

Deciphering Genetically Influenced Metatypes for Gastric Cancer Risk Stratification and Targeted Primary Prevention

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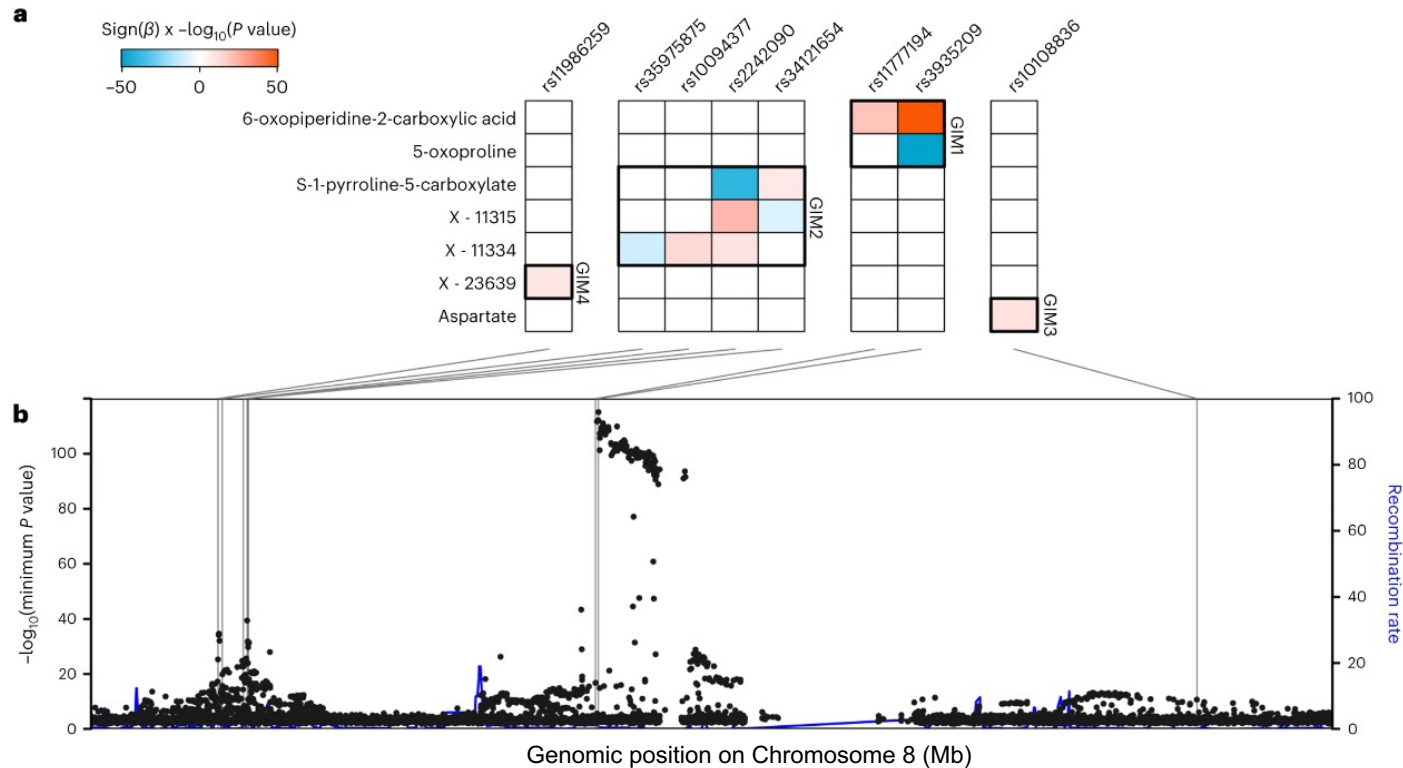


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Genetically influenced metabolotypes (GIMs)

Definition of GIMS

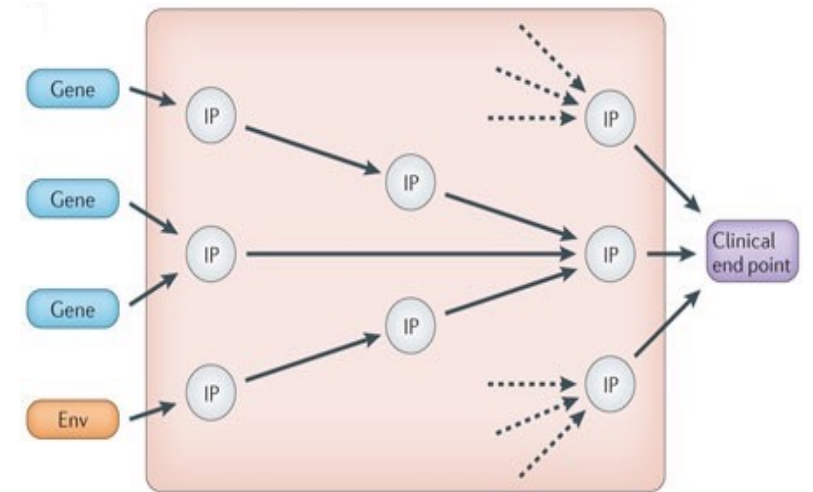
Nat Med 28, 2321–2332 (2022).



Genetically Influenced Metabolotypes (GIMs) are defined by various groups of metabolite quantitative trait loci (mQTLs)

Intermediate phenotypes

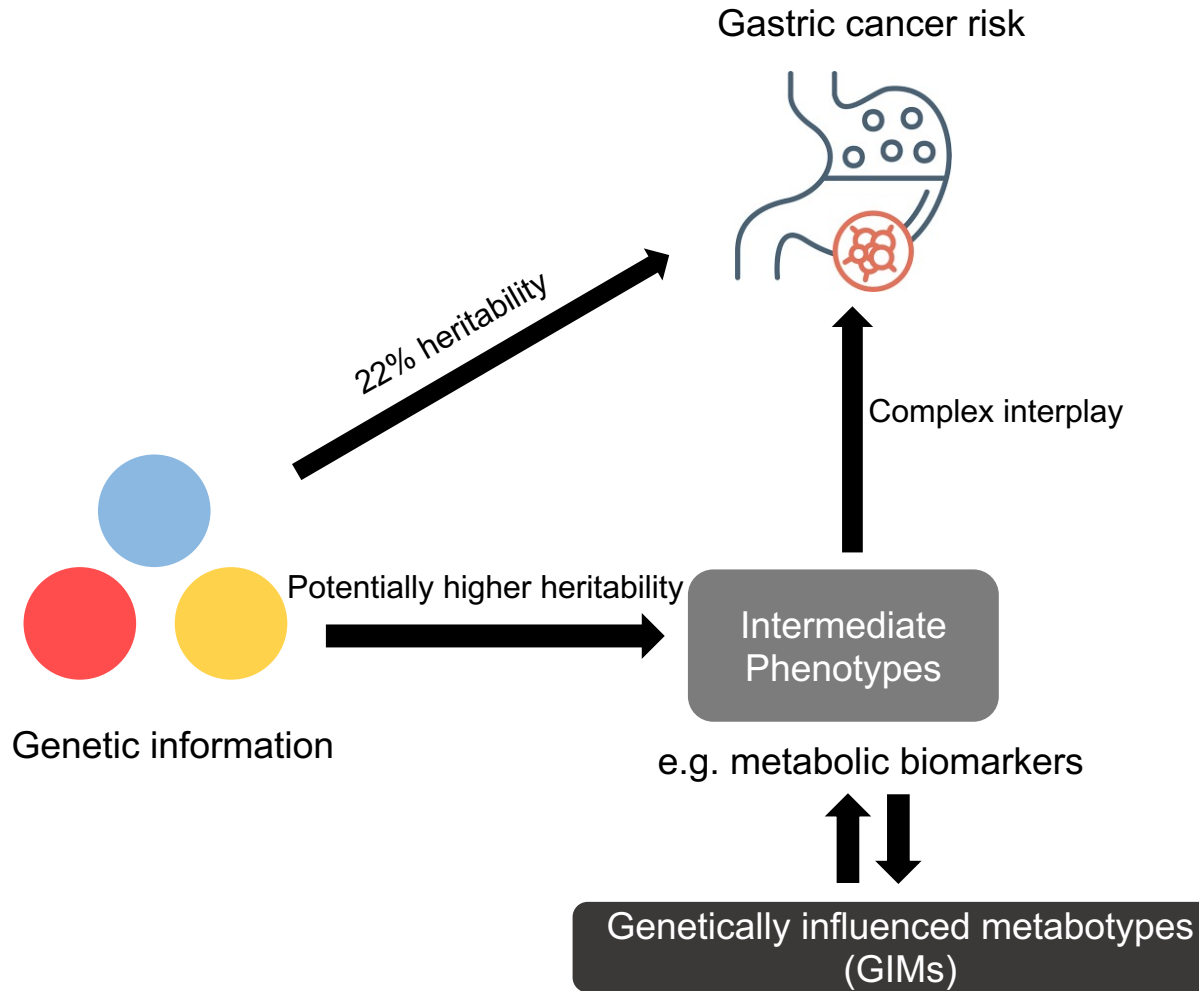
Nat Rev Genet 13, 759–769 (2012).



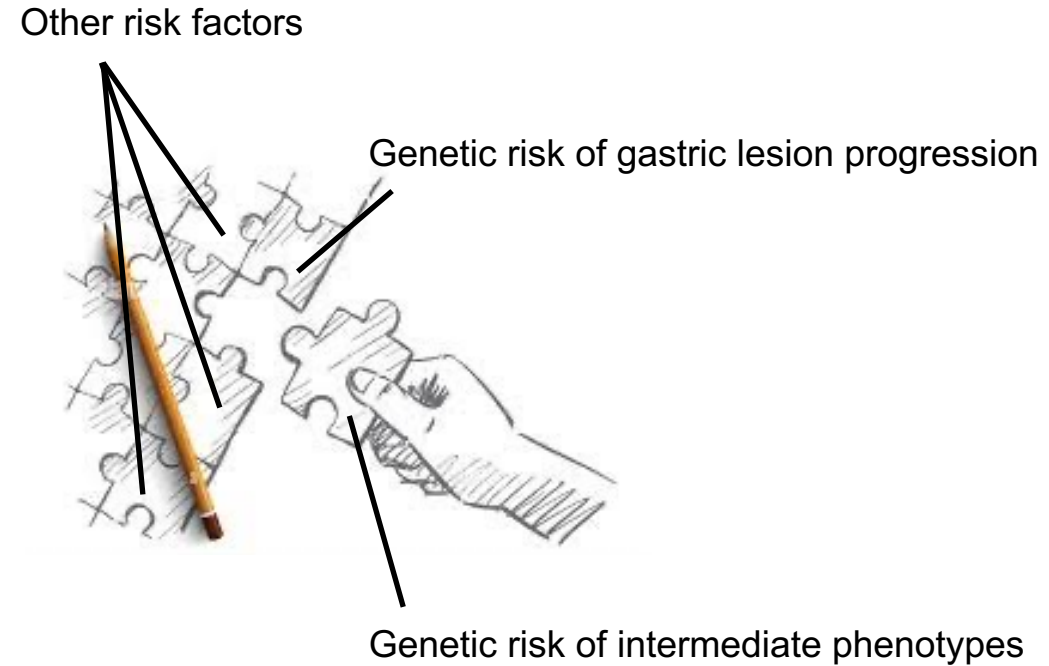
- Metabolic biomarkers are important intermediate phenotypes before diseases occur
- GIMs can be derived from metabolome GWAS

Hum Mol Genet 24(R1):R93-R101 (2015).

A different avenue for gastric cancer risk stratification

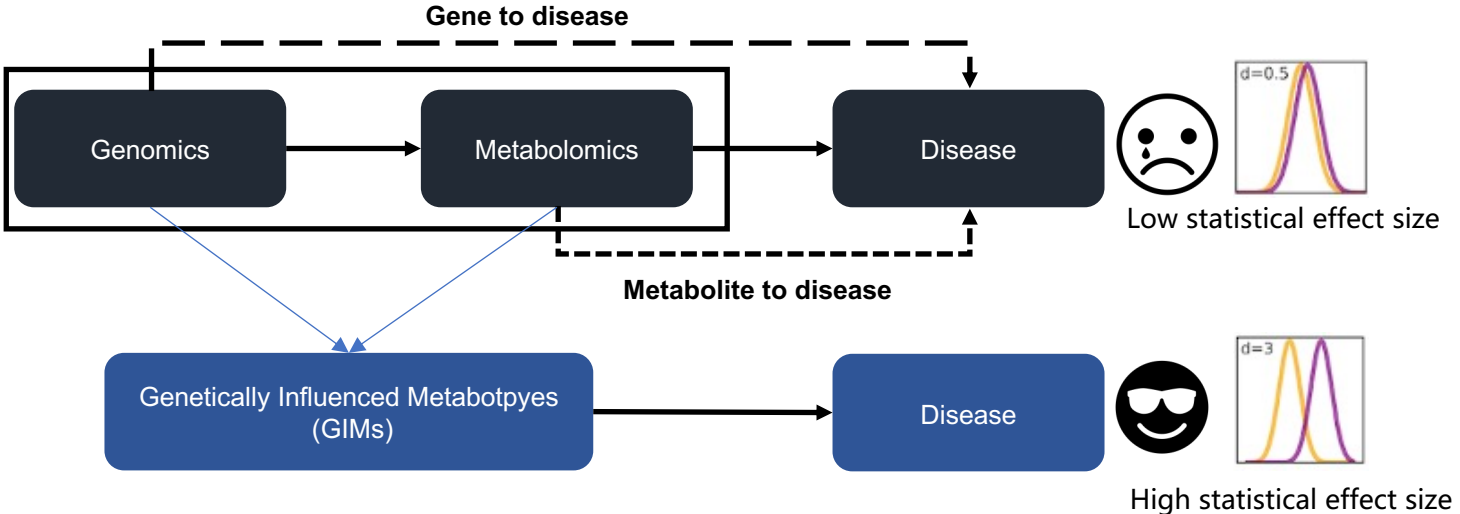


Delineating gastric cancer risk



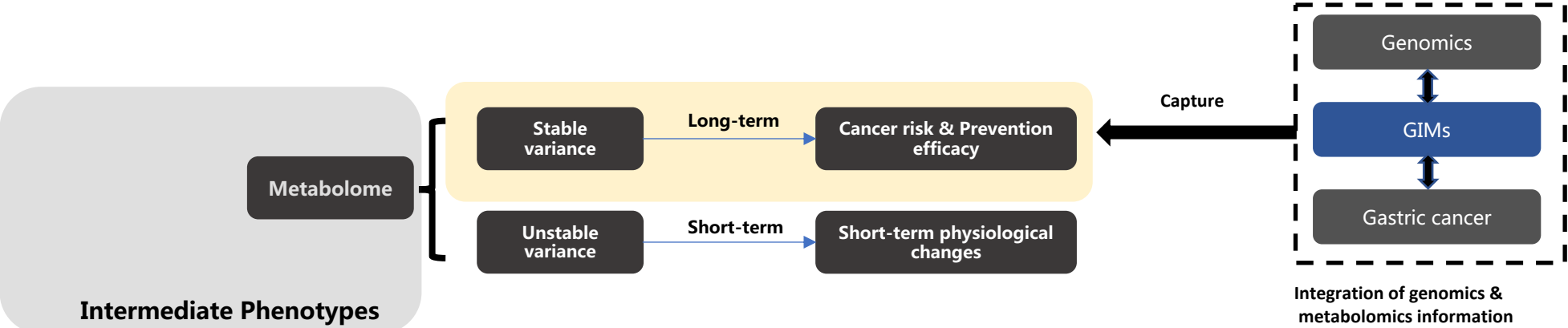
Why GIMs

GIMs may exhibit higher statistical power than traditional disease trait loci



Nat Genet 46, 543–550 (2014)
Nat Med 28, 2321–2332 (2022)

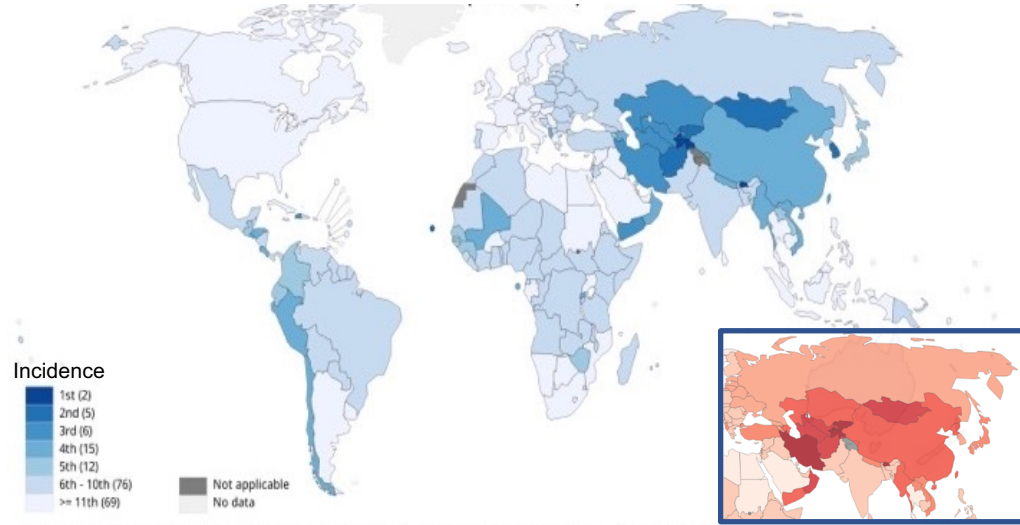
GIMs may capture stable variance of metabolic profiles



Mol Syst Biol., 2011, 7(1): 525.

Gastric cancer

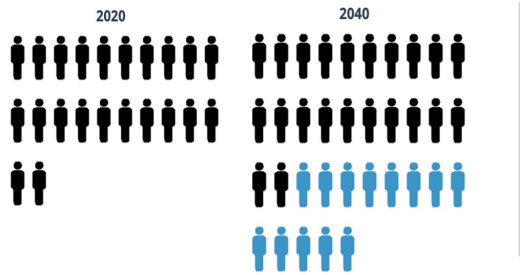
Epidemiologic characteristics



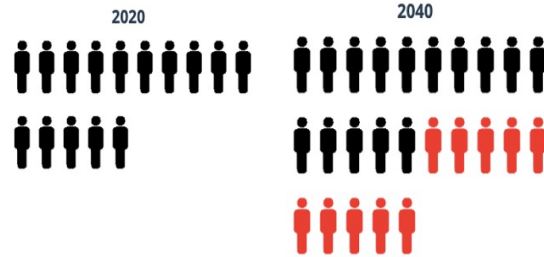
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Data source: GLOBOCAN 2020
Map production: IARC
(http://globocan.iarc.fr/today)
World Health Organization
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Estimated number of new cases



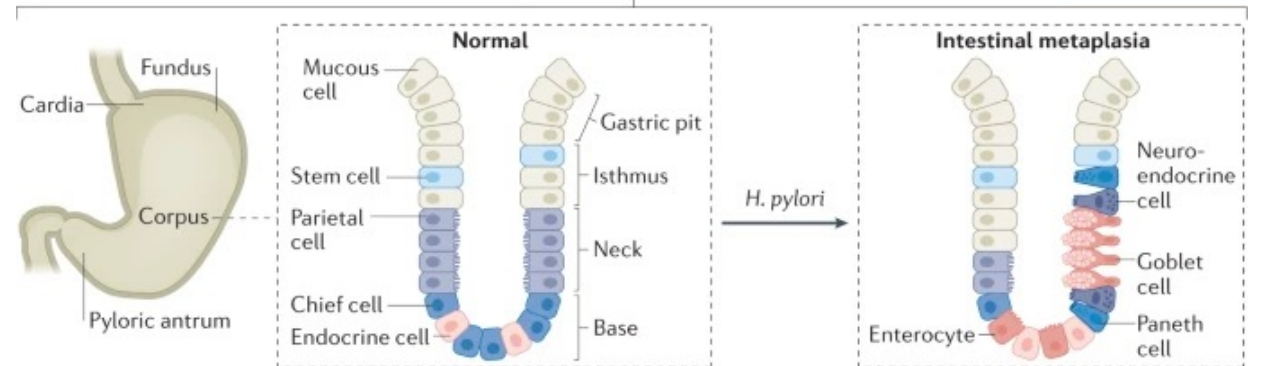
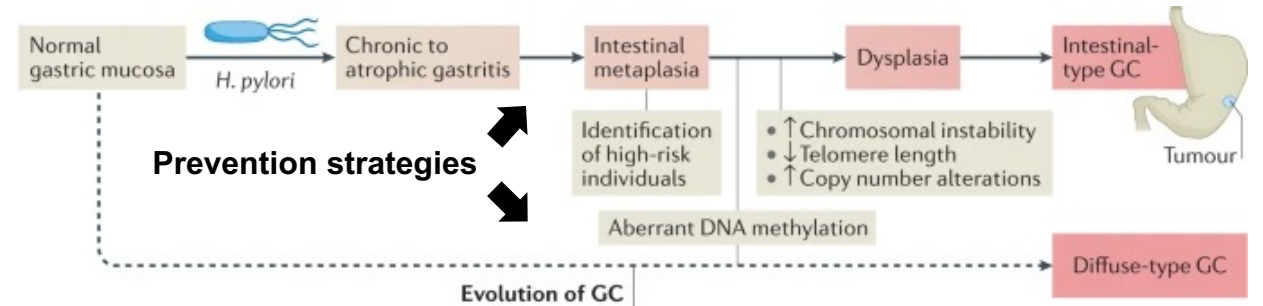
Estimated number of deaths



Risk factors

- *Helicobacter pylori* (*H. pylori*) infection ★
- Smoking
- Alcoholic consumption
- Low intake of fruit & vegetables
- High salt diet
- High intake of red & processed meats

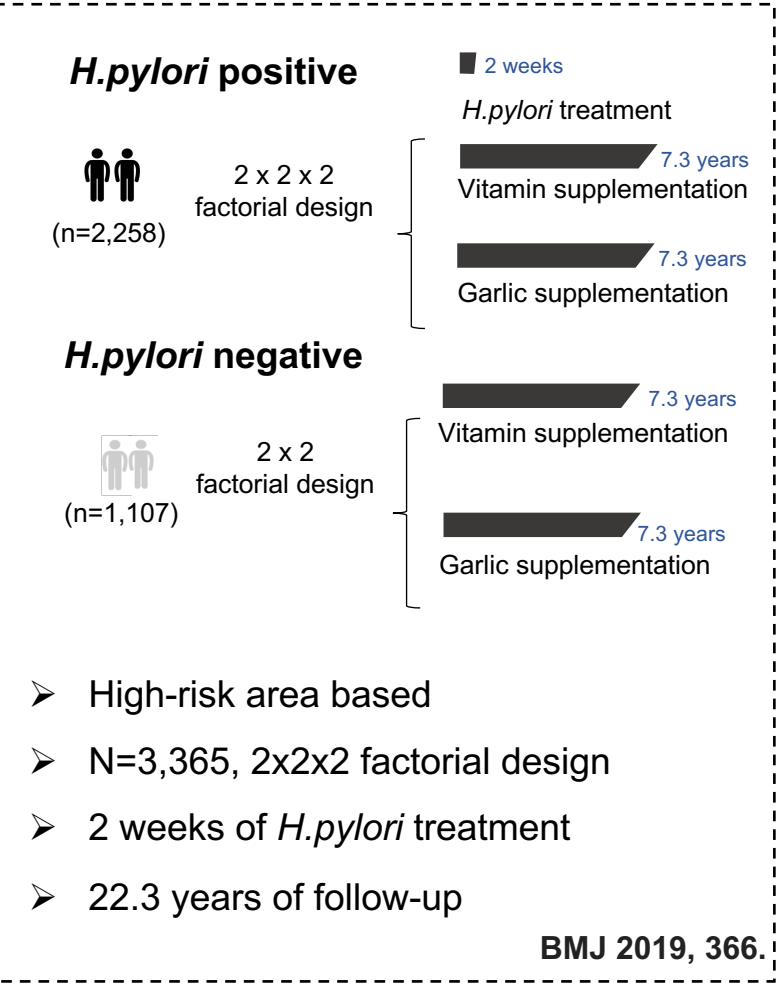
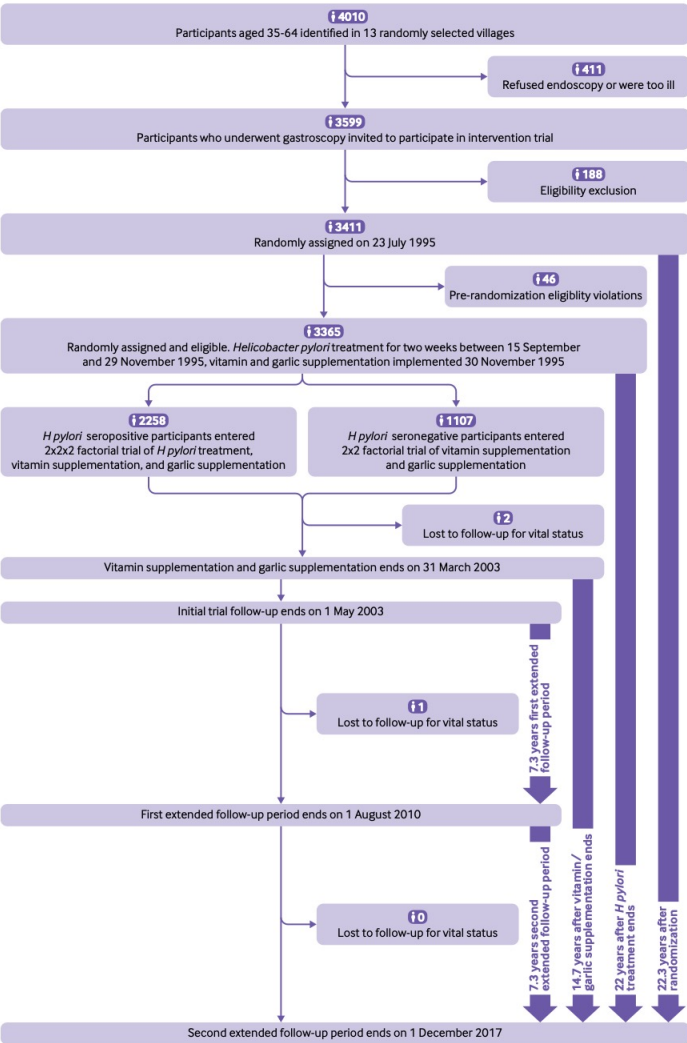
Evolution of gastric cancer (GC)



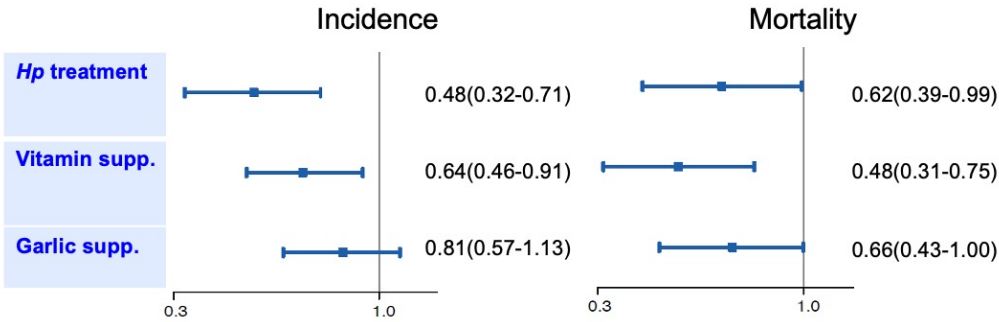
Nature reviews cancer, 22(2), 71-84..

Efforts towards gastric cancer prevention

The Shandong Intervention Trial (SIT) Study



BMJ 2019, 366.



Implications

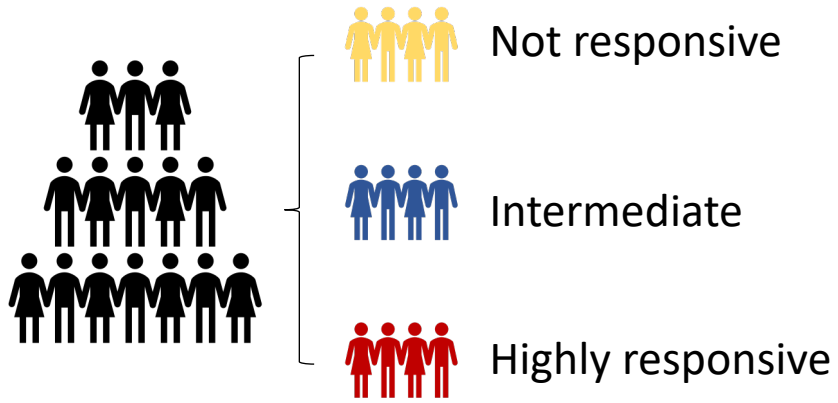
- ✓ *H. pylori* eradication (2 weeks)
- ✓ Vitamin supplementation (7 yrs)
- ✓ Garlic supplementation (7 yrs)

Incidence ↓

Mortality ↓

H. pylori treatment for two weeks and vitamin or garlic supplementation for seven years were significantly associated with a reduced **incidence** of GC, as well as a reduced risk of **death** due to GC for more than **22 years**.

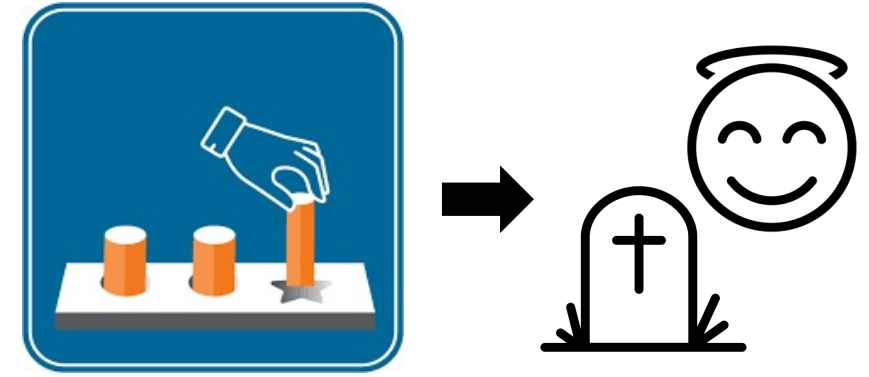
Problems still exist



Not all of the subjects are completely responsive !

e.g.

- There's still a possibility of failure in *H.pylori* eradication.
- Long-term effects of gastric cancer prevention is only evident in certain subgroups.



“One-size-fits-all” prevention strategies



Fine-tuned personalized prevention strategies



- Under high risk of gastric cancer
- Benefits most from prevention

Identification of the target population

Research aim

Profile and identify the high-risk target population that might benefit most from early interventions

What kind of profiles are we going to depict?

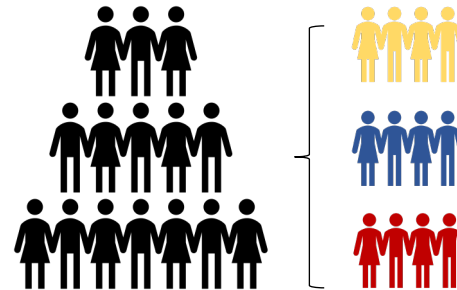
- Genetically Influenced metabotypes (GIM)

How do we derive the profiles?

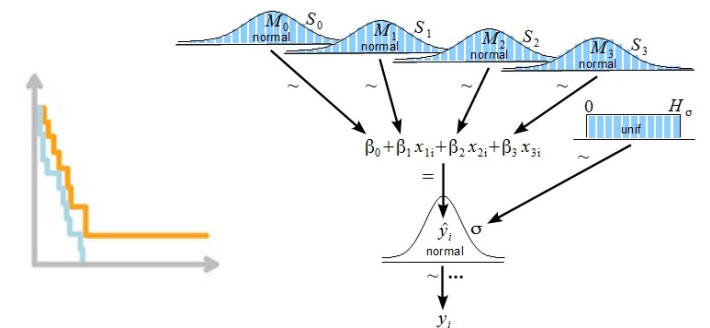
- Integration of genomics and metabolomics information from large-scale datasets
- External validation in disease-specific cohorts



Integration of genomics & metabolomics



Projection of genetically Influenced metabotypes (GIMs)



Application & evaluation of GIMs for the primary prevention of GC

Study design & Methods

Establishing a cohort for gastric cancer research

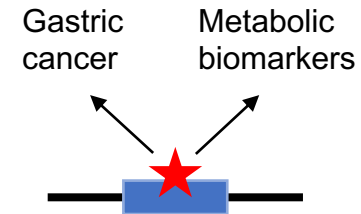
- Must have both metabolomics and genotype data with quality control
- Match with ICD-10; Gastric cancer must be primary
- Exclude cases with specified diseases and pregnancy

mGWAS & genome wide pleiotropic analysis

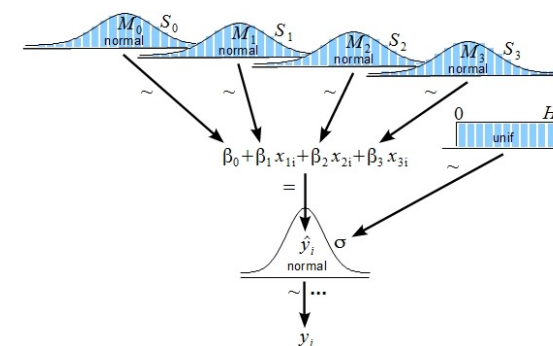
- Metabolome GWAS adjusted by multiple potential confounders
- Public available GWAS data



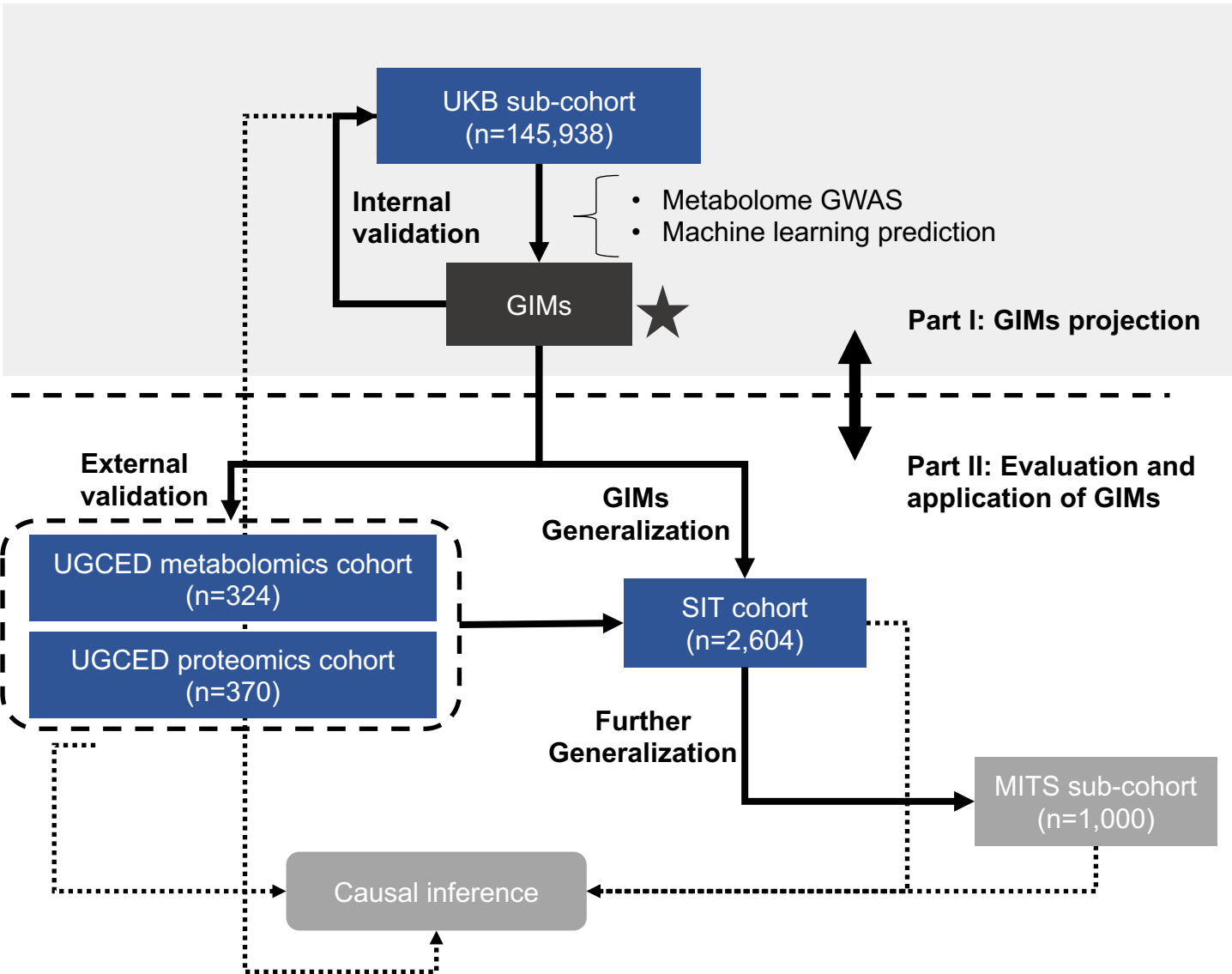
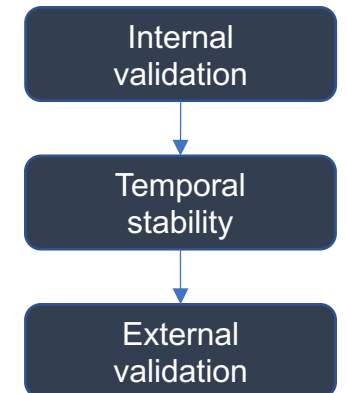
- Nat Genet 53, 1616–1621 (2021).
- Nat Genet 53, 1415–1424 (2021).
- Nat Commun 11, 4423 (2020).



Projecting GIMs: Model training and evaluation

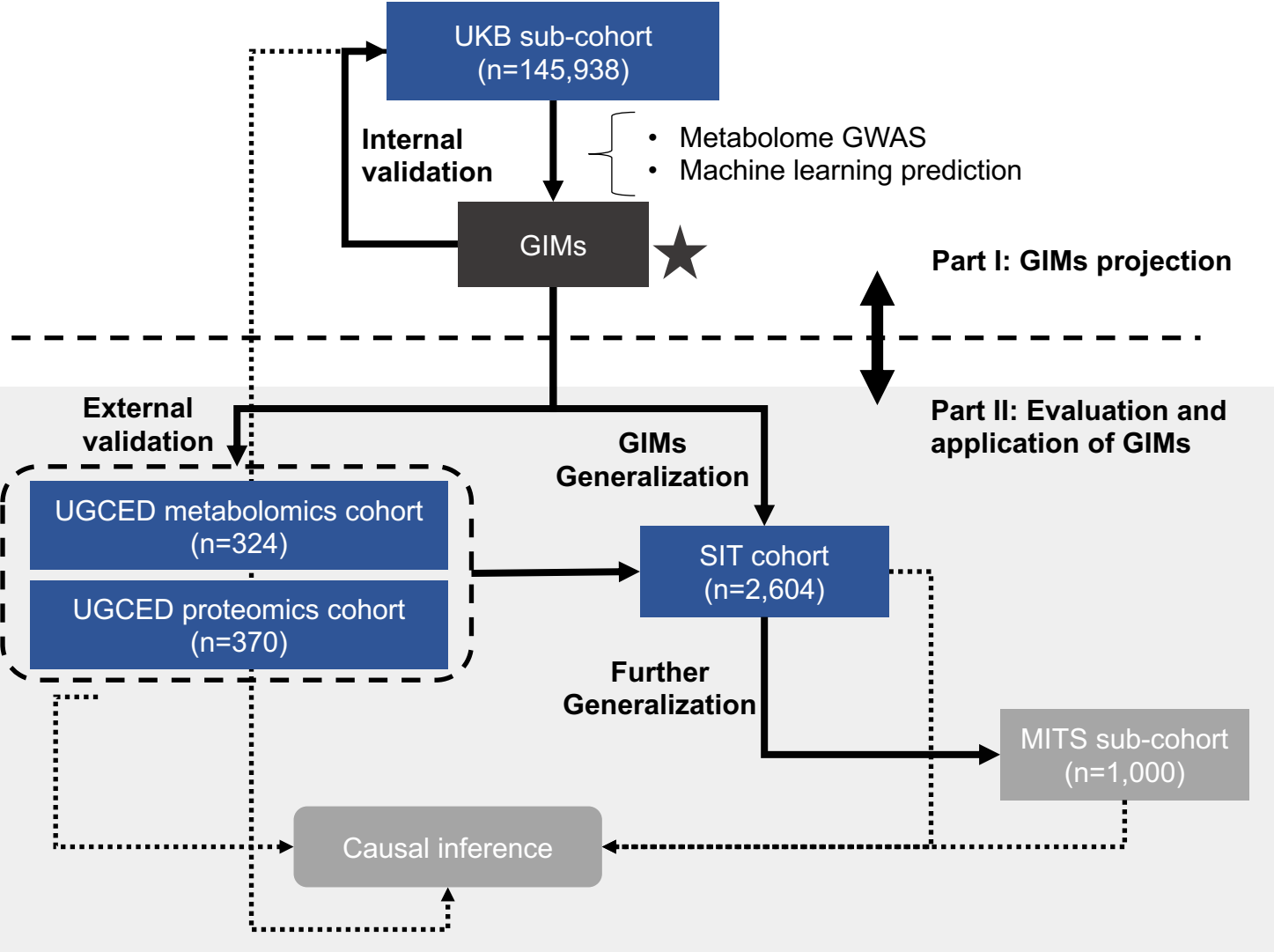


Machine learning predictions



° Genotypic information is available in the UGCED and SIT and MITS sub-cohort

Study design & Methods



BMJ 2019, 366.
 JAMA Network Open, 2021, 4(6)
 EBioMedicine, 2021, 74.
 Theranostics, 2022, 12(10)

- **UGCED:** Upper Gastrointestinal Cancer Early Diagnosis
- **SIT:** Shandong Intervention Trial
- **MITS:** Mass Intervention Trial in Shandong

UGCED Cohort :

- LC-MS metabolomics (n=324) & Proteomics data (n=370)
- Multiple cases of precancerous lesions and early cancer
- Prospective endoscopic follow-up at multiple time points

SIT Cohort:

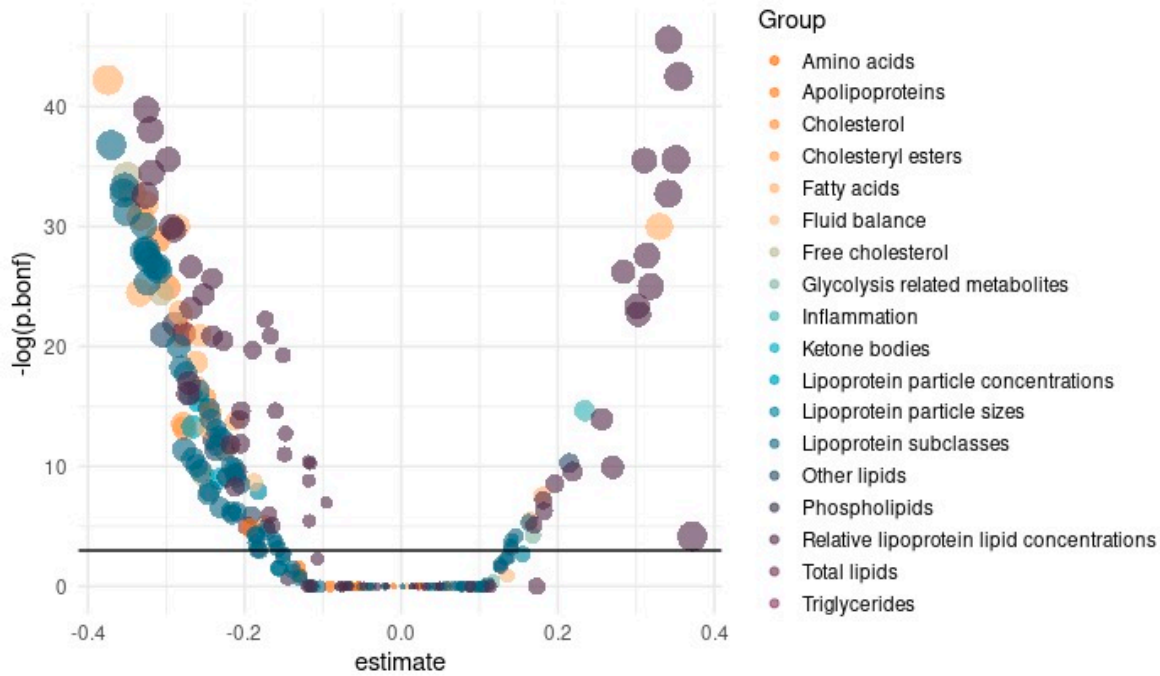
- Randomized, 2x2x2 factorial intervention trial (NCT00339768)
- Based on a high-risk area of gastric cancer
- N=3,365, 2x2x2 factorial design
- 2 weeks of treatment
- 22.3 years of follow-up

° Genotypic information is available in the UGCED and SIT and MITS sub-cohort

Metabolic biomarkers & polygenic insights

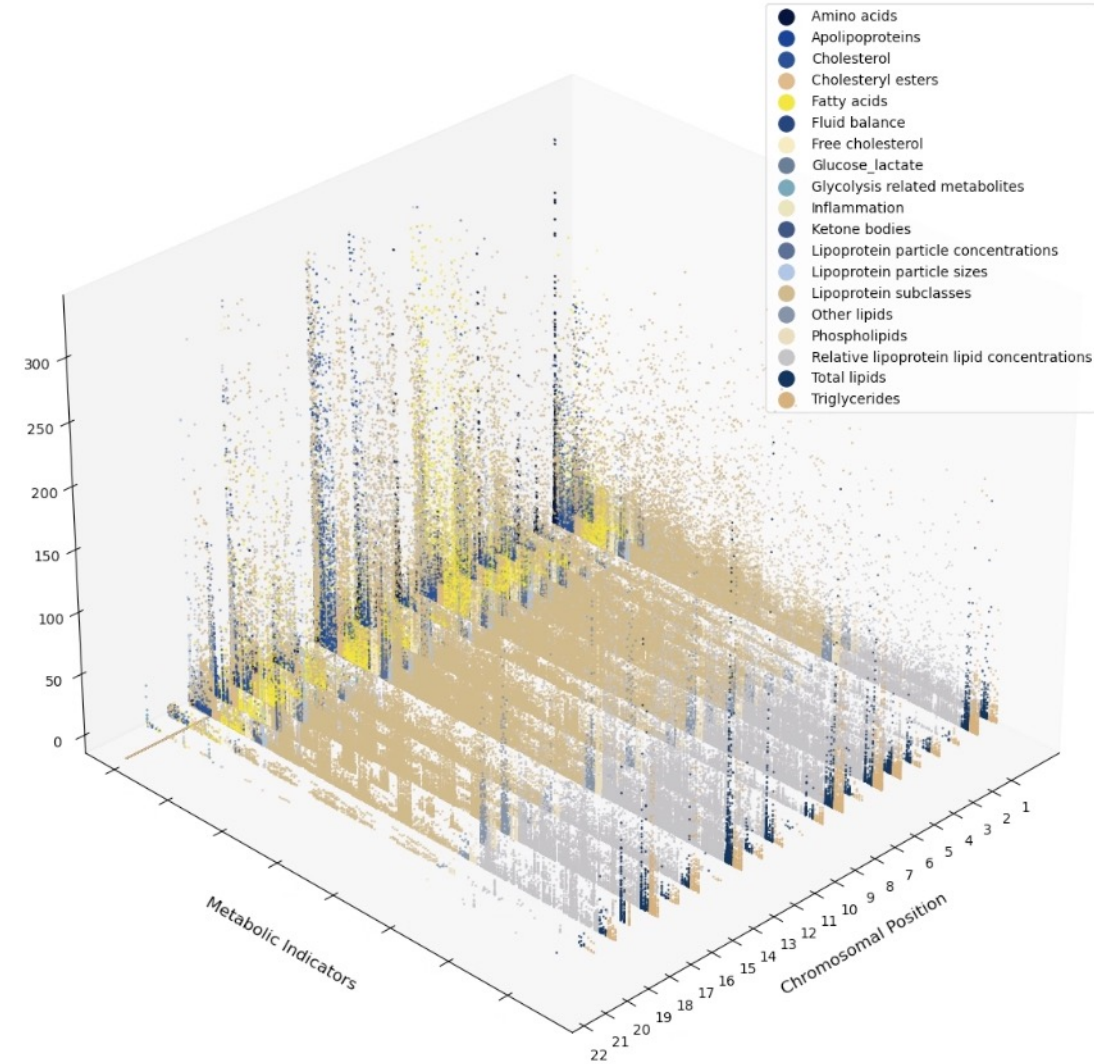
True metabolic profiles are associated with gastric cancer risk

NMR metabolic profiles: GC vs health control



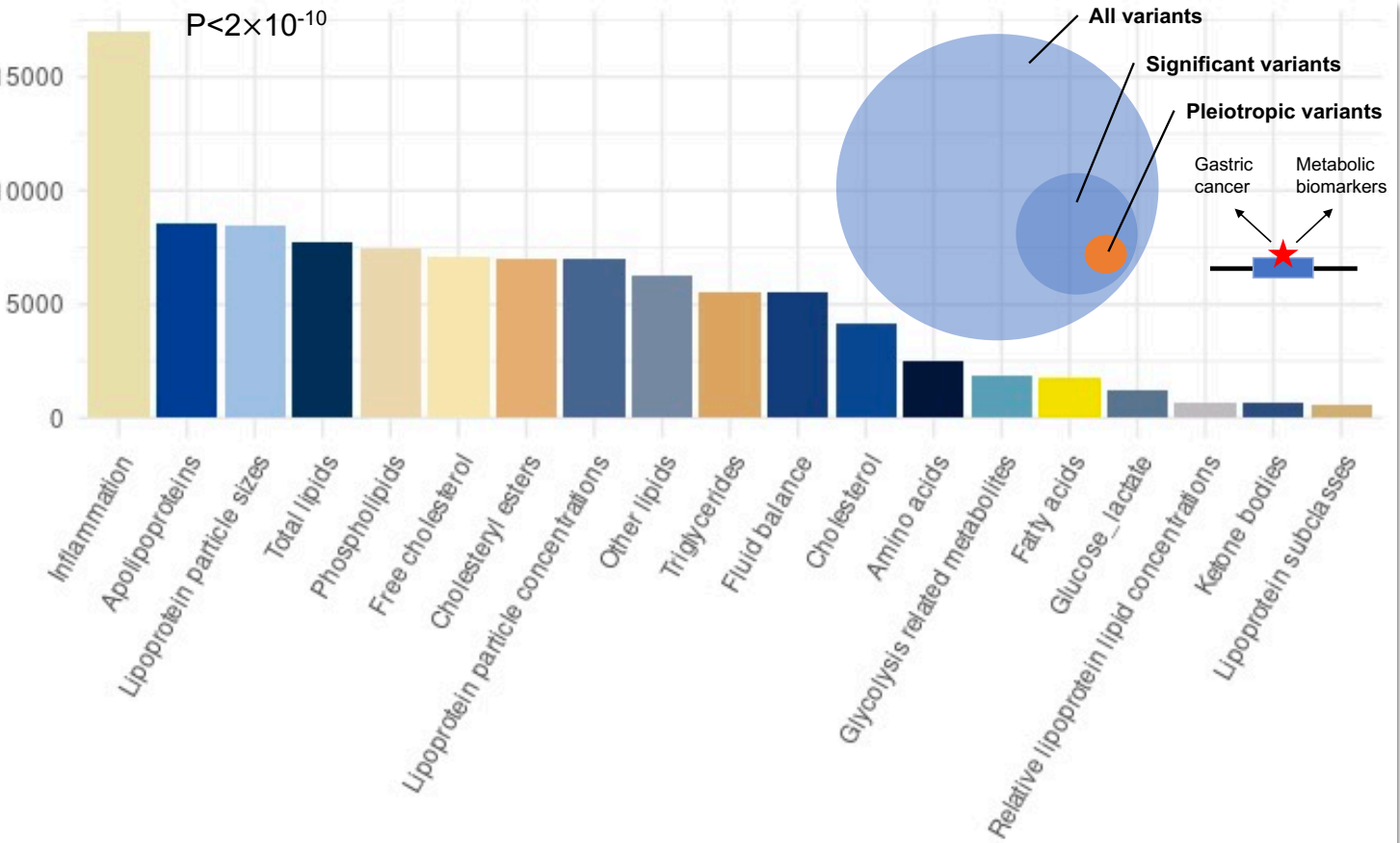
- Blood metabolic profiles are associated with gastric cancer risk
- 70k+ significant variants are identified for variation of 249 biomarkers
- Polygenic effects exist for multiple metabolic biomarkers (traits)

mGWAS for 249 NMR metabolic indicators



Genetic associations with metabolic profiles

Average number of mGWAS significant variants by metabolic categories



Genome-wide pleiotropic analysis

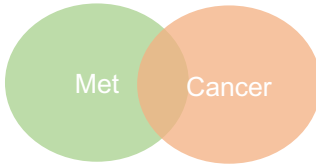
Metabolome GWAS → β_1, Z_1

- 249 metabolome-GWAS

Gastric Cancer GWAS → β_2, Z_2

- Nat Genet 53, 1616–1621 (2021).
- Nat Genet 53, 1415–1424 (2021).
- Nat Commun 11, 4423 (2020).

$H_0: \beta_1 * \beta_2 = 0$
 $H_1: \beta_1 * \beta_2 \neq 0$



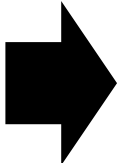
- De-correlate Z values if sample overlap issues exist
- Genome-wide significance threshold: $P < 5 \times 10^{-8}$

Pleiotropic variants and genes

Summary of pleiotropic variants

# Genomic risk loci	29
# Lead SNPs	72
# Ind. Sig. SNPs	166
# Candidate SNPs	4540
# Candidate GWAS tagged SNPs	535

48 potentially pleiotropic genes



Test for phenotypic specificity of the pleiotropic genes

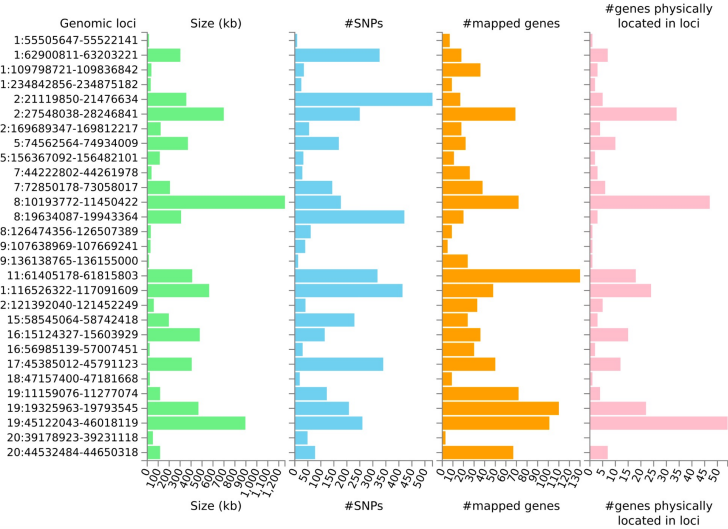
	Alimentary and digestive phenotypes	Non-alimentary and digestive phenotypes
Potentially pleiotropic genes	A1	A2
Non-pleiotropic	A3	A4



- H_0 : Pleiotropic genes do not have phenotype specificity
- H_1 : Pleiotropic genes have phenotype specificity

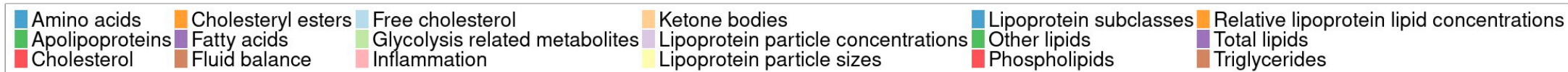
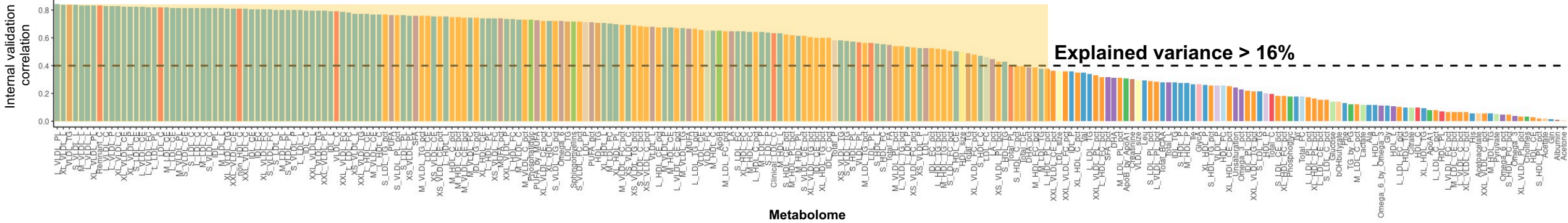
When using digestive/alimentary phenotype (MP:0005381) as the target phenotype:

The odds ratio (OR) for the potentially pleiotropic gene set associated with digestive tract disease phenotype is **2.35 (95% CI: 1.10-4.64)**.

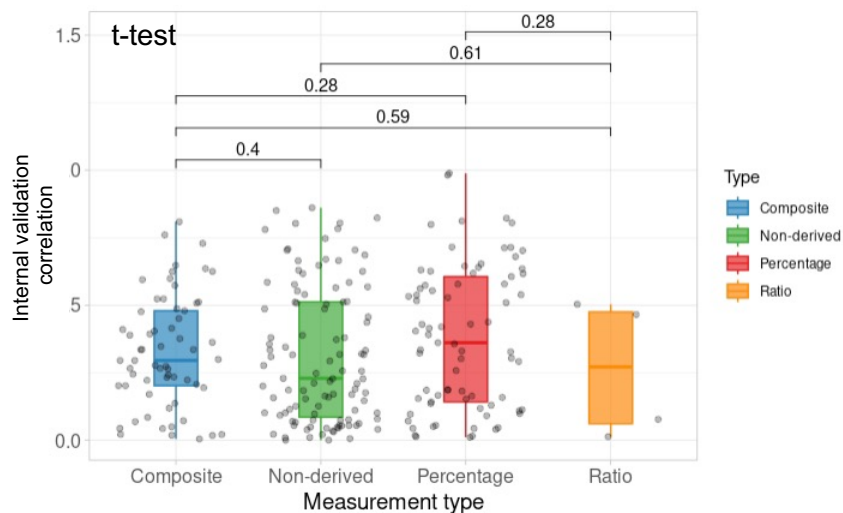


Machine learning models predicting GIMs

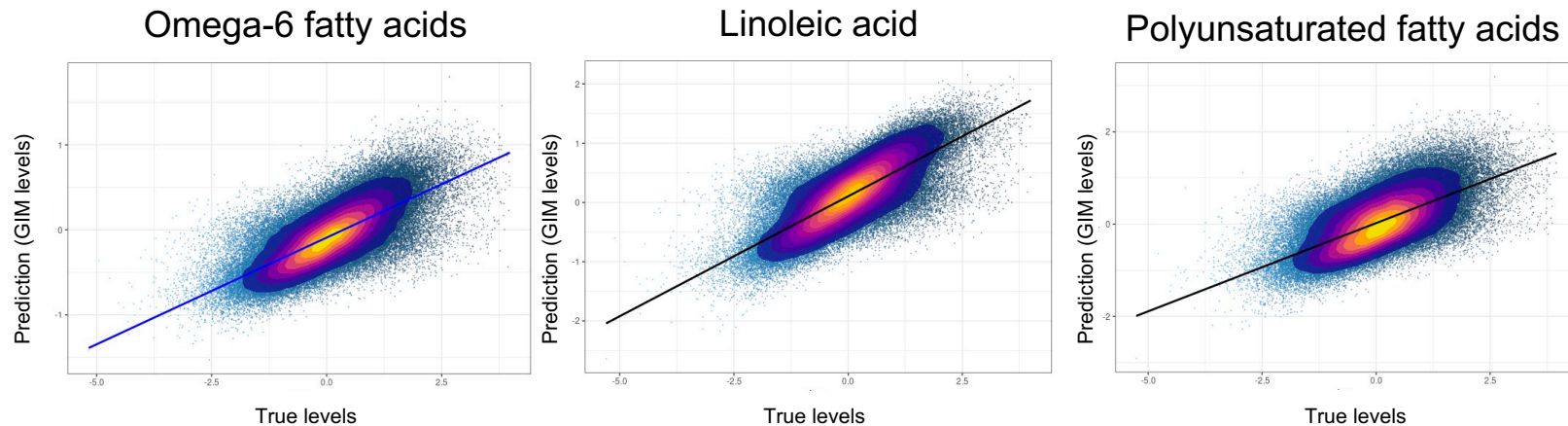
Overall performance



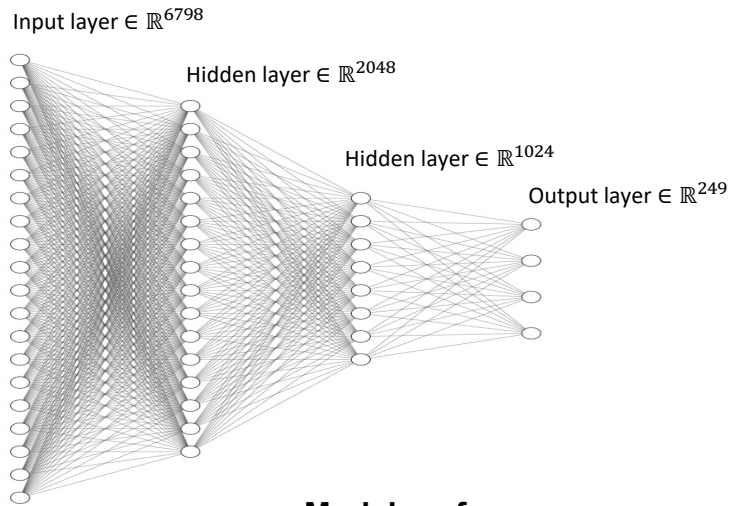
Performance by measurement types



Performance by individual biomarkers (e.g. for fatty acids)



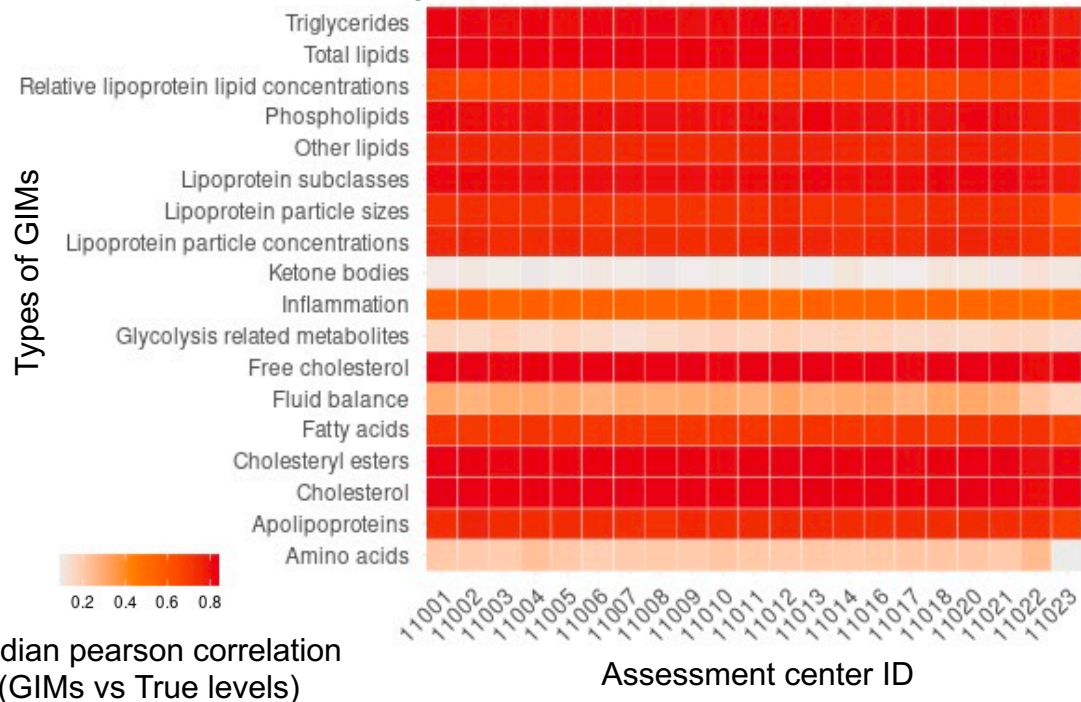
Machine learning models predicting GIMs



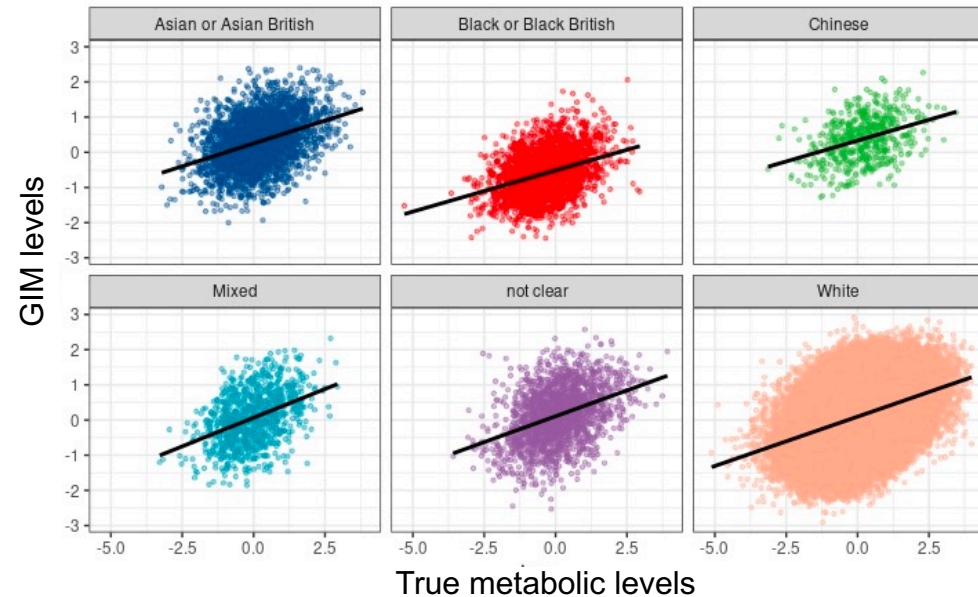
Why neural networks

- Capable of capturing potential interaction effects
- Theoretically can fit any function in nature
- 2048 and 1024 neurons in the 1st and 2nd hidden layer, respectively
- Batch normalization and dropout techniques were applied to reduce overfit

Model performance across different assessment centers

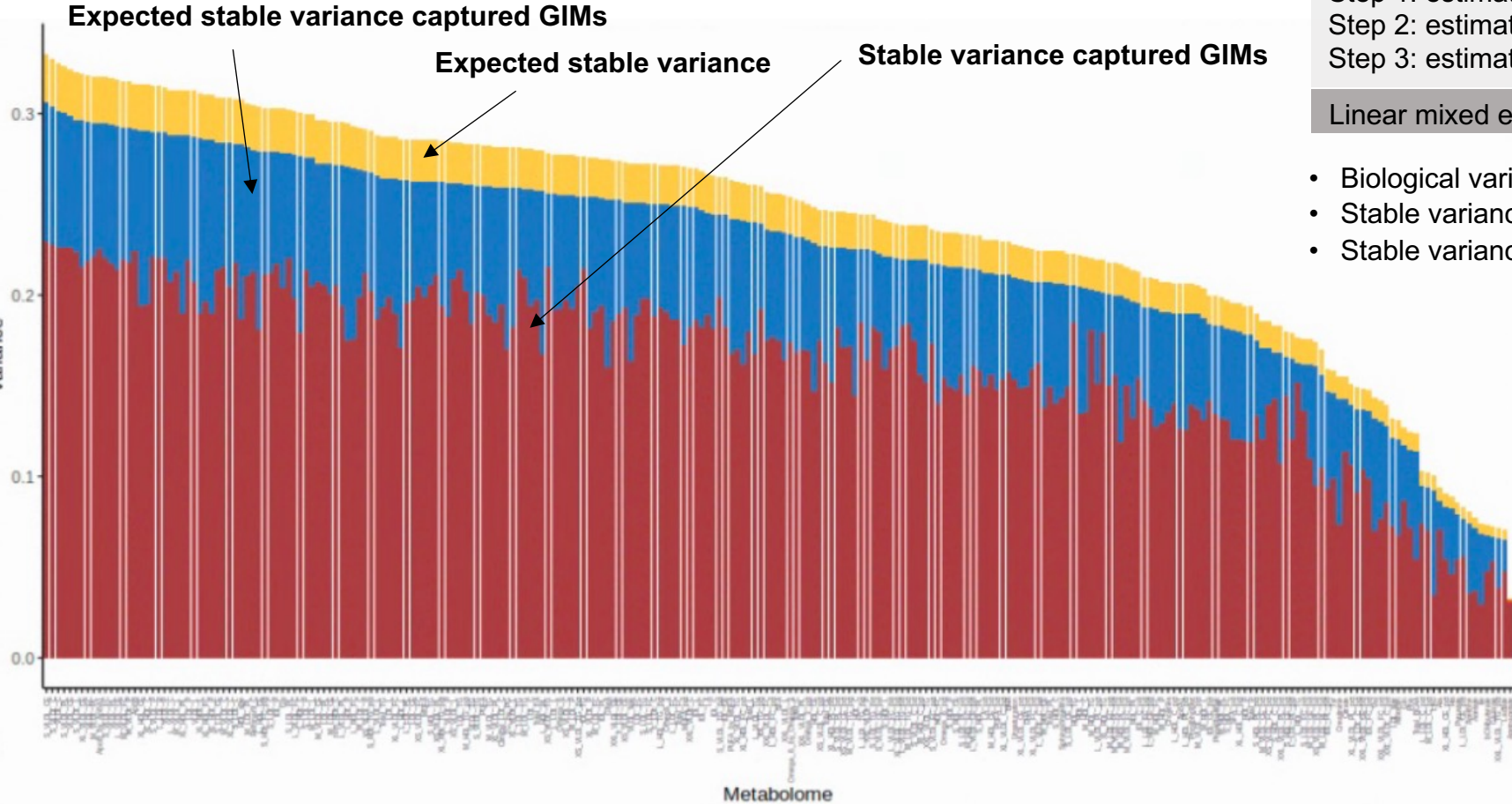


Model performance across different ethnic groups (e.g. for Omega-6 fatty acids)



GIMs are temporarily stable for long-term cancer risk indication

Evaluation on the temporal stability of GIMs

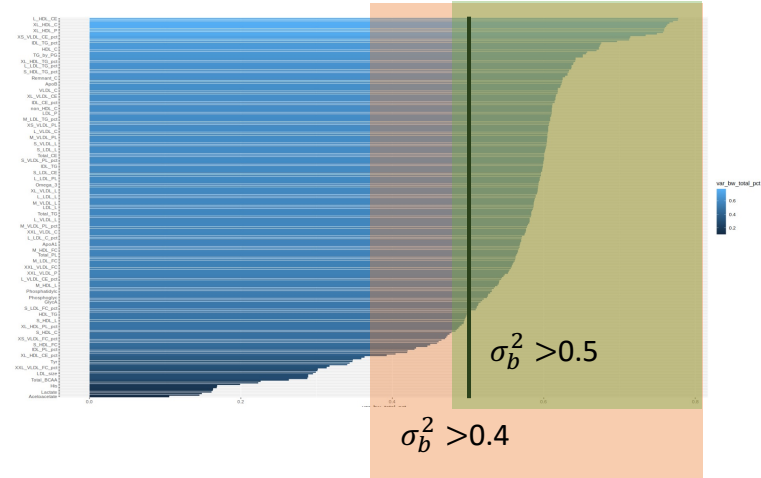


Estimation of stable variance from GIMs

- Step 1: estimate the biological variation of each metabolic trait
- Step 2: estimate the stable variance of the biological variation
- Step 3: estimate the stable variance accounted by genomics

Linear mixed effect model was used for variance decomposition

- Biological variance = $\sigma_{between}^2 + \sigma_{within}^2$
- Stable variance = 60% * ($\sigma_{between}^2 + \sigma_{within}^2$)
- Stable variance accounted by genetics = 42~50% * ($\sigma_{between}^2 + \sigma_{within}^2$)



Good sign of the ability for risk stratification

GIMs are temporarily stable for long-term cancer risk indication

UKB metabolic biomarker measurements

Time point 1

Year: 2006-2010

True levels

Time point 2

Year: 2012-2013

True levels

+



Estimation of true stable variance

Time point 1

Year: 2006-2010

GIMs levels

Time point 2

Year: 2012-2013

True levels

+



Estimation of GIMs-captured stable variance

Estimation of stable variance from GIMs

- Step 1: estimate the biological variation of each metabolic trait
- Step 2: estimate the stable variance of the biological variation
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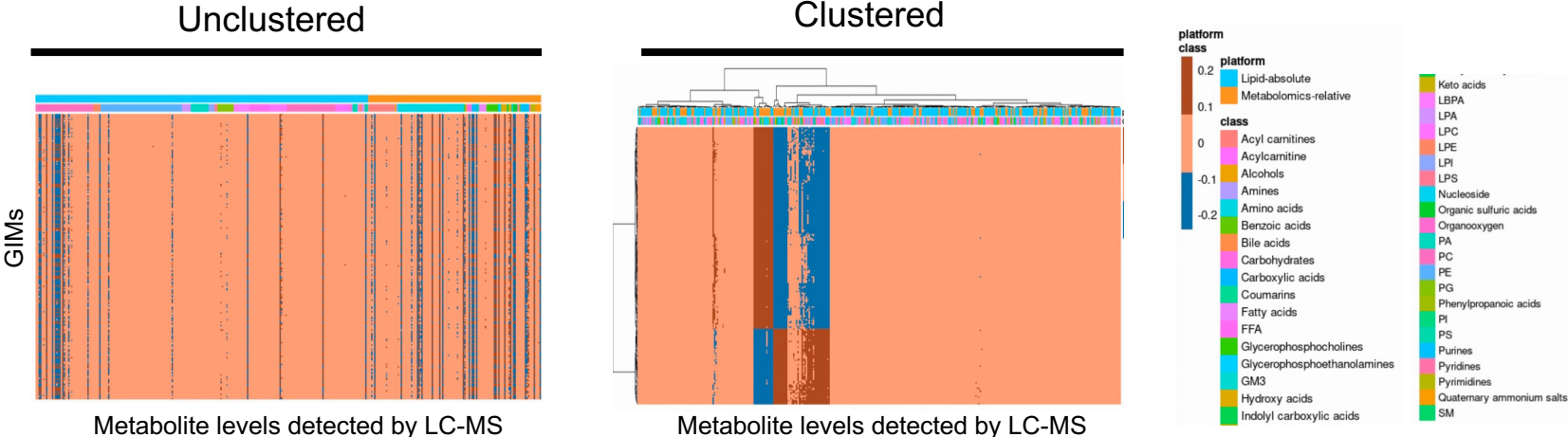
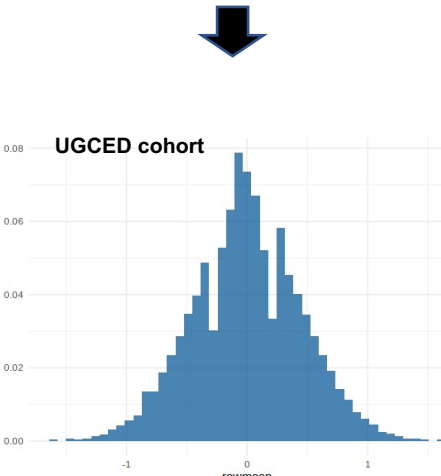
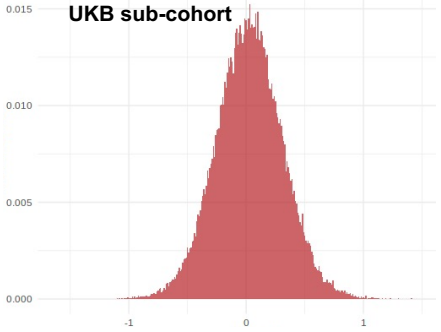
Linear mixed effect model was used for variance decomposition

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GIMs coincide with external metabolomics and proteomics profiles

GIMs display associations with the metabolomic profiles in UGCED cohort

GIMs projection



Protein-coding pleiotropic genes associated with risk of early gastric cancer

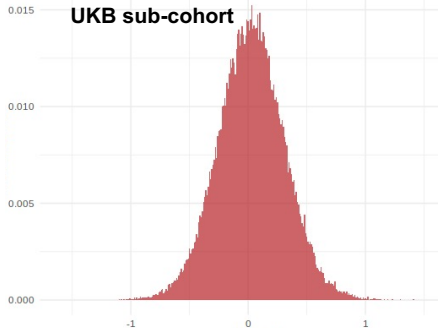
Gene Symbol	OR (95% CI) ^a	nominal p-value	FDR q-value ^b
KPNB1	5.00 (2.23-14.04)	<0.001	0.011
NPEPPS	2.63 (1.34-5.77)	0.008	0.033
APOB	3.11 (1.78-6.84)	0.001	0.011
PDXDC1	2.49 (1.32-5.14)	0.007	0.032
TOMM40	4.02 (1.98-10.70)	0.001	0.012
UBE2L3	0.32 (0.10-0.79)	0.029	0.078
KANK2	2.16 (1.15-4.50)	0.026	0.073

^aOdds ratios were calculated by multivariate logistic regression comparing early gastric cancer and chronic atrophic gastritis

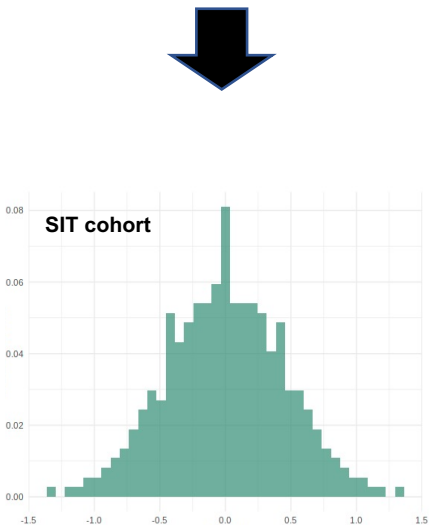
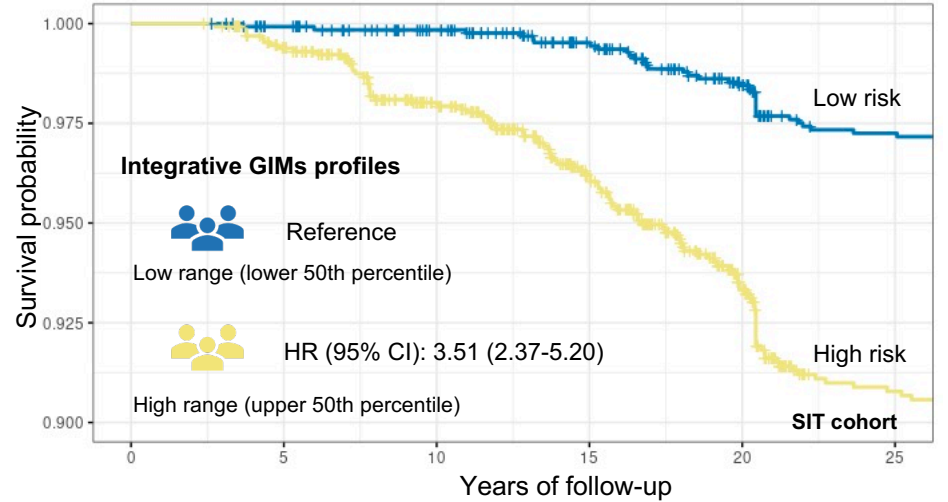
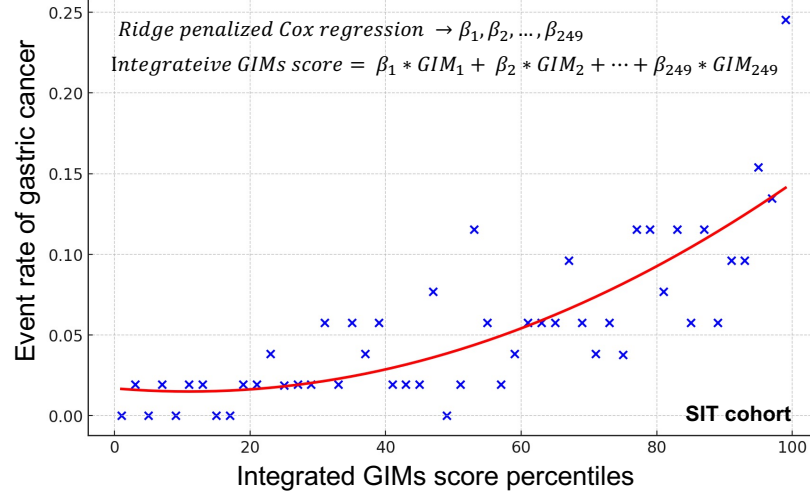
^bFDR was controlled for the statistical testing procedure for 2682 proteins

GIMs stratify gastric cancer risk with biological consistency

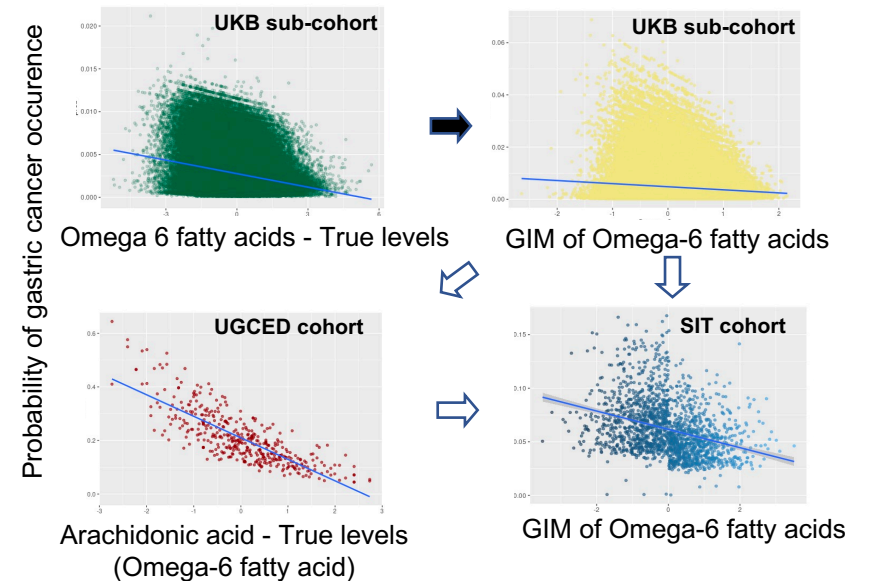
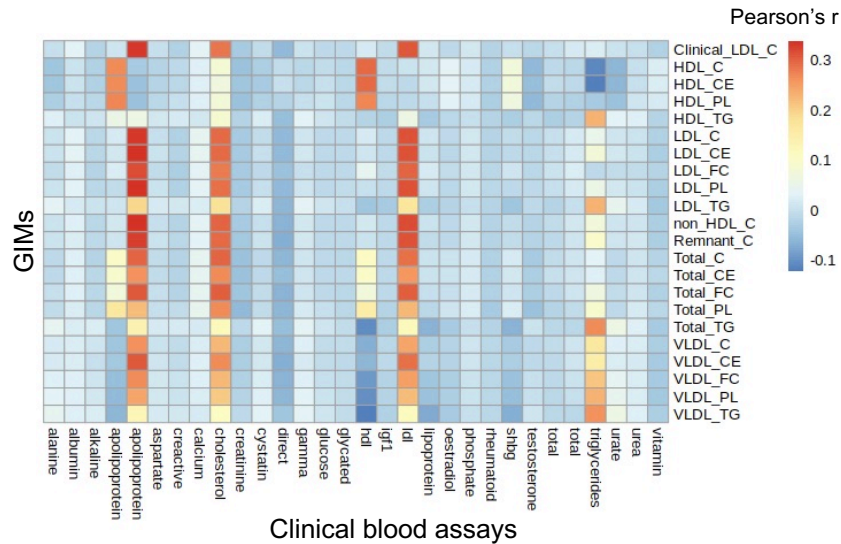
GIMs projection



Risk stratification



Biological consistency

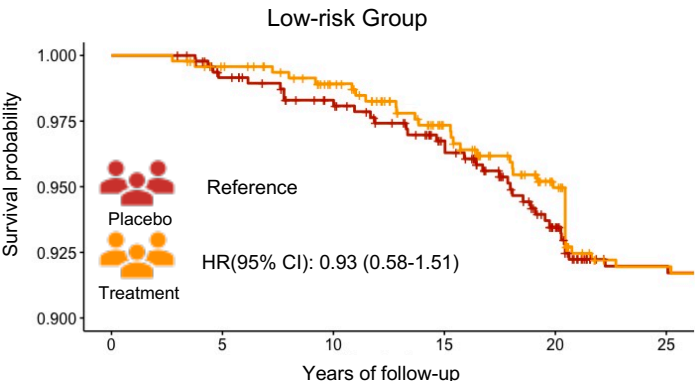
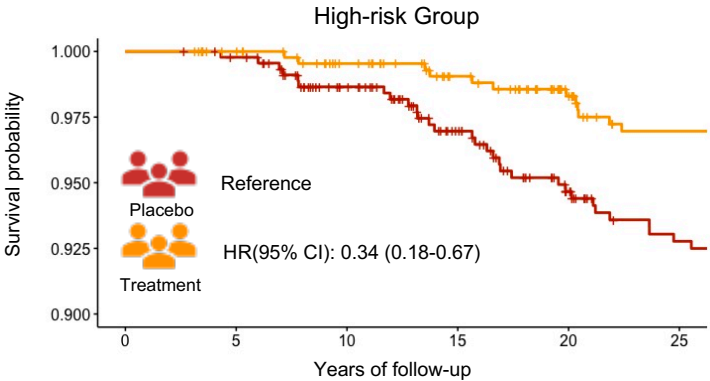


GIMs identify target population for gastric cancer prevention

Efficacy of interventions in preventing gastric cancer across GIMs-defined risk subgroups

Risk group	No. of cancer (Person-years)		HR	95%CI	P for interaction
	Placebo	Treatment			
<i>H.pylori</i> eradication					
★ High-risk	35(11282)	12(10876)	0.34	0.18-0.67	0.02
Low-risk	36(113645)	31(10705)	0.93	0.58-1.51	
Vitamin supplementation					
High-risk	28 (15493)	16 (15192)	0.57	0.30-1.03	0.19
Low-risk	48 (15862)	47 (15574)	0.99	0.69-1.55	
Garlic supplementation					
High-risk	28 (15520)	16 (15096)	0.58	0.32-1.08	0.19
Low-risk	48 (15863)	47 (15642)	0.96	0.64-1.44	

For *H.pylori* treatment



- Similar eradication rates noted between the high and low-risk subgroups.
- Higher responsiveness to *H. pylori* treatment for gastric cancer prevention observed in high-risk subjects.

Summary

Conclusion

- GIMs may be indicators of the risk of developing GC, offering new insights into understanding GC etiology.
- GIMs may be an effect modifier for *H.pylori* treatment, thus serving as biomarkers for targeted populations of GC primary prevention.

Ongoing efforts

- Extra external validation by independent cohorts (sub-cohort from MITS)
- Development of causal learning framework for casual inference between the key genetic variants and GIMs

PERSPECTIVE

<https://doi.org/10.1038/s42256-022-00445-z>

nature
machine intelligence

**Stable learning establishes some common ground
between causal inference and machine learning**

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- Meng-Yuan Wang, Master's student

Collaborators:

- Peng Cui, Ph.D. (Tsinghua University)
- Yue He, Ph.D. (Tsinghua University)
- Wei-Dong Liu, B.S. (Linqu County Public Health Bureau, Shandong, China)



Best Oral Presentation Award
in 2023 AACR-KCA Joint Conference
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