

Advancing Nutrition Research Through Systems Epidemiology

The National Academies of
Sciences • Engineering • Medicine

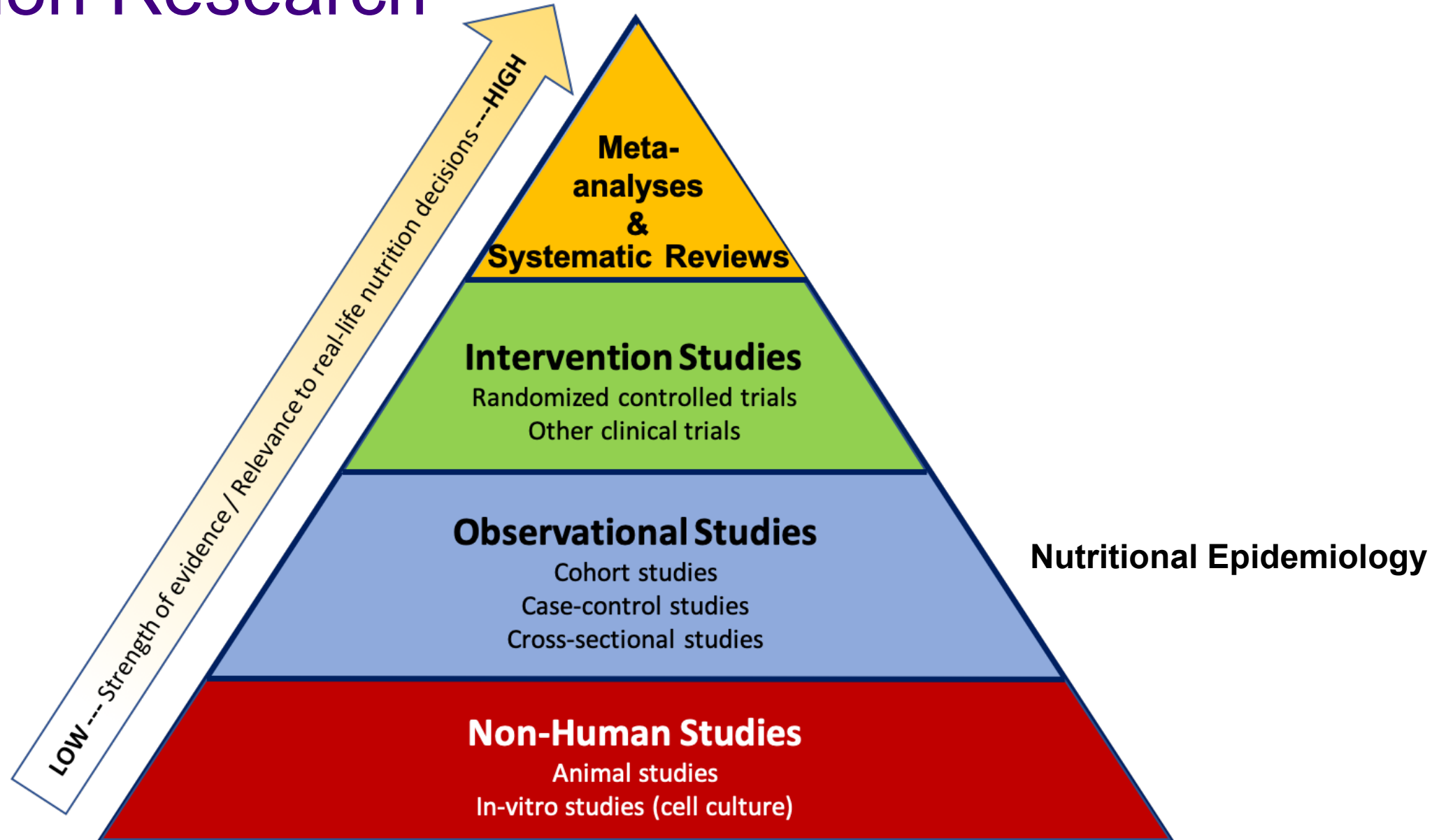
Marilyn Cornelis, PhD

No Disclosures

Today's Talk

1. Traditional vs Systems epidemiology
2. Applied systems epidemiology & nutrition
3. Future: Personalized nutrition research

Nutrition Research



Limitations of Nutritional Epidemiology

- Classical limitations (measurement error, confounding)
 - Subjective diet data collection
 - Limitation in food composition tables
 - Unclear diet-disease temporal relationship
- Complex nature of diet (chemicals, foods, diet patterns)
 - Food matrix interactions (vitamin C & iron, fiber & carotenoids, cooking)
- Variation in dietary intake and physiological exposure
 - within-person, between-person, between-populations
- No insight to causality or mechanisms

the “OMICS”

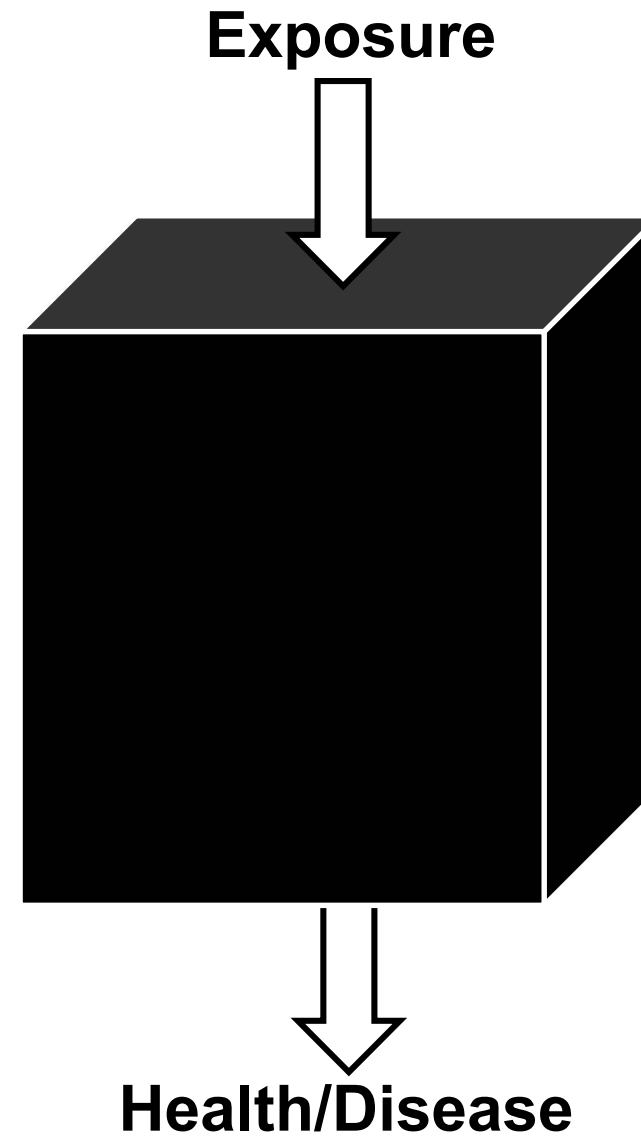
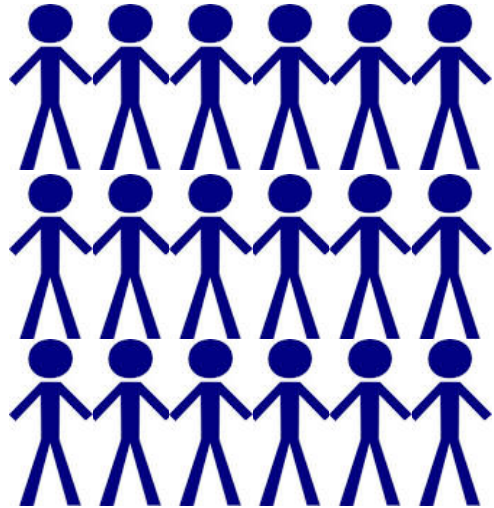


The collective technologies used to explore the roles, relationships, and actions of the various types of molecules that make up the cells of an organism

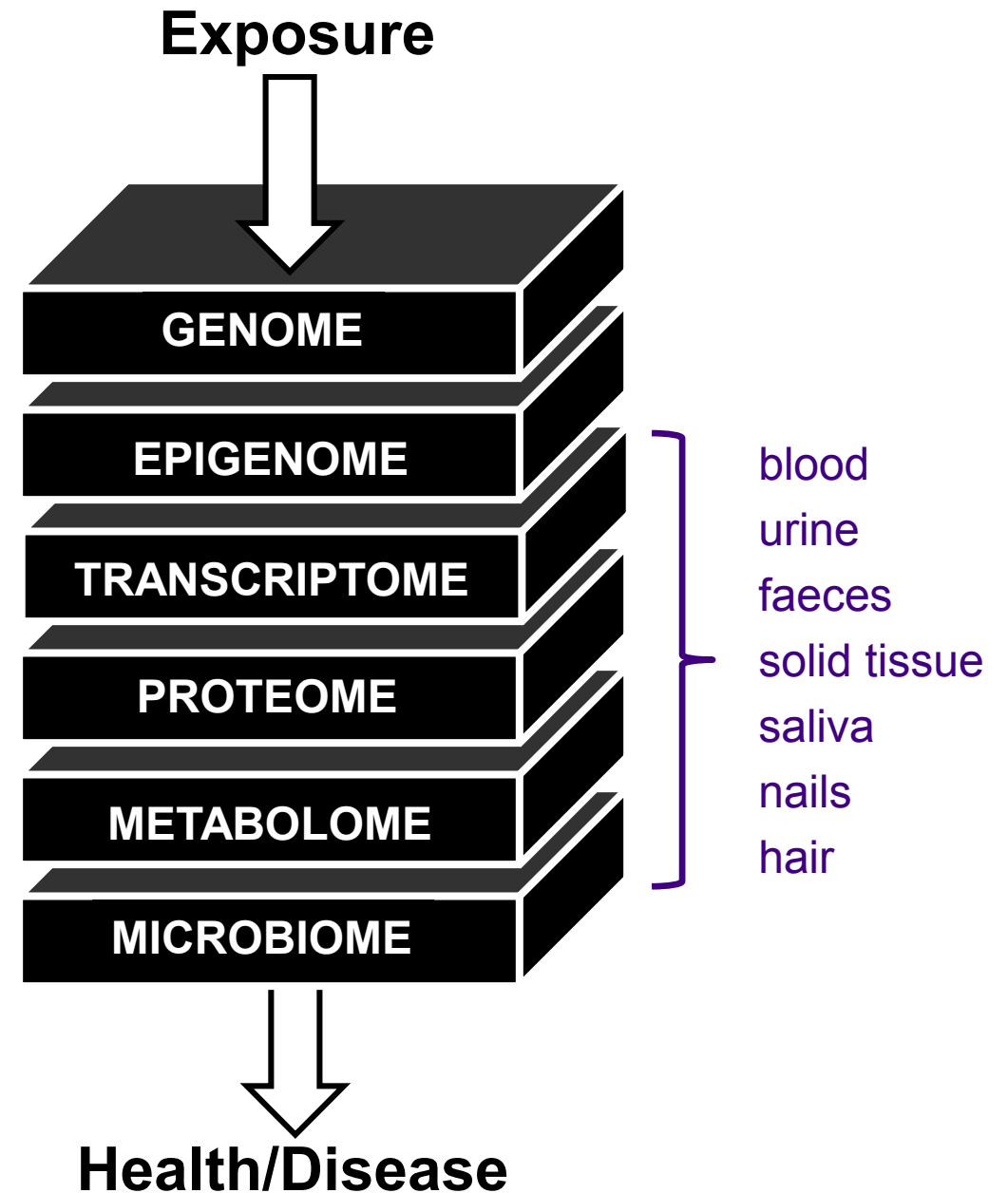
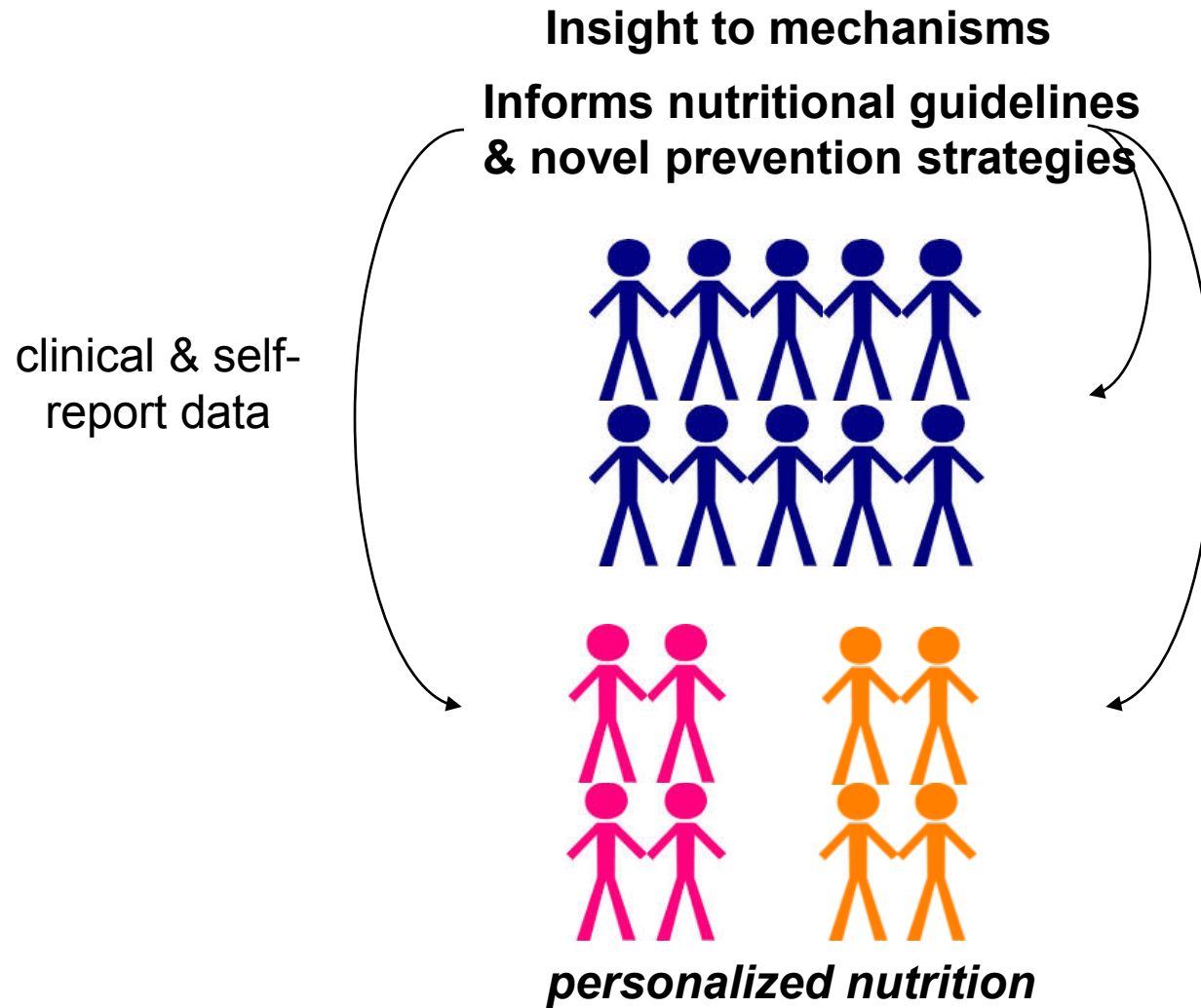
high-throughput
‘global view’
hypothesis generating

Traditional Epidemiology

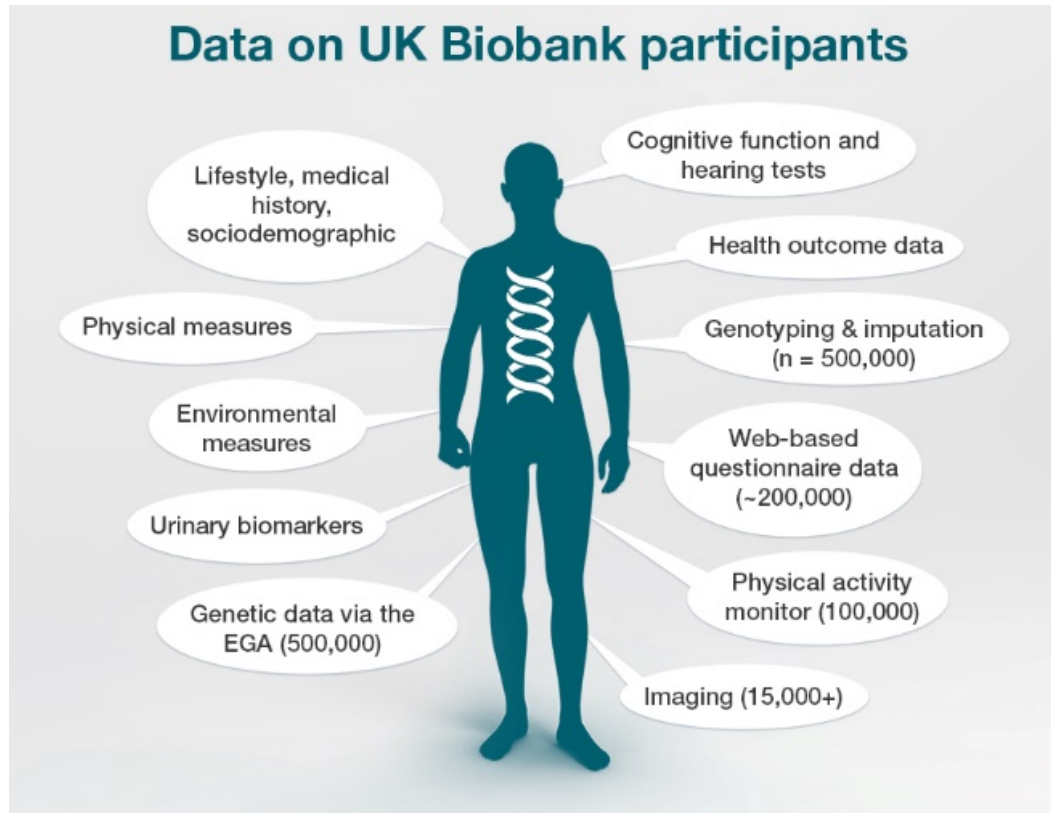
clinical & self-report data



'Systems' Epidemiology



2006-2010



500,000+ participants aged 37-73 y 22 centers across England, Wales and Scotland

touchscreen questionnaires on sociodemographic factors, lifestyle and medical history

in-person questionnaire, physical assessment, and biospecimen collection

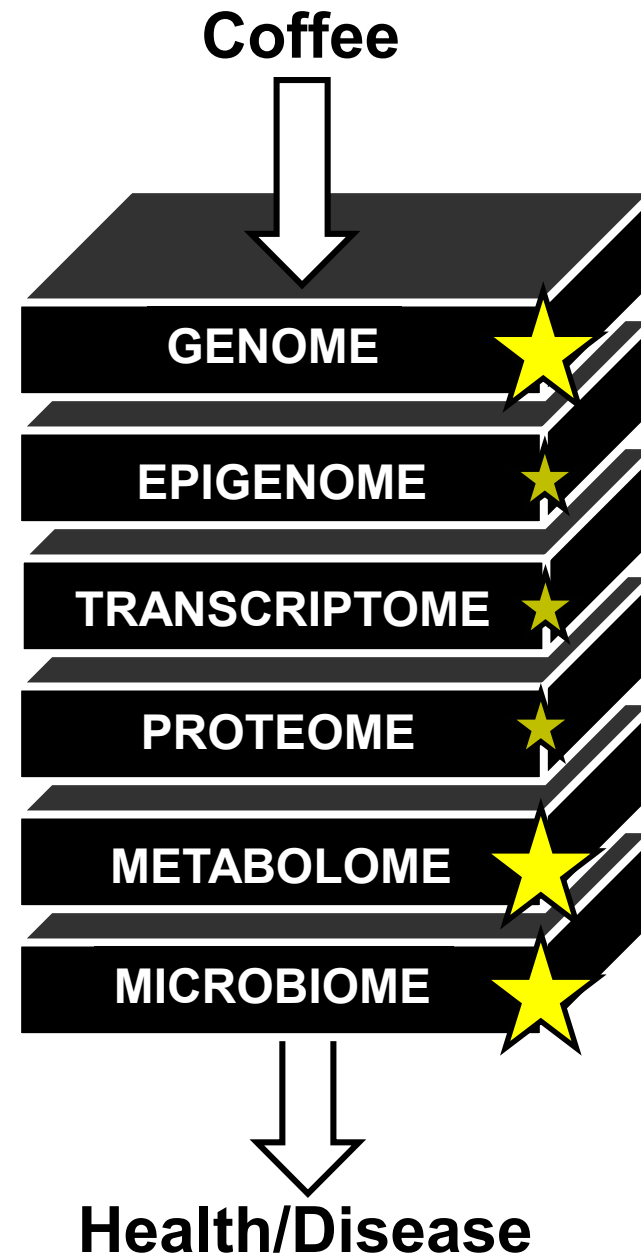
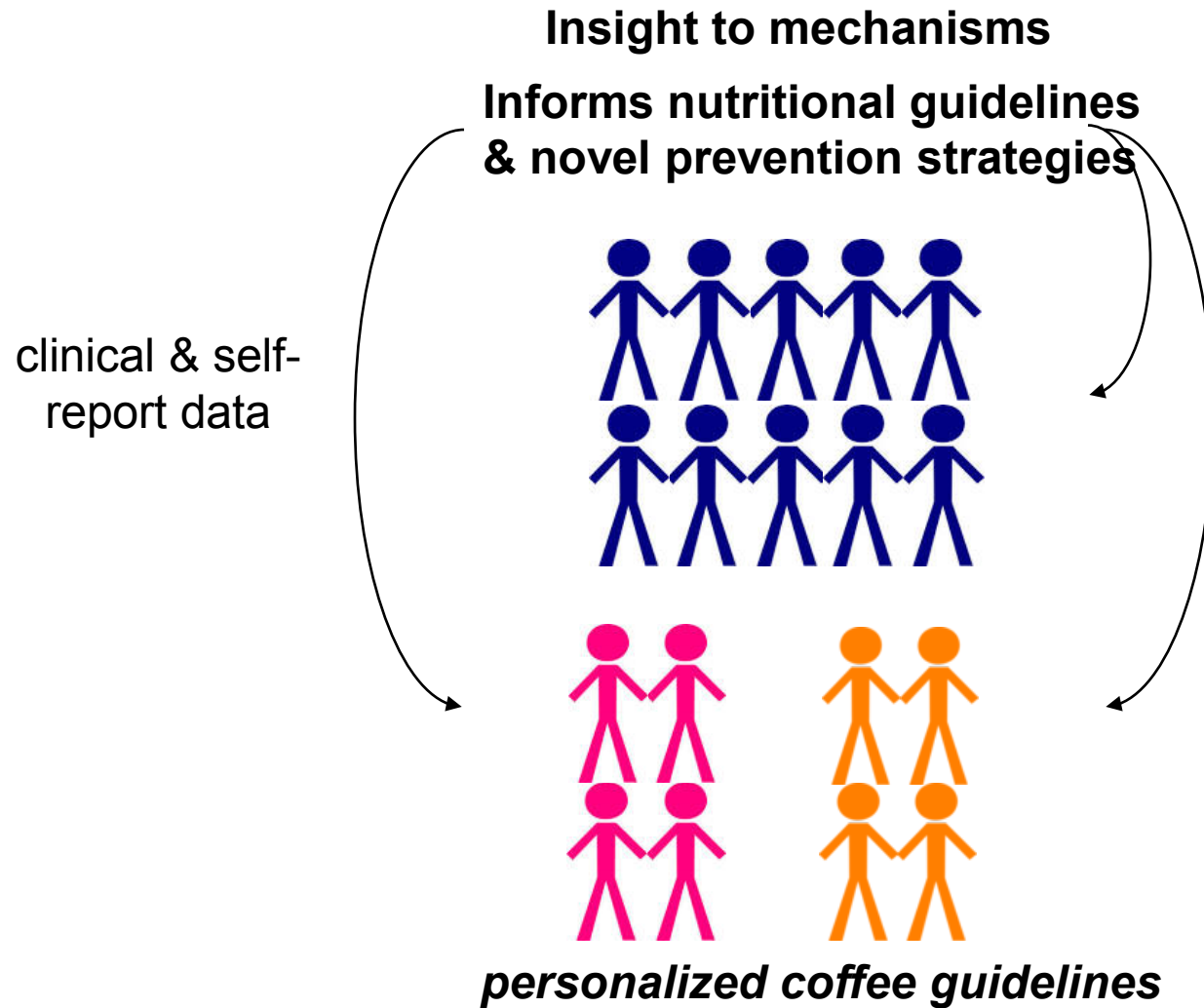
on-line data collection

continued follow-up

Proteomics
Transcriptomics
Metabolomics
Genomics

Figure sources: <https://www.ebi.ac.uk/about/news/feature-story/biobanks-genetic-data-demand>
Naomi Allen, Senior Epidemiologist, UK Biobank (July 2017)

'Systems' Epidemiology



Key Themes from Observational Studies of Coffee and Health

Poole et al, BMJ 2017

All cause mortality
CVD-mortality
Incident CVD

Beneficial: Greatest risk reduction with 3 to 5 cups/d

Cancer

Increased risk for lung cancer

No relationship or dose-response risk reduction for other cancers

Liver and gastrointestinal outcomes

Metabolic disease

Neurological outcomes

Beneficial: dose-response risk reduction

Antenatal exposure to coffee: **No relationship or increased risk**

Musculoskeletal outcomes

Potential risk among women but not men

Renal outcomes

Gynecological outcomes

No relationship

Good news: It's totally fine to drink lots (and lots) of coffee. The government just said so



Old guideline: Not addressed.

2015 guideline: Up to 5 cups a day.

Measuring Coffee Intake





black
60-90

green
35-70

← mg/8oz →

arabica
100-170

robusta
185-265

caffeine

catechins
theaflavins
tannins
l-theanine

caffeine

chlorogenic acids
melanoidins
trigonelline
diterpenes

Individuals vary in their physiological exposure and response to coffee

Exposure: absorption, distribution, metabolism, excretion

caffeine: $T_{1/2}$ of 2-12 hours

pharmacokinetics

Response: i.e psychostimulant effects



pharmacodynamics

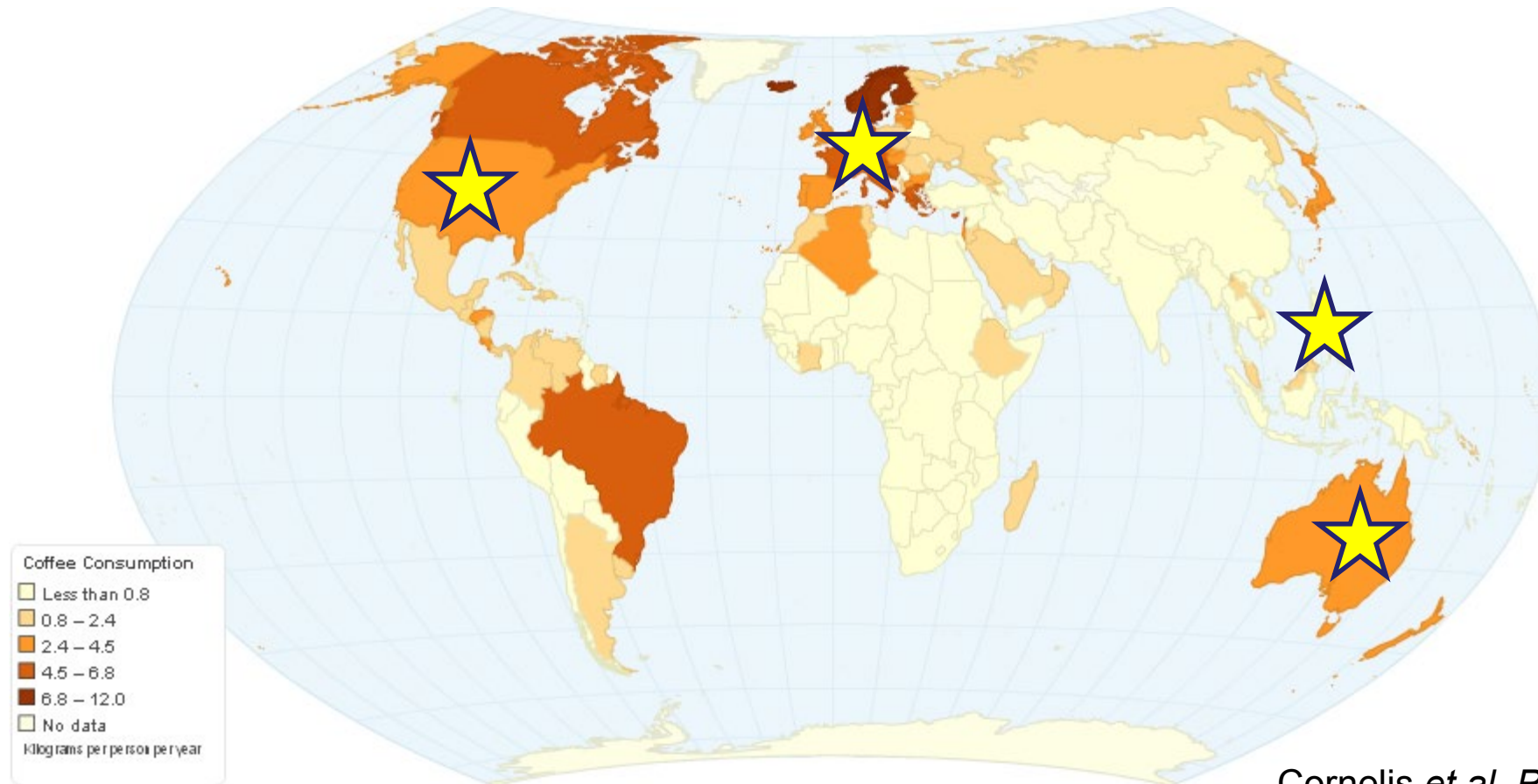
Human Genetics



Genome-wide association study
(GWAS)

GWAS OF COFFEE & CAFFEINE DRINKING BEHAVIOR

GWAS OF CAFFEINE METABOLITES



Cornelis *et al*, *PLoS Genetics*, 2010
Cornelis *et al*, *Mol Psychiatry*, 2015
Cornelis *et al*, *Hum Mol Genetics*, 2016
Nakagawa *et al*, *Scientific Rep*, 2018
Zhong *et al*, *Hum Mol Genetics*, 2019
Jia *et al*, *BMC Genet* 2019

GWAS summary

pharmacokinetics

pleiotropic

pharmacodynamics

pleiotropic

Candidate Gene	Effect of reference allele	
	caffeine metabolites	caffeine & coffee intake
<i>AHR</i>		
<i>CYP1A2</i>		
<i>POR</i>		
<i>CYP2A6</i>		
<i>ABCG2</i>		
<i>GCKR</i>		
<i>MLXIPL</i>		
<i>BDNF</i>		
<i>SLC6A4</i>		
<i>ADORA2A</i>		
<i>OR8U8</i>		
<i>SEC16B</i>		
<i>TMEM18</i>		
<i>MC4R</i>		
<i>AKAP6</i>		

*HUMAN COFFEE DRINKING: MANIPULATION OF
CONCENTRATION AND CAFFEINE DOSE*

ROLAND R. GRIFFITHS, GEORGE E. BIGELOW, IRA A. LIEBSON,
MARY O'KEEFFE, DAVID O'LEARY, AND NASON RUSS

THE JOHNS HOPKINS UNIVERSITY SCHOOL OF MEDICINE

In a residential research ward coffee drinking was studied in 9 volunteer human subjects with histories of heavy coffee drinking. A series of five experiments was undertaken to characterize ad-libitum coffee consumption and to investigate the effects of manipulating coffee concentration, caffeine dose per cup, and caffeine preloads prior to coffee drinking. Manipulations were double-blind and scheduled in randomized sequences across days. When cups of coffee were freely available, coffee drinking tended to be rather regularly spaced during the day with intercup intervals becoming progressively longer throughout the day; experimental manipulations showed that this lengthening of intercup intervals was not due to accumulating caffeine levels. Number of cups of coffee consumed was an inverted U-shaped function of both coffee concentration and caffeine dose per cup; however, coffee-concentration and dose-per-cup manipulations did not produce similar effects on other measures of coffee drinking (intercup interval, time to drink a cup, within-day distribution of cups). Caffeine preload produced dose-related decreases in number of cups consumed. As a whole, these experiments provide some limited evidence for both the suppressive and the reinforcing effects of caffeine on coffee consumption. Examination of total daily coffee and caffeine intake across experiments, however, provides no evidence for precise regulation (i.e., titration) of coffee or caffeine intake.

Key words: coffee, caffeine, drug self-administration, tremor, subjective effects, coffee drinking, humans

How can we use these genetic findings?



risk assessment
intervention design



biological & mechanistic insight



food & drug manufacturing & marketing



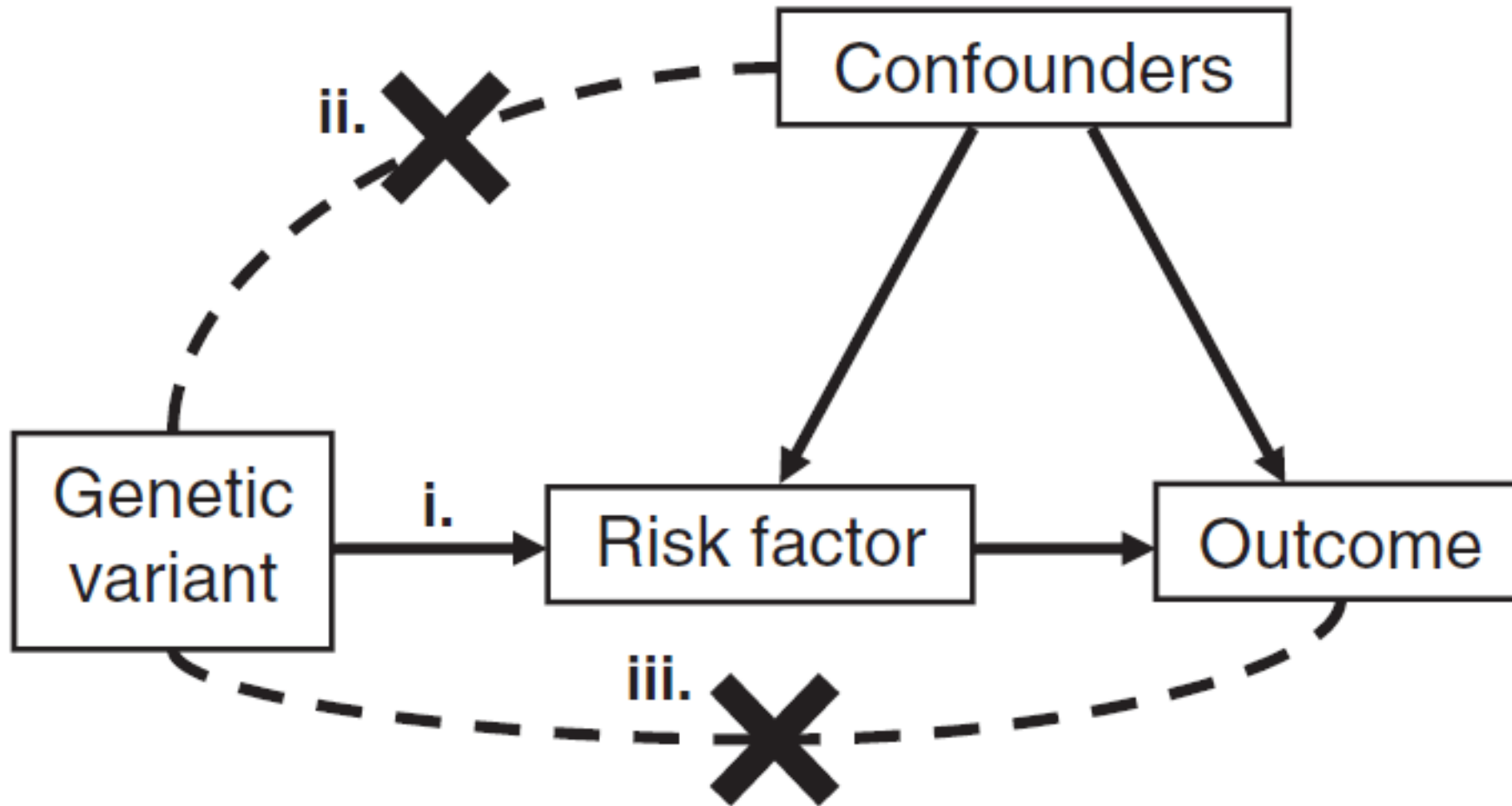
GENETICALLY WIRED

YOUR DNA AFFECTS HOW YOUR BODY REACTS TO CAFFEINE.
GET TESTED WITH [23ANDME.COM](https://23andme.com) TO LEARN ABOUT YOUR LIKELY RESPONSE



Mendelian Randomization

Assumptions



Review

Mendelian Randomization Studies of Coffee and Caffeine Consumption

Marilyn C. Cornelis ^{1,*} and Marcus R. Munafo ²

Applications

- 15+ published MR studies

T2D, CVD, Alzheimer's, Parkinson's, gout, cancers, osteoarthritis, sleep disturbances, substance use

- Most studies provide no consistent support for a causal role

Review

Mendelian Randomization Studies of Coffee and Caffeine Consumption

Marilyn C. Cornelis ^{1,*} and Marcus R. Munafo ²

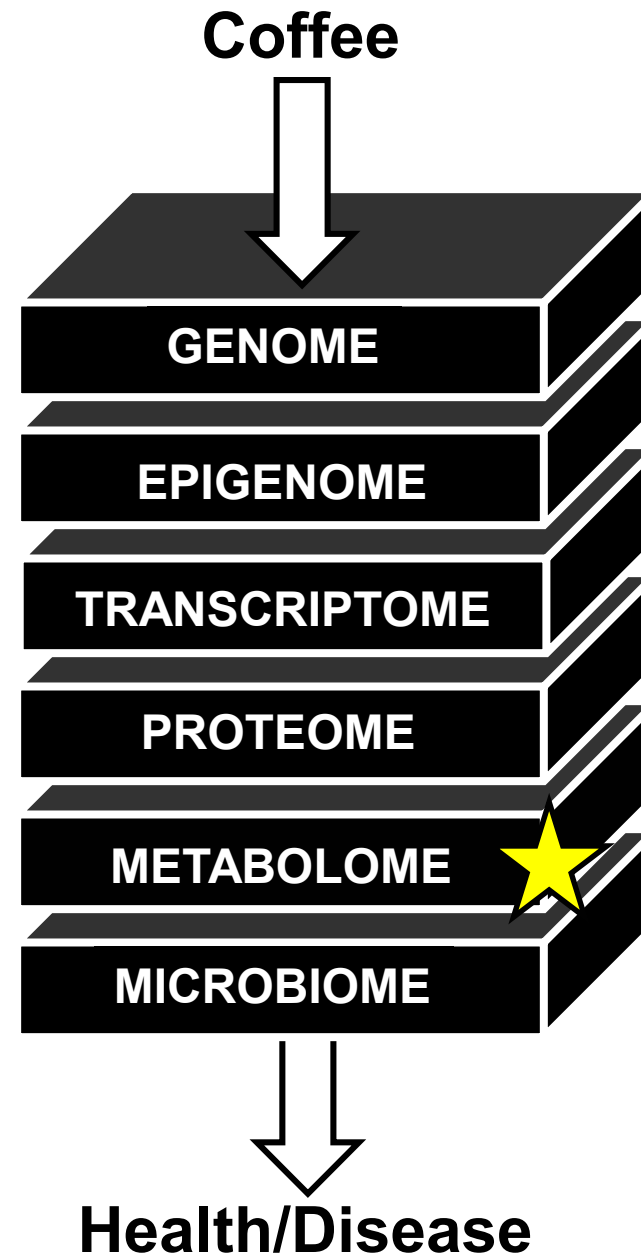
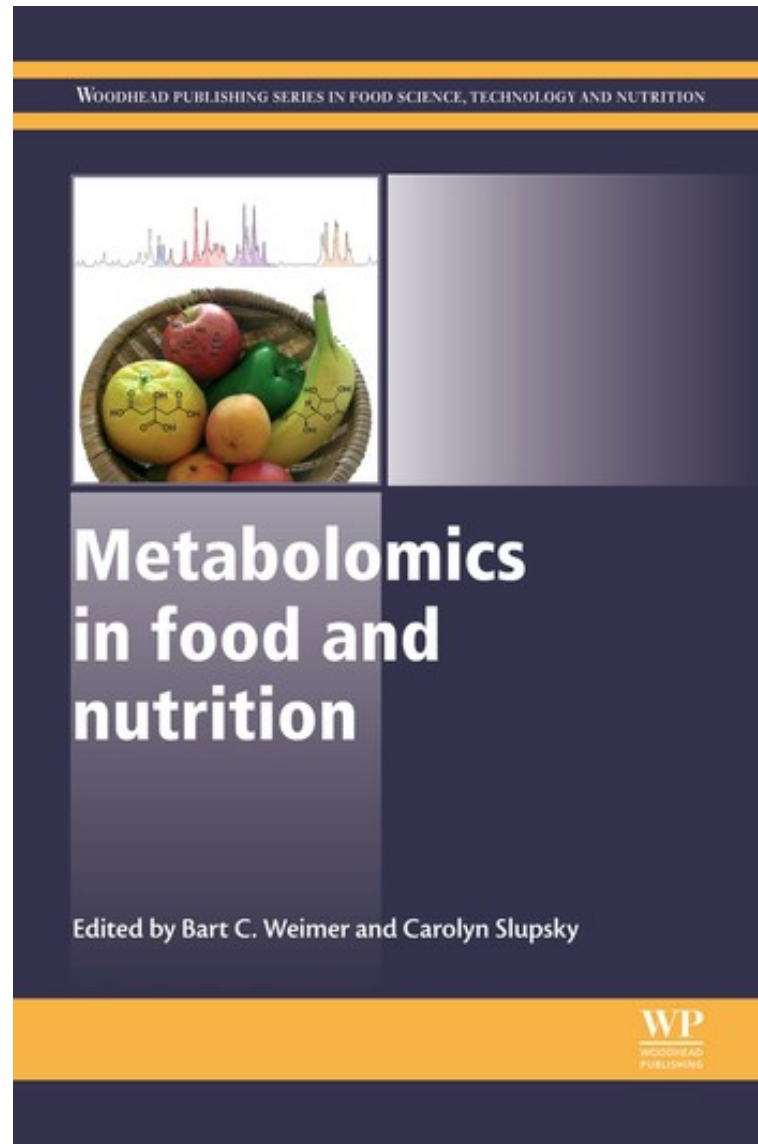
Challenges

- Trait heterogeneity

AHR & CYP1A2 SNPs ↑ caffeine/coffee behavior, ↓ caffeine metabolites
 ↑ decaf coffee (former regular drinkers?)
 ↑ black coffee (*submitted*)
 ↓ sugar sweetened beverages, water (UK Biobank)

- Power
- Pleiotropy
- Others: collider bias, handling potential nonlinear effects, interpretation

'Systems' Epidemiology



Effects of coffee consumption on subclinical inflammation and other risk factors for type 2 diabetes: a clinical trial¹⁻³

Kerstin Kempf, Christian Herder, Iris Erlund, Hubert Kolb, Stephan Martin, Maren Carstensen, Wolfgang Koenig, Jouko Sundvall, Siamak Bidel, Suvi Kuha, and Jaakko Tuomilehto
Am J Clin Nutr, 2010

Characteristics (N=47, high T2D risk)	
age, years	54 (9)
female, n (%)	36 (77)
BMI, kg/m ²	29 (5)
waist circumference, cm	98 (11)
SBP, mm Hg	141 (15)
DBP, mm Hg	90 (9)
current smoker, n (%)	2 (4)
coffee intake, 150-ml cups/d	4 (2)



3-stage clinical trial

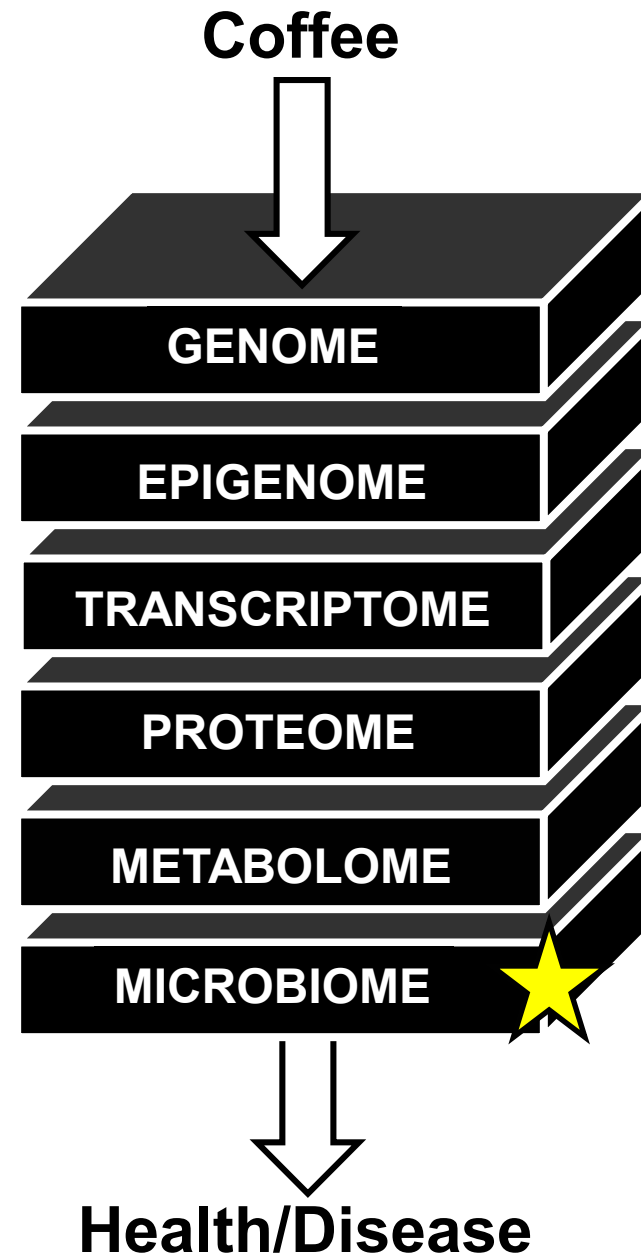
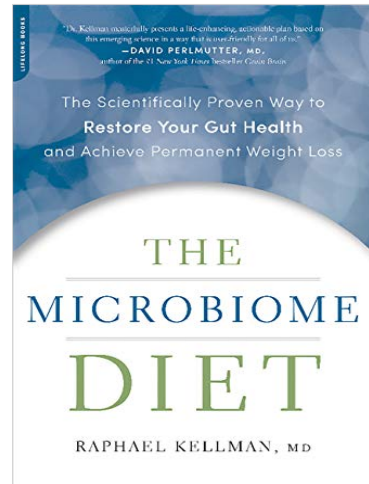
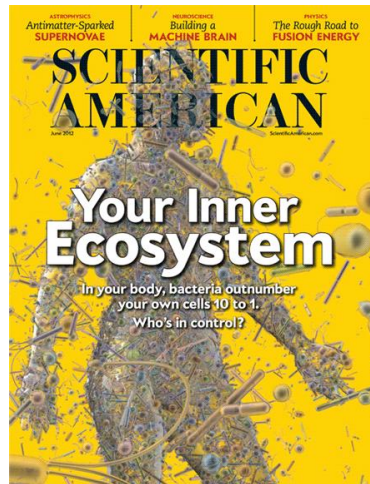
1 month: 0 cups/d (blood draw)
1 month: 4 cups/d (blood draw)
1 month: 8 cups/d (blood draw)

Plasma metabolite profiling (UPLC-MS/MS) → 733 metabolites

Cornelis et al. *J Internal Med* 2016

Pathway	Subpathway		↑	↓
Amino Acid (15)		Creatine Metabolism	2	
		Histidine Metabolism	1	1
		Leucine, Isoleucine and Valine Metabolism	1	
		Methionine, Cysteine, SAM and Taurine Metabolism	2	
		Polyamine Metabolism	2	
		Tryptophan Metabolism	2	1
		Tyrosine Metabolism	1	
		Urea cycle; Arginine and Proline Metabolism		1
Carbohydrate (2)		Aminosugar Metabolism	1	
		Glycolysis, Gluconeogenesis, and Pyruvate Metabolism		1
Cofactors and Vitamins (1)		Nicotinate and Nicotinamide Metabolism	1	
Energy (2)		Oxidative Phosphorylation	1	
		TCA Cycle	1	
Lipid (24)		Diacylglycerol		1
	❖	Endocannabinoid		4
	❖	Fatty Acid Metabolism (Acyl Choline)		6
		Glycerolipid Metabolism		1
		Phospholipid Metabolism		1
		Polyunsaturated Fatty Acid (n3 and n6)		1
		Secondary Bile Acid Metabolism		1
		Sphingolipid Metabolism	1	
	❖	Steroid	3	2
		Sterol	1	1
Nucleotide (4)		Purine Metabolism, (Hypo)Xanthine/Inosine containing	1	
		Purine Metabolism, Adenine containing	1	
		Purine Metabolism, Guanine containing	1	
		Pyrimidine Metabolism, Uracil containing		1
Peptide (2)		Dipeptide Derivative	1	
		Fibrinogen Cleavage Peptide	1	
Xenobiotics (32)	❖	Benzoate Metabolism	9	
		Chemical	3	
		Food Component/Plant	6	
	❖	Xanthine Metabolism	14	
Unknown (34)		Unknown	23*	10*

'Systems' Epidemiology



Population-based metagenomics analysis reveals markers for gut microbiome composition and diversity

N=1135, LifeLines-DEEP (Netherlands)

Stool samples

207 factors (76 diet)

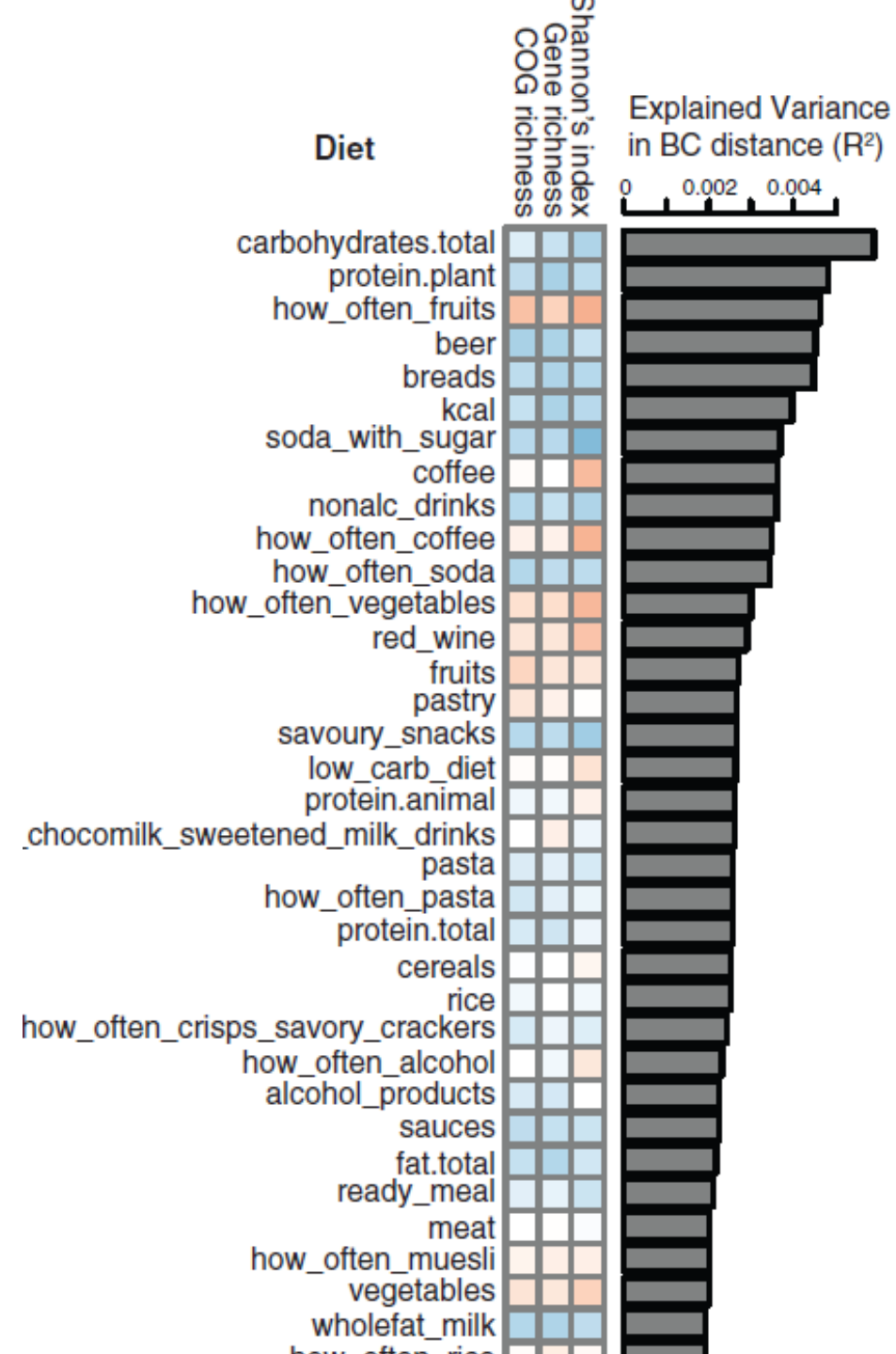
Coffee

Diversity

Lachnospiraceae

Veillonella parvula

Haemophilus parainfluenzae



Personalized (Precision) Nutrition

Develop robust & objective biomarkers of nutrient exposure and response/effect

- validate subjective measures of intake
 - nutritional status & monitoring
 - monitor compliance and individual response
 - improve health prediction models
 - 'tools' for insight to mechanisms linking nutrition to disease
-
- Promote and maintain optimal health!

Nutrition for Precision Health



National Institutes of Health

1



Examine **baseline diet** in an **observational study** followed by a mixed meal challenge test

10,000 *All of Us* participants

2



Examine responses to 3 short-term intervention diets in free-living **controlled feeding** studies

1,000-2,000 Module 1 participants

3



Examine responses to 3 short-term intervention diets in **domiciled controlled feeding** studies

500-1,000 Module 1 participants

In all 3 modules

- Collect microbiome, physiological, metabolic, behavioral, cognitive, and environmental data, and leverage existing genomic, EHR, and survey data, and conduct mixed meal challenges to model the impact of diet and dietary patterns on physiological responses
- Use machine learning and artificial intelligence to develop predictive algorithms

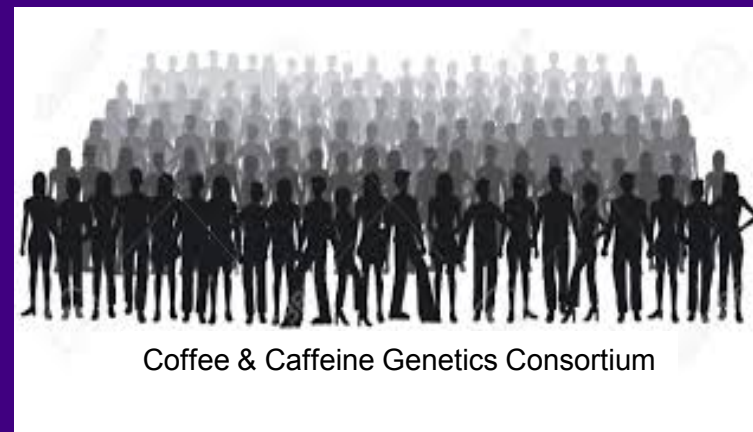
Acknowledgments

Funding

Brain & Behavior Research Foundation
American Diabetes Association
National Institutes of Health (NIDCD, NIA)

Coffee trial collaborators

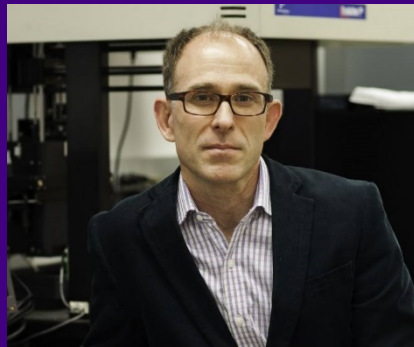
Iris Erlund
Christian Herder
Johan Westerhuis
Jaakko Tuomilehto



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Ahmed El-Sohemy
University of Toronto



Peter Kraft
Harvard



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Nation Univ Singapore