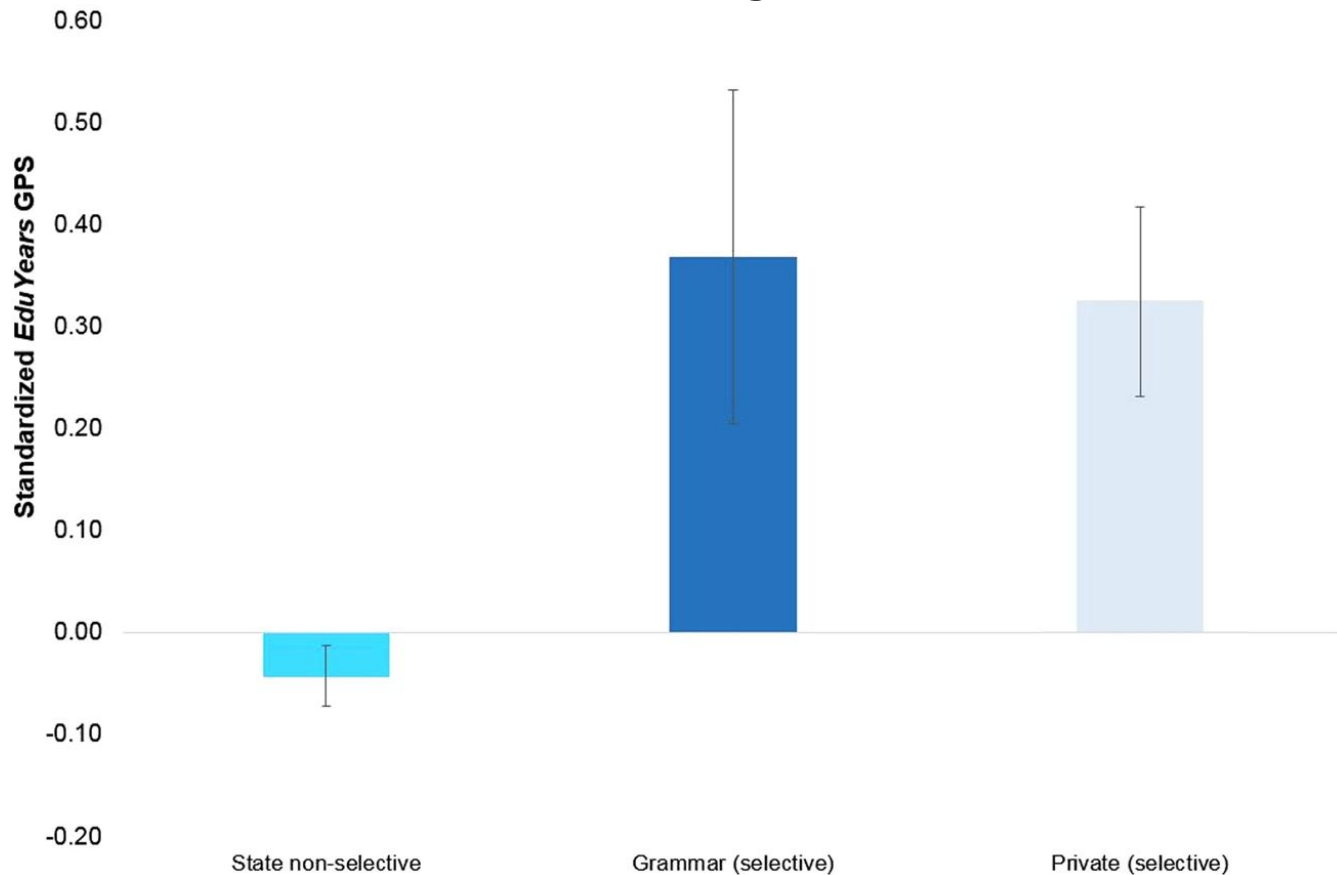
Belsky et al., (2016)
Psychological Science

Higher education PGS makes more from the SES



Belsky et al., (2016)
Psychological Science

Selective schools have higher Edu PGS students



Adding exotic phenotypes to datasets

- Church attendance
- Childhood math and reading skills
- Narcissism
- Rhythm perception

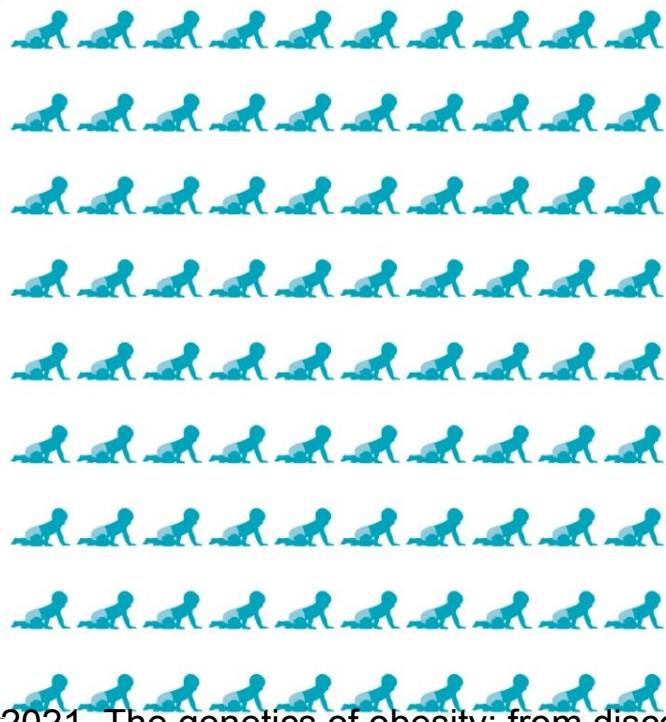
Alemu et al., (2025). An Updated Polygenic Index Repository: Expanded Phenotypes, New Cohorts, and Improved Causal Inference

Polygenic score is potential not destiny

High genetic
risk of obesity
(PGS ≥ 90 th pct)



Low genetic
risk of obesity
(PGS < 90 th pct)



Australia to ban life insurance companies from discriminating based on genetic testing results

Albanese government says people have been reluctant to get life-saving early testing because of the risk of being refused insurance

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Karen Middleton *Political editor*

Tue 10 Sep 2024 14.55 CEST

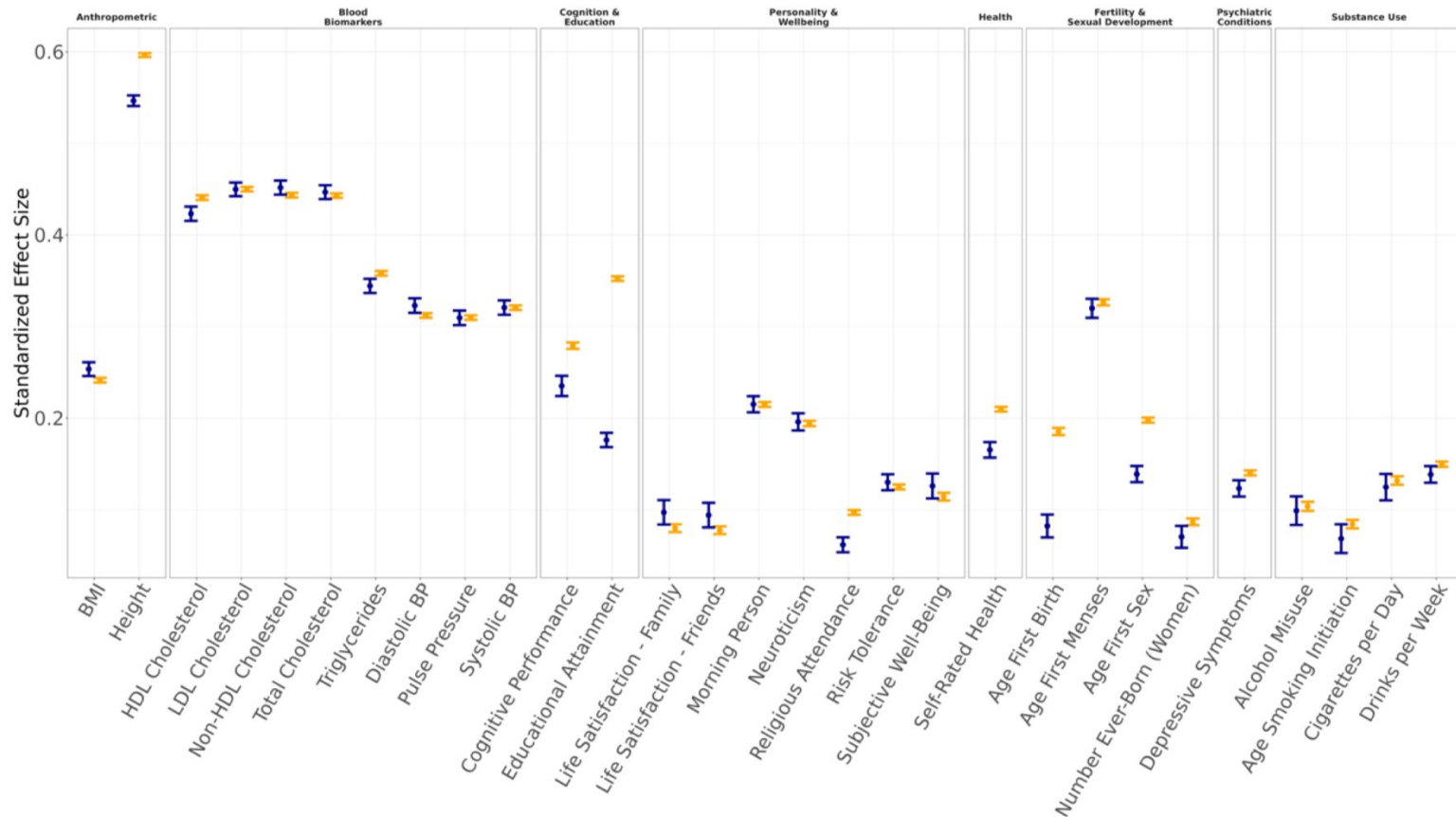
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<https://www.theguardian.com/australia-news/article/2024/sep/10/australia-insurance-company-discrimination-genetic-testing>

B.

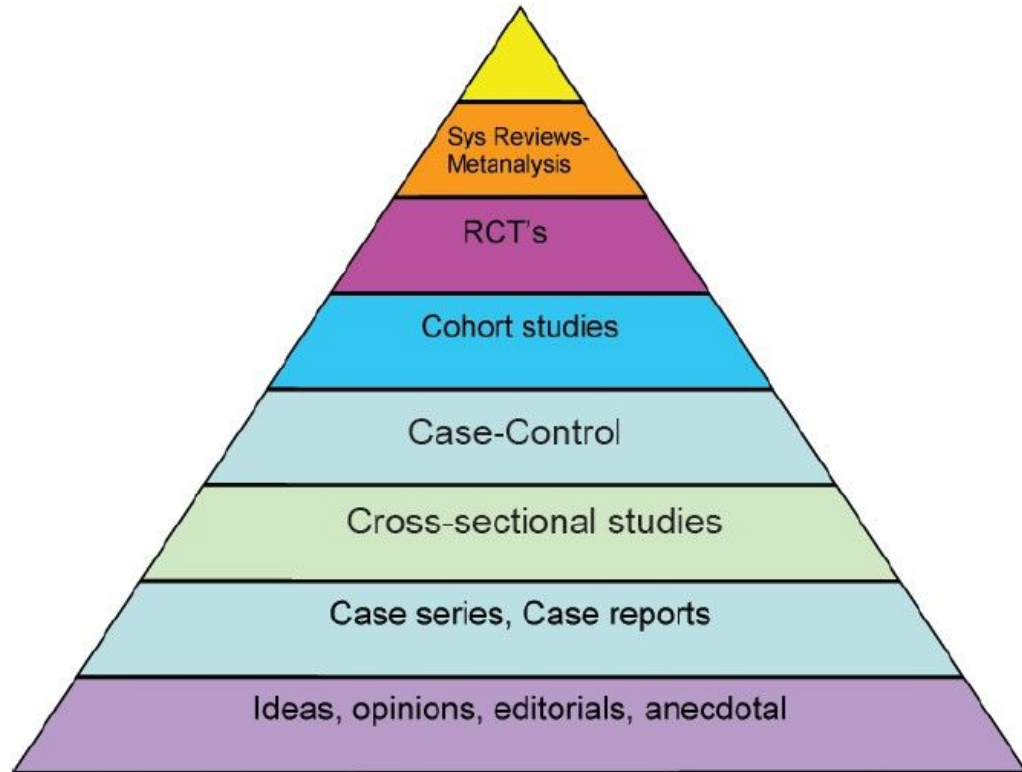
Within-family PGI-s



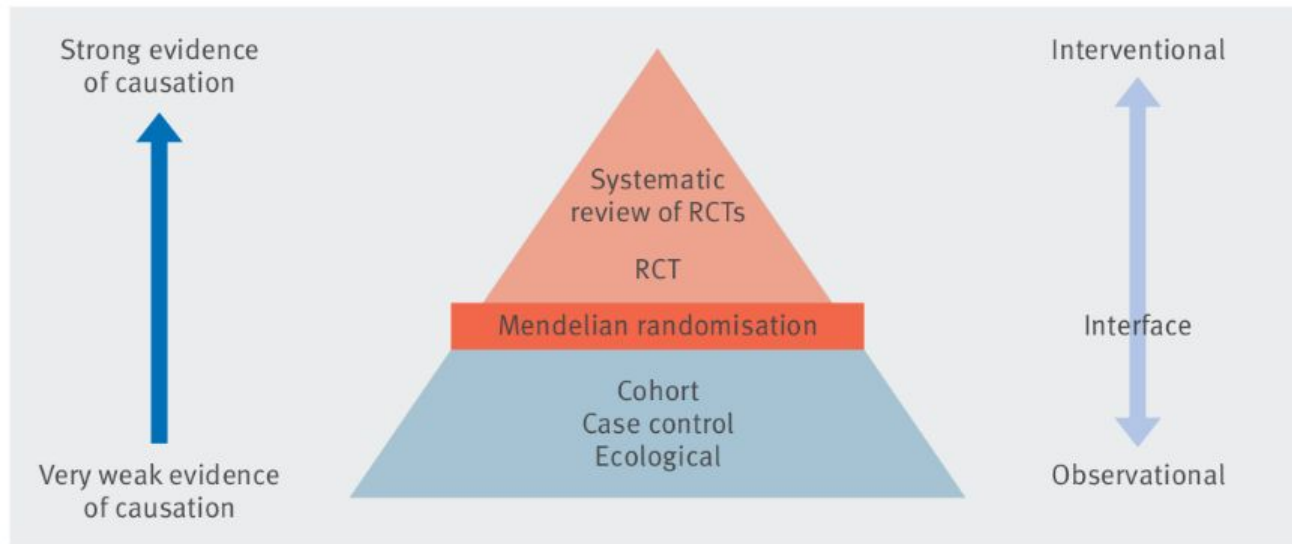
Alemu et al., (2025).
An Updated Polygenic
Index Repository:
Expanded
Phenotypes, New
Cohorts, and Improved
Causal Inference

Notes: Causal effects and population associations of PGIs in UKB. Causal effects were estimated in the sample of first-degree relatives, and population associations in a sample of unrelated individuals (third partition of UKB). For binary phenotypes, population associations were estimated using logistic

Causality



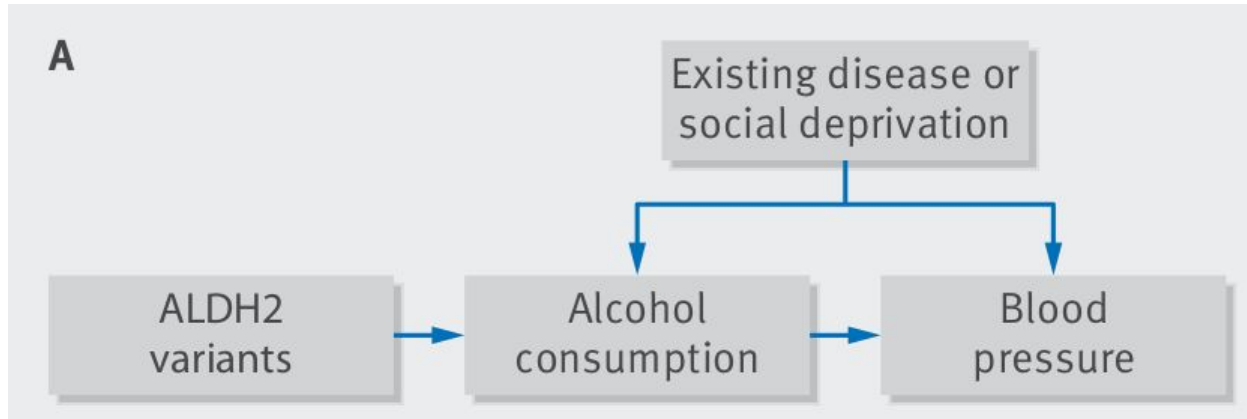
<https://blogs.bmj.com/adc/2014/11/03/the-crumbling-of-the-pyramid-of-evidence/>

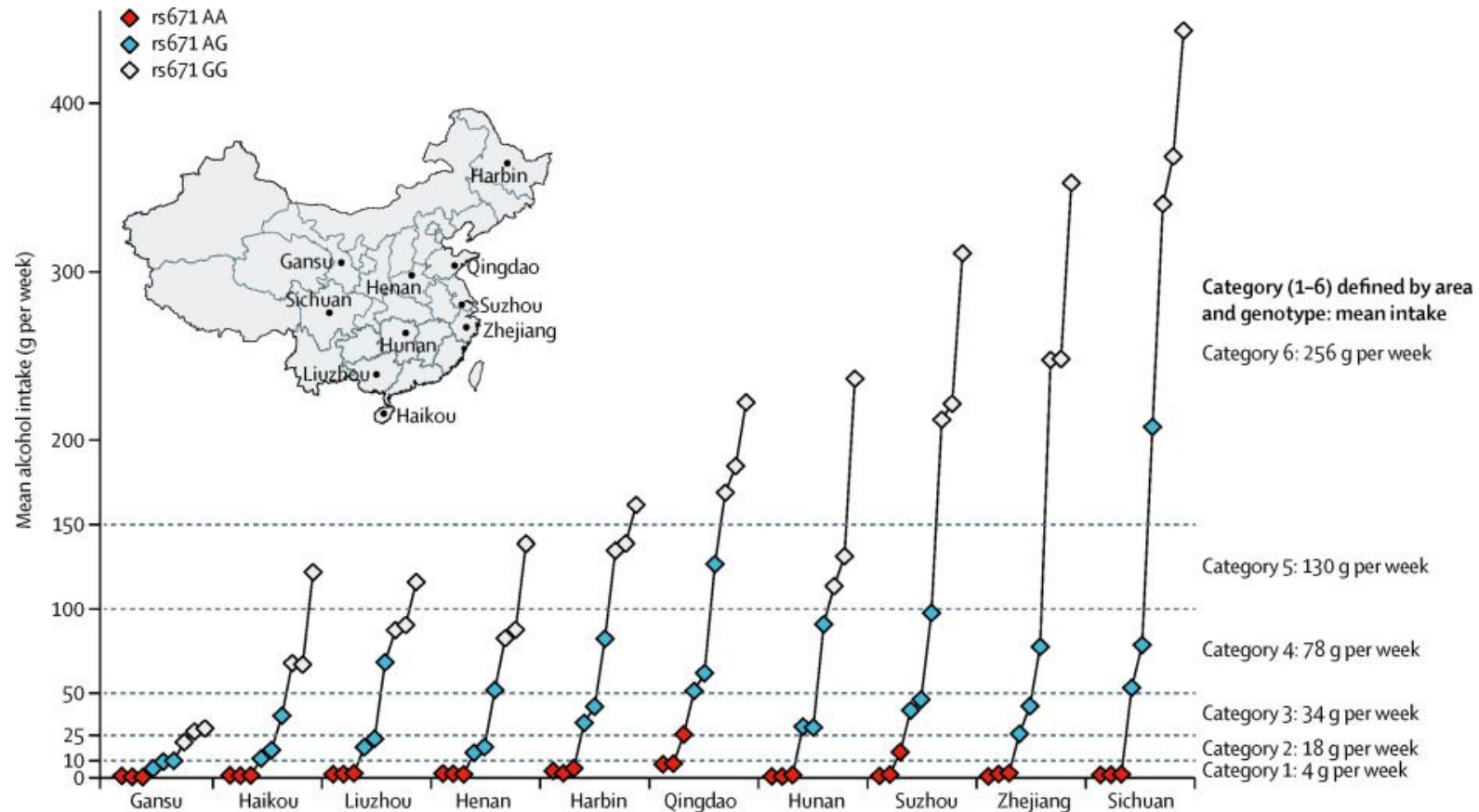




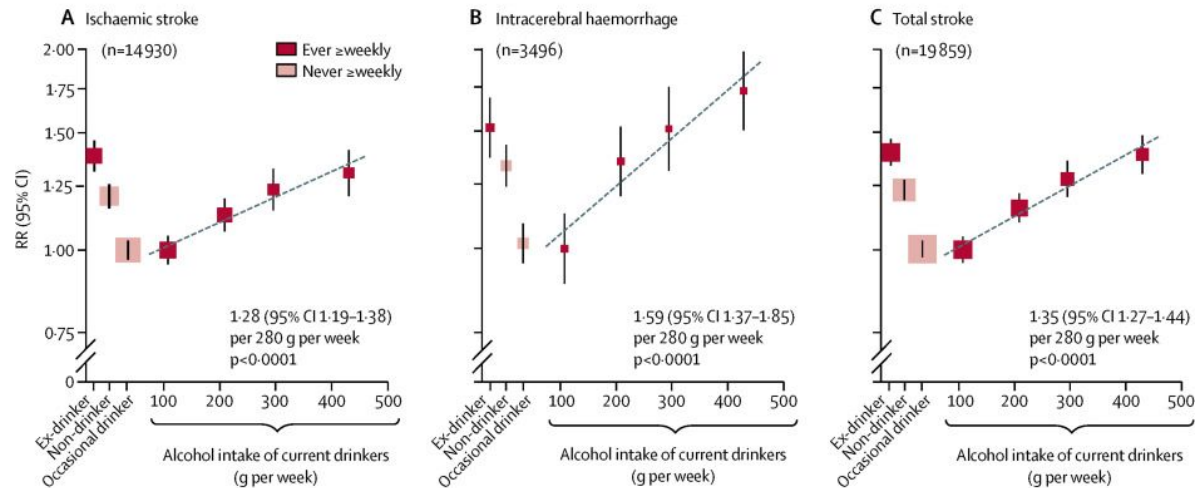
Lawlor et al., (2016) Int. J. Epidemiol. Munafò & Smith (2018) Nature

Mendelian randomisation –natural lottery (RCT)





Conventional epidemiological analyses



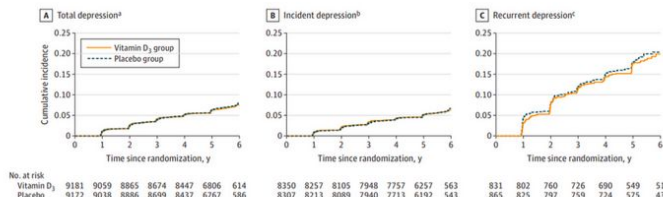


Sek Kathiresan MD ✓ @skathire · Aug 5

Observational studies: Vitamin D supplementation associated with improvement of every disease under the sun

Hundreds of millions of \$ of Vitamin D randomized controlled trials: NO

Below latest: Vitamin D and depression in 18,000 people.



Effect of Vitamin D3 Supplementation vs Placebo on Risk of Depression...

This randomized clinical trial compares the effects of vitamin D₃ supplementation vs placebo on depression risk and mood scores in me...

jamanetwork.com

13

77

188



george davey smith

@mendel_random

Yet another example of when RCT and Mendelian randomization data triangulate to give a clear answer in an area where conventional naive observational epidemiology has delivered a mass of conflicting and confusing evidence. Viva triangulation! [nature.com/articles/d4158...](https://www.nature.com/articles/d4158...)



Martijn Katan @martijnkatan · Aug 5

It's final: vitamin D does not reduce risk of depression or mood changes. Doctors at Harvard compared vitamin D with placebo in 18 000 people for 5 years, and found no effect. Earlier trials and Mendelian randomization studies also found no effect. [jamanetwork.com/journals/jama/...](https://jamanetwork.com/journals/jama/)

2:22 PM · Aug 5, 2020 · [Twitter for iPhone](#)

60 Retweets and comments 165 Likes

Interesting experiments

- Education causes higher short-sightedness and better cardiovascular health
- Obesity causes personality, cognition, and brain structure. Some effects in reverse
- Coffee has negative impact on cardiovascular health
- Low birth weight causes mental disorders
- Schizophrenia likely causes cannabis use

<https://www.bmj.com/content/358/bmj.j3542>

<https://www.nature.com/articles/s41366-021-00885-4> ; <https://onlinelibrary.wiley.com/doi/full/10.1111/desc.13392>

<https://www.bmj.com/content/361/bmj.k2022>

<https://novaator.err.ee/1608082954/varske-uuring-toob-valja-kohvi-kahjuliku-moju>

<https://www.cambridge.org/core/journals/the-british-journal-of-psychiatry/article/contribution-of-birth-weight-to-mental-health-cognitive-and-socioeconomic-outcomes-twow-sample-mendelian-randomisation/66F6555503E55EC367B285DD04912250>

<https://jamanetwork.com/journals/jamapsychiatry/article-abstract/2772632>

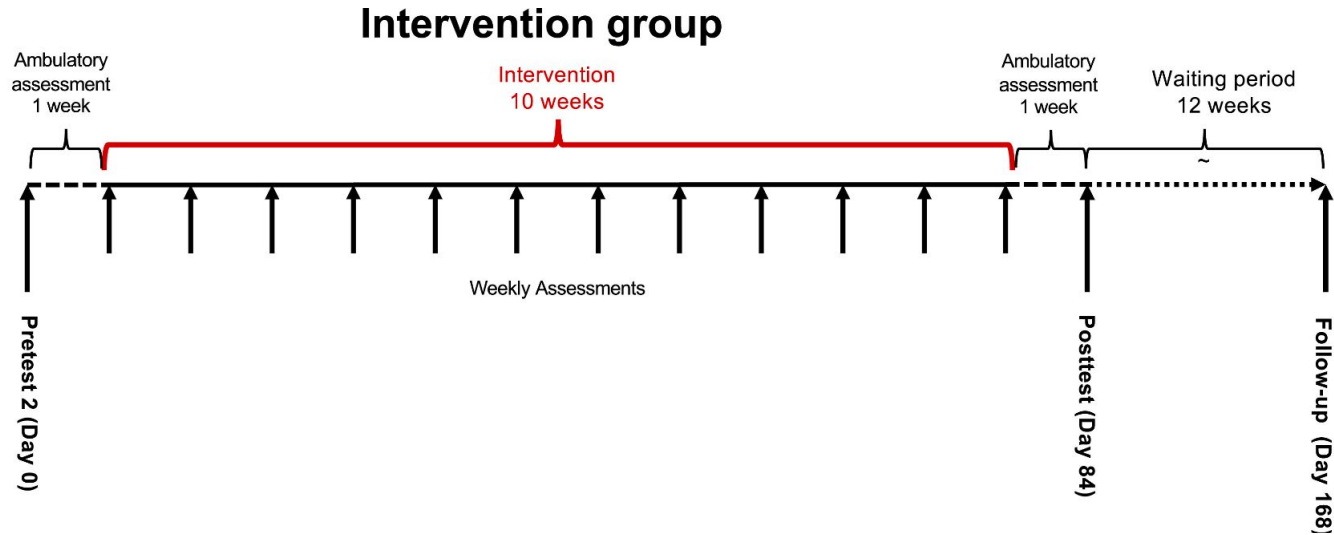
Table S38: Results of putatively causal Mendelian randomization tests

			Mendelian Randomization Estimator		
Direction	Exposure	Outcome	Weighted median	MR-CAUSE	Weighted mode
Personality -> Biobehavioral outcome	Extraversion	Age at first sex	-.15 (-.09, -.20)	-.06 (-.10, -.02)	-.15 (-.04, -.27)
		COVID infection	.16 (.09, .24)	.09 (.04, .13)	.15 (-.07, .36)
		Drinks per week	.11 (.08, .14)	.07 (.05, .10)	.06, (-.07, .18)
		Spells in hospital	-.09 (-.14, -.05)	-.09 (-.12, -.07)	-.11 (-.30, .07)
		Study part.: IDK	-.04 (-.06, -.01)	-.04 (-.06, .02)	-.05 (-.13, .04)

Biobehavioral Outcome -> Personality	BMI	Agreeableness	-.04 (-.05, -.02)	-.04 (-.06, -.02)	-.06 (-.12, -.00)
		Conscientiousness	-.06 (-.07, -.04)	-.05 (-.08, -.02)	-.05 (-.11, -.00)

Note: MR-CAUSE = Mendelian Randomization Causal Analysis Using Summary Effect estimates. Study Part.: = Study participation. IDK = "I don't know" response. Summary statistics for outcomes are described in Supplementary Table S31. Numbers in parentheses indicate 95% confidence intervals (for weighted median and weighted mode tests) or 95% credible intervals (for MR-CAUSE tests). Bolded numbers indicate 95% confidence/credible interval excludes 0. Results presented here only include exposure-outcome pairs where the 95% credible interval/confidence interval for at least 2 out of 3 tests excludes zero, and all three tests produce estimates in the same direction.

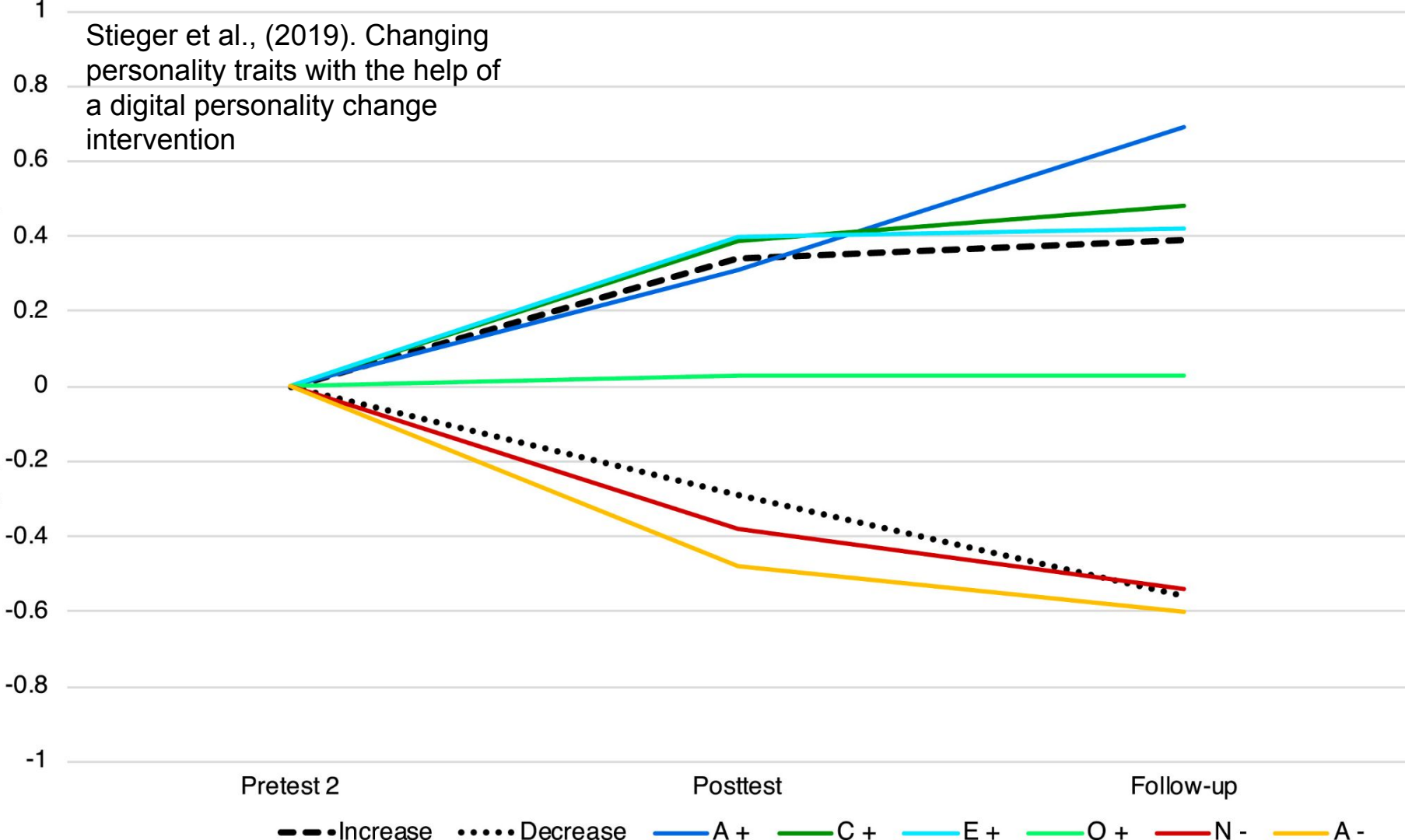
How to change personality? With an app!



Stieger et al., (2019). Changing personality traits with the help of a digital personality change intervention

Stieger et al., (2019). Changing personality traits with the help of a digital personality change intervention

Change (in Standard Deviations)





<https://www.scoutnetworkblog.com/10-characteristics-of-a-professional-plumber/>

Personality Profiles of 263 Occupations

While HR testing common, public norms are missing

ISCO / Onet mapped to personality

2-7% Big Five variance, 12% nuance variance

84



Neuroticism

Highest-scoring jobs			
Job	Mean	<i>SD</i>	<i>N</i>
Actors	57.94	10.97	63
Visual Artists	55.06	9.60	208
Graphic and Multimedia Designers	54.76	10.86	232
Musicians, Singers and Composers	54.03	9.81	188
Translators, Interpreters & Other Linguists	53.97	11.29	313
Authors & Rel. Writers	53.96	11.82	41
Journalists	53.87	11.28	219
Web & Multimedia Developers	53.82	11.25	38
Handicraft Workers	53.52	12.22	80
Broadcasting & Audiovisual Technicians	53.49	9.42	67

Extraversion

Highest-scoring jobs			
Job	Mean	<i>SD</i>	<i>N</i>
Advertising & Public Relations Managers	55.11	9.19	136
Actors	55.01	10.13	63
Conference & Event Planners	54.83	8.71	29
Fitness & Recreation Instructors & Programme Leaders	54.78	8.39	29
Sports, Recreation & Cultural Centre Managers	54.55	8.72	84
Sales & Marketing Managers	54.29	9.91	1000
Human Resource Managers	54.17	9.45	362
Child Care Services Managers	53.98	8.70	97
Training & Staff Development Professionals	53.69	9.28	216
Restaurant Managers	53.60	10.03	80

Openness

Highest-scoring jobs			
Job	Mean	<i>SD</i>	<i>N</i>
Visual Artists	58.52	9.53	208
Language Teachers	57.04	10.76	87
Authors & Rel. Writers	56.89	8.72	41
Psychologists	56.47	8.98	245
University & Higher Education Teachers	56.18	9.44	1000
Research Professionals N.E.C.	56.07	9.40	70
Actors	55.66	8.81	63
ICT Services Managers	55.56	10.33	172
Religious Professionals	55.56	9.64	29
Secondary Education Teachers	55.40	9.64	45

Agreeableness

Highest-scoring jobs			
Job	Mean	<i>SD</i>	<i>N</i>
Electronics Engineers	55.71	9.81	50
Web & Multimedia Developers	54.63	8.91	38
Psychologists	54.34	9.87	245
Religious Profs	54.11	10.44	29
Health Profs N.E.C.	53.36	11.18	59
Audiologists and Speech Therapists	53.16	9.49	122
Child Care Services Managers	53.06	10.04	97
Software Developers	52.96	10.16	876
Research Profs N.E.C.	52.61	9.38	70
Garment Patternmakers/ Cutters	52.60	9.38	68

Conscientiousness

Highest-scoring jobs			
Job	Mean	<i>SD</i>	<i>N</i>
Ships' Engineers	53.90	8.50	40
Dental Assistants & Therapists	53.68	11.70	25
Construction Managers	53.45	9.12	108
Finance Managers	53.42	8.99	393
Health Profs (unsp.)	53.25	9.47	140
Sheet Metal Workers	53.07	10.43	34
Chefs	52.94	10.03	115
Ships' Deck Crews & Rel. Workers	52.84	9.79	40
Ships' Deck Officers & Pilots	52.66	7.96	134
Unsp. Deputy Managers	52.66	8.51	161

Apps

<https://apps.psych.ut.ee/JobProfiles/>

www.whichjob.me



Show entries

Search:

	Code	Job	N	Neuroticism (M)	Extraversion (M)	Openness (M)	Agreeableness (M)	Conscientiousness (M)
159	2120	Mathematicians, Actuaries and Statisticians	106	49.82	46.98	52.62	51.1	47.98

Showing 1 to 1 of 1 entries (filtered from 263 total entries)

Previous

1

Next

1. Psychologist
2. Religious professional
3. Health professional
4. Research professional
5. Uni teacher
6. Database & network specialist
7. Language teacher
8. ICT service management
9. Aircraft pilot
0. Training & staff development



1. Painter
2. Plumber
3. Pre-press technician
4. Manufacturing labourer
5. Sales worker
6. Transport & storage labourer
7. Assembler
8. Electric & electronic equipment assembler
9. Operator
10. Mail carrier & sorter

Summary

- Personality ties to many health & life outcomes
 - More so than demographics
 - Useful for predictions & personalised messages
- Those ties become stronger when combining multiple information sources
- Personality genetics widen the outcomes further
- Personality has causal impact on health and behaviour.
 - Some associations also in reverse
- Practical app - whichjob.me
- Reach out: uku.vainik@ut.ee
- <https://bsky.app/profile/ukuvainik.bsky.social>

