



NuGOweek 2015, 12th edition

MECHANISMS OF A LONG-LIFE HEALTH

Nutritional interventions for weight loss and maintenance based on the genotype



**Prof. J. Alfredo Martínez,
Universidad de Navarra
Spain**

PERSONALIZED WEIGHT MANAGEMENT



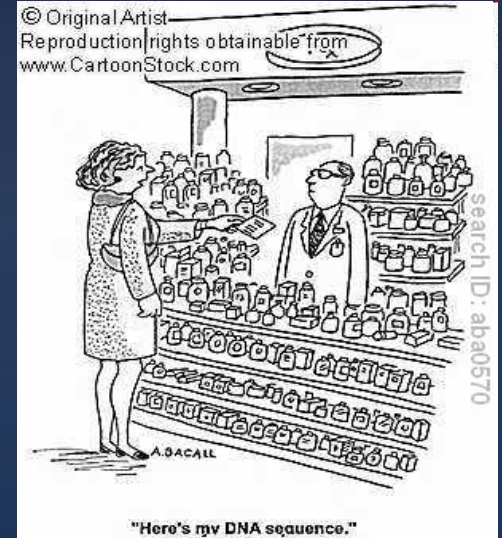
INDIVIDUALIZED NUTRITION

PERSONALIZED NUTRITION BASED ON GENOTYPE

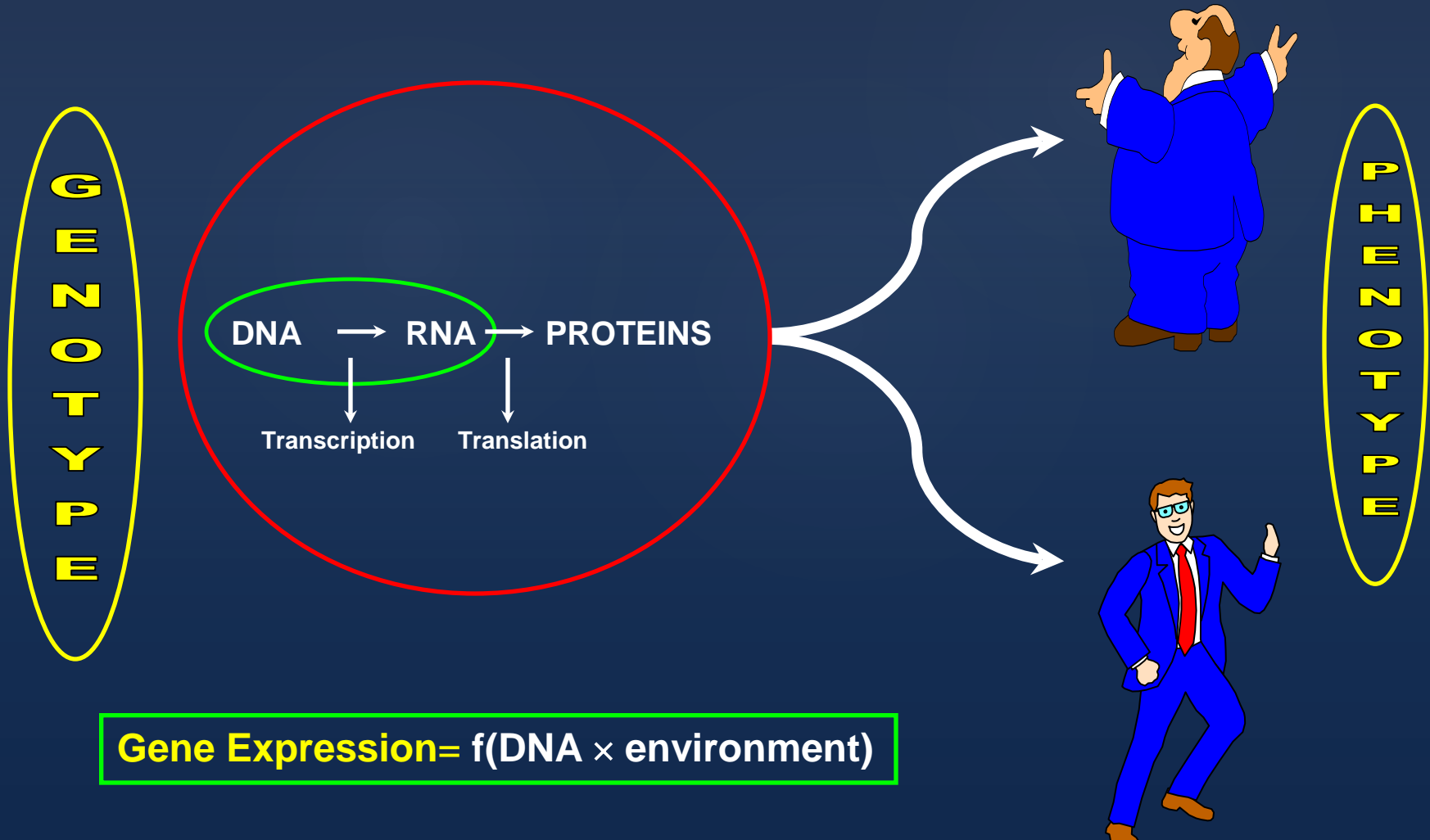
Genetic make-up can determine unique nutritional requirements and responses to different foods and nutrients

Based on:

- The **sequencing** of the human genome,
- subsequent analyses of **human genetic variation**,
- studies that **associate gene variants with disease markers**
- Impact of nutrition/nutrients **on gene expression**



GENOTYPE x NUTRITION → METABOTYPE



Gene Expression = f(DNA × environment)

NUTRIENTS FUNCTIONS

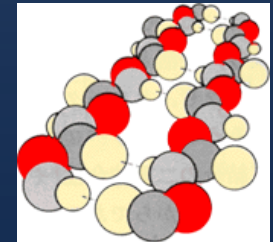
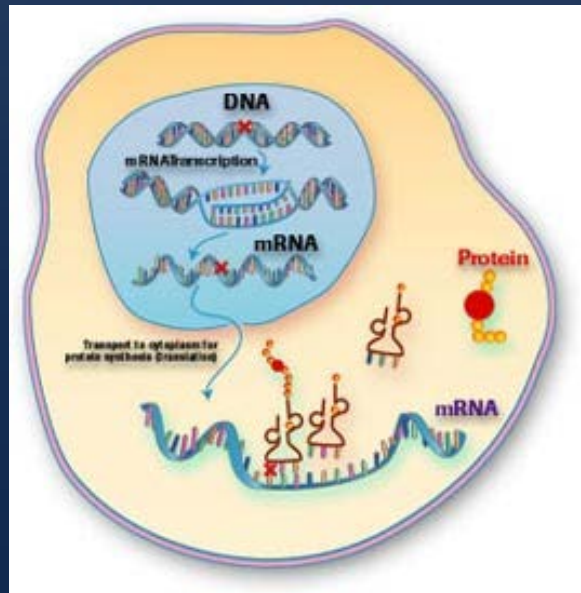
Nutrients



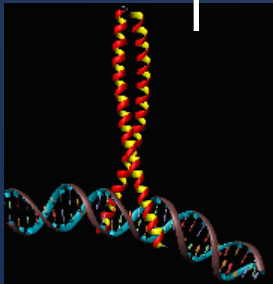
Energy

Regulatory Elements

Structural components



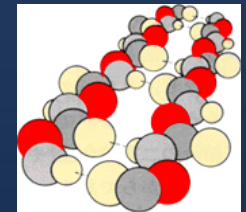
GENE EXPRESSION: NUTRITIONAL CONTROL



Fatty Acids
Retinoids
Vitamin D
Glucose
Energy

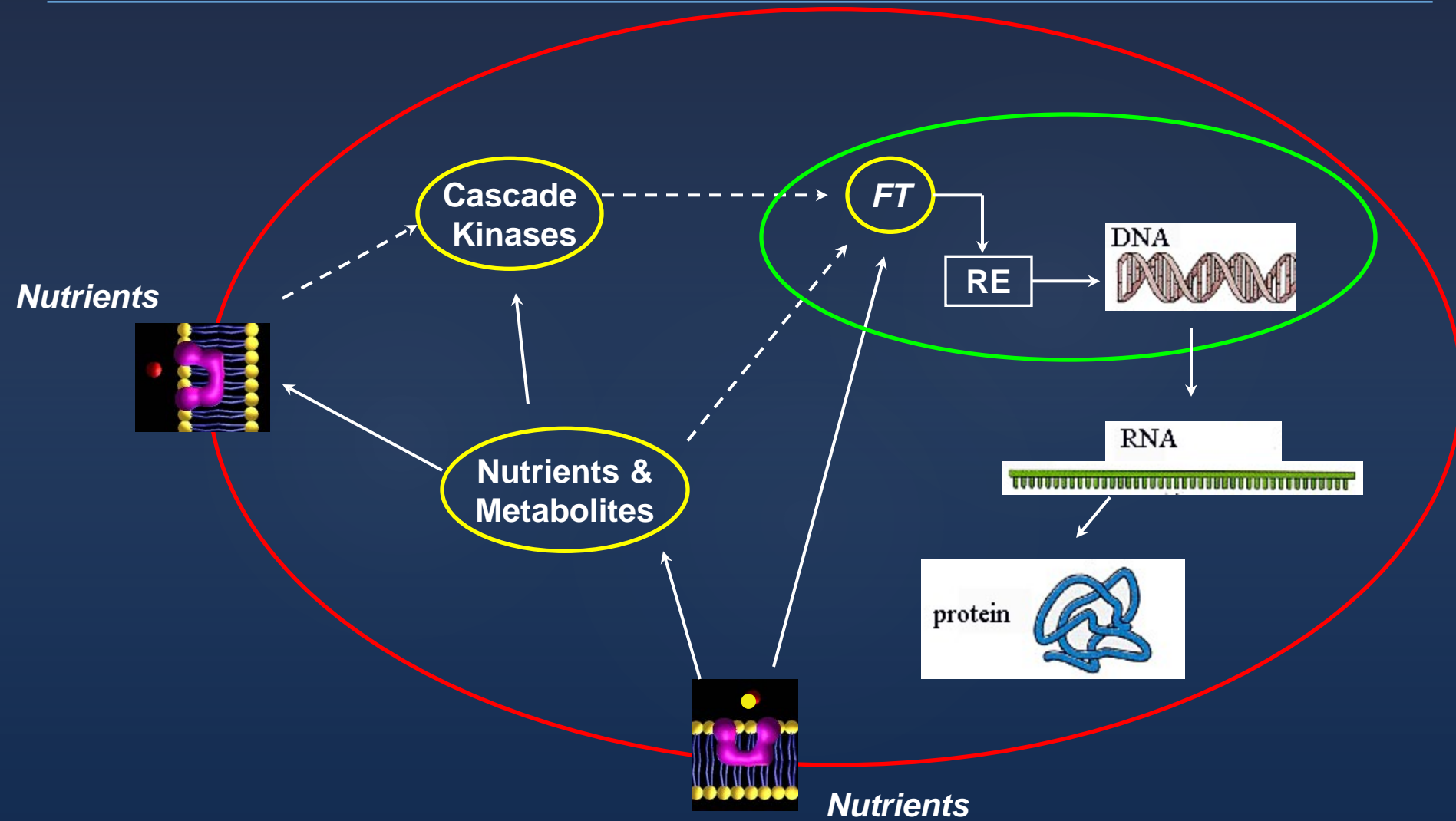


Amino acids
Iron
Selenium



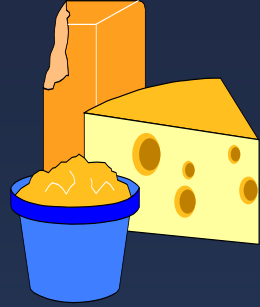
Minerals
Vitamins

GENE EXPRESSION CONTROL: MECHANISMS



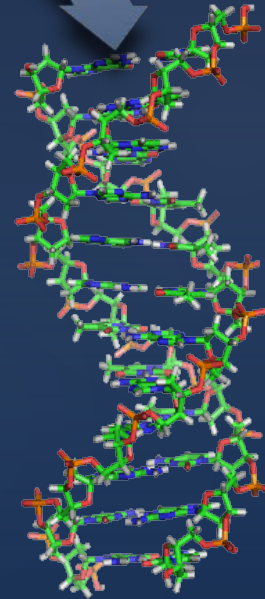
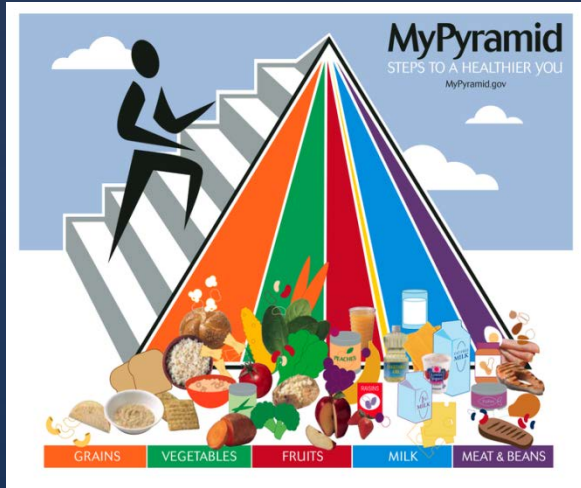
- Mechanisms :**
- Receptors (membrane/nucleus)
 - Metabolism intermediate
 - Transcription Factors (*FT*): affinity & concentrations

Nutrigenomics and Nutrigenetics



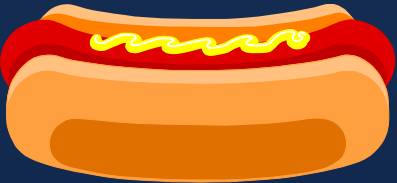
Dietary effects on gene expression

NUTRIGENOMICS

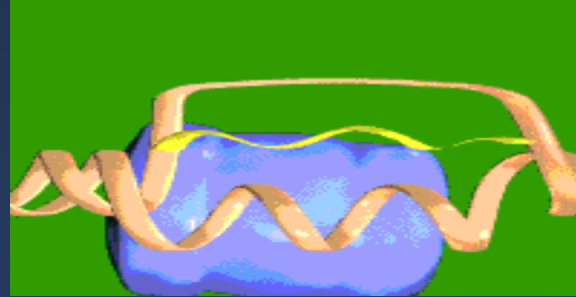


NUTRIGENETICS

Genotype influences the response related with nutrition and personalised metabolism



NUTRIGENOMIC INTERACTIONS



Nutrition

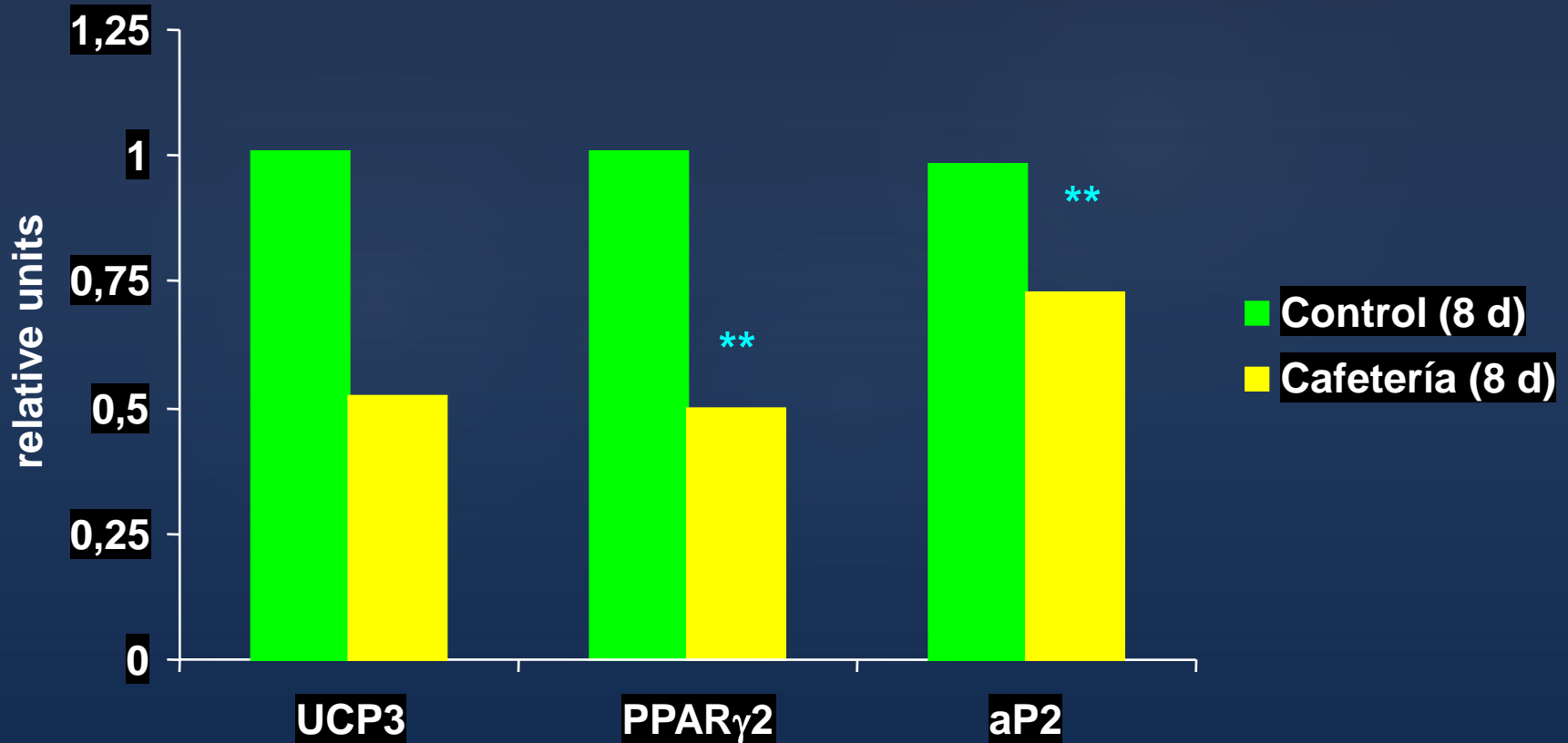


**GENE
Expression**

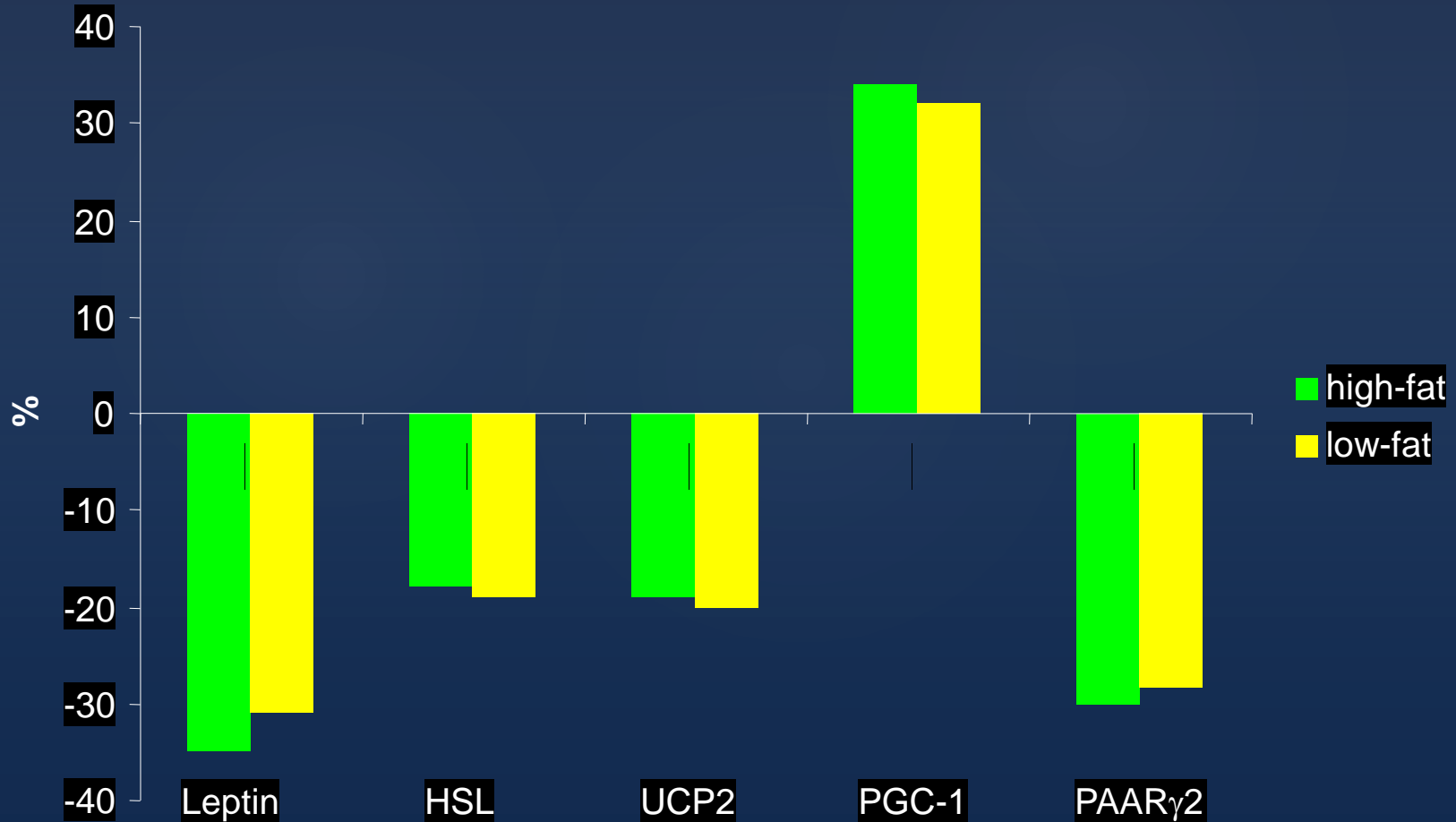


Phenotype

DIET DEPENDENT GENE EXPRESSION



FAT INTAKE AND mRNA LEVELS AFTER ENERGY RESTRICTION



Differential Expression of Oxidative Stress and Inflammation Related Genes in Peripheral Blood Mononuclear Cells in Response to a Low-Calorie Diet: A Nutrigenomics Study

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Abstract

Nutrigenomics is a new application of omics technologies in nutritional science. Nutrigenomics aims to identify molecular markers of diet-related diseases and mechanisms of interindividual variability in response to food. The aim of this study was to evaluate peripheral blood mononuclear cells (PBMC) as a model system and readily available source of RNA to discern gene expression signatures in relation to personalized therapy of obesity. PBMC were collected from obese men before and after an 8-week low-calorie diet (LCD) to lose weight. Changes in gene expression before and after the LCD were initially screened using a DNA-microarray platform and validated by qRT-PCR. Global gene expression analysis identified 385 differentially expressed transcripts after the LCD. Further analyses showed a decrease in some specific oxidative stress and inflammation genes. Interestingly, expression of these genes was directly related to body weight, while a lower IL8 gene expression was associated with higher fat mass decrease. Collectively, these observations suggest that PBMCs are a suitable RNA source and model system to perform nutrigenomics studies related to obesity and development of personalized dietary treatments. IL8 gene expression warrant further research as a putative novel biomarker of changes in body fat percentage in response to an LCD.

Sirtuin gene expression in human mononuclear cells is modulated by caloric restriction

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ABSTRACT

Background Sirtuins may provide novel targets for treating some diseases associated with oxidative stress, such as obesity and its comorbidities. However, there are a few *in vivo* studies in humans about the potential role of sirtuins as therapeutic targets among obese patients undergoing caloric restriction. Therefore, the aim of this study was to assess if the gene expression of sirtuins is modulated in peripheral blood mononuclear cells (PBMC) by a hypocaloric diet devised to lose weight in humans.

Materials and methods Gene expression of two sirtuins (SIRT1 and SIRT2) in the PBMC of obese subjects ($32.3 \pm 5.5 \text{ kg m}^{-2}$) before and following an 8-week hypocaloric diet was investigated. NADH-coenzyme Q reductase (NDUFS2) and cytochrome c oxidase assembly protein (COX15) gene expression was selected together with plasma antioxidant power and nitric oxide as markers of antioxidant status. A quantitative real-time polymerase chain reaction approach was performed to assess the nutrigenomics outcome. Moreover, 2-keto[1- ^{13}C]socioacetoate breath test (KICA-BT) parameters were evaluated to study mitochondrial oxidation *in vivo*.

Results The intervention up-regulated the expression of both sirtuins, being inversely associated with total antioxidant capacity and directly related to nitric oxide, mitochondrial oxidation assessed by the KICA-BT and the expression of the mitochondrial proteins COX15 and NDUFS2.

Conclusion SIRT1 and SIRT2 may serve as key regulators for some obesity comorbidities related to antioxidant status, while PBMC could be a model to study the effect of the sirtuin response in obesity therapy.

Keywords ^{13}C -KICA breath test, caloric restriction, mitochondrial function, oxidative stress, PBMC gene expression, sirtuins.

Eur J Clin Invest 2008; 38 (8): 672–678

Expression of Two Inflammation-Related Genes (RIPK3 and RNF216) in Mononuclear Cells Is Associated with Weight-Loss Regain in Obese Subjects

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Key Words

Nutrigenomics · RIPK3 · RNF216 · Gene expression · Obesity · Weight-loss regain · Weight maintenance · Peripheral blood mononuclear cells · Dietary intervention

Abstract

Background/Aims: Nutrigenomics is providing molecular biomarkers concerning the assessment of diet-related diseases. We analyzed the expression of two interacting genes (RIPK3 and RNF216) in obese subjects receiving a low-calorie diet (LCD) and during the subsequent weight changes. **Methods:** Two groups of obese subjects (BMI 32.3 ± 5.5 ; age 37.7 ± 7.1 years) were selected according to the 6-month weight-regain outcome after the weight-loss induced by an 8-week LCD ($n = 12$). Body composition and mRNA levels of RIPK3 and RNF216 in peripheral blood mononuclear cells (PBMC) were evaluated by qRT-PCR at three time-points (week 0, week 8 and week 32). **Results:** All subjects lost weight significantly ($-5.8 \pm 2.3\%$, $p < 0.001$) and were grouped depending on the successful weight-loss maintenance (weight-loss regain $\leq 10\%$ or $>10\%$). At baseline (week 0), no differences were observed in the mRNA levels between groups ($p > 0.05$). However, at the end of the LCD (week 8), association analysis revealed that higher mRNA levels in PBMC of RIPK3 and RNF216 were able to detect those

individuals who are more prone to regain weight 6-month after the nutritional intervention ($p < 0.05$). **Conclusions:** Gene expression of RIPK3 and RNF216 in PBMC could identify those obese subjects, who will regain more weight after a successful initial weight loss. The mRNA levels of these genes could be suggested as nutrigenomic biomarkers for predicting the obesity treatment outcome.

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Introduction

Obesity is a multifactorial condition, associated with multiple morbidities, which is showing a rising prevalence worldwide [1, 2]. Weight reduction methods are mainly focused on dietary changes and increased physical activity approaches [3], which often produce successful short-term results. Indeed, weight cycling and relapse are common features after weight-loss treatment of obesity [4]. The failure to maintain weight loss could be partially explained by genetic factors or by the interaction between genes and the environment [5, 6].

In the last years, novel research strategies have been applied to understand the molecular mechanisms involved in the excess fat mass and weight-lowering regulation [7]. In this sense, the nutrigenomics field involves the study of

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TOOLS: Microchip Scanning



Macronutrient Metabolism

Fold	Code	Name
~49.2	D45862	Leptin, ob
15.7 ⁺	J02773	Low molecular weight FABP
7.3	J00713	Carboxypeptidase-a- 5
~6.7 ⁺	U64451	Short-branched chain acyl-CoA DH precursor
~4.9 ⁺	AF063302	Carnitine palmitoyltransferase I beta
~4.6 ⁺	AF034577	Pyruvate dehydrogenase kinase isoenzyme 4
4.1	M95591	Squalene synthetase
3.3	S69874	Fatty acid-binding protein (FABP)
3.2	K03249	Enoyl-CoA-hydratase-3-hydroxyacyl-CoA DH
3	AB002558	Glycerol 3-phosphate dehydrogenase
2.9	AB005743	Fatty acid transporter
2.8	L07114	Apolipoprotein B
2.5	U20643	Aldolase A
2.5	M26594	Malic enzyme
2.4	M60322	Aldose reductase
2.2	S56481	Beta 3-adrenergic receptor
2.2	S81497	Lysosomal acid lipase
2.2	J02585	Liver stearyl-CoA desaturase
2.2	X15580	6-phosphofructo-2-kinase/fructose-2,6-bisphosphatase
2.2	L12016	Tricarboxylate transport protein
2.2	U32314	Pyruvate carboxylase
2.2	D10354	Alanine aminotransferase
2.2	L25331	Lysyl hydroxylase
2.1	D43623	Carnitine palmitoyltransferase I like protein
2	D10655	Dihydrolipamide acetyltransferase
2	AF035943	Uncoupling protein-3

Transcription factor	Code	Name
3.7 ⁺	AB015724	Nuclear receptor binding factor-1
2.8 ⁺	X12752	DNA binding protein C/EBP
2.5	S77528	C/EBP-related transcription factor
2.1	AB011365	PPAR-gamma protein
2	AF022081	Small nuclear RING finger protein
2	X13167	NF-1 like DNA-binding protein

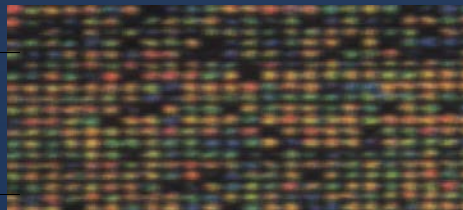
Hormone receptor and signal transduction

~10.7 ⁺	M96159	Adenylyl cyclase type V
4	S79241	Oxytocin receptor
3.6 ⁺	U93880	Insulin receptor substrate-3 (IRS-3)
3	K03045	Retinol-binding protein (RBP)
2.9	D38036	Truncated TSH receptor
2.9	Z83757	Growth hormone receptor
2	X92069	P2X5 receptor (ATP-gated ion channels)
2.8	E12286	GM2 activator protein
2.7	X17053	Immediate-early serum-responsive JE
2.6	S74351	Protein tyrosine phosphatase
2.6 ⁺	X06107	Insulin-like growth factor I
2.5	M64300	Signal-related Kinase (ERK2)
2.4	D85183	SHP5-1 (protein tyrosine phosphatase)
2.4	L13619	Insulin-induced growth-respons protein
2.4 ⁺	L35767	Very low density lipoprotein receptor,
2.3	S49003	Short isoform growth hormone receptor
2.3	D85435	Protein kinase C delta-bindig protein
2.2	D89655	Scavenger receptor class B
2.2	U21101	Cyclic GMP stimulated phosphodiesterase
2.2 ⁺	J03819	Thyroid (T3) hormone receptor
2	AF022952	Vascular endothelial growth factor B
2	S50461	Signal-transducing G protein alpha 12 subunit
2	L25633	Neuroendocrine-specific protein
2	M12492	Type II cAMP-dependent PK regulatory subunit

Cellular cytoskeleton

~4.9 ⁺	K00512	Myelin basic protein
~4.0 ⁺	AF004811	Moesin
3.5	X60351	Alpha B-crystallin
3.1	AF041373	Clathrin assembly protein short form
2.7	U50717	Synaptic density protein PSD-93
2.5	M83196	Microtubule-associated protein 1A

= corresponds to a transcript absent in the control group (basal line).



Macronutrient Metabolism

Fold	Code	Name
-22.5	AF001898	Aldehyde dehydrogenase (ALDH)
-22.1 ⁺	AB009999	CDP-diaclyglycerol synthase
~20.0 ⁺	AB017260	High-affinity carnitine transporter
-19.0 ⁺	D37920	Squalene epoxidase
-9.1	L25387	Phosphofructokinase C
~6.4 ⁺	AB010428	Acyl-CoA hydrolase
-6.0	S68135	GLUT1
-3.8	M18467	Aspartate aminotransferase
-2.9	AF080468	Glycogen storage disease type 1b protein
-2.8	S49760	Diaclyglycerol kinase
-2.6	X04979	Apolipoprotein E
-2.4	M93297	Ornithine aminotransferase
-2.2	L07736	Carnitine palmitoyl-transferase I

Redox and stress proteins

-7.8-34.1 ⁺	S82820	Glutathione S-transferase Yc2 subunit
-4.8-6.2	X62660	Glutathione S-transferase subunit 8
-4.2	M11794	Metallothionein-2 and metallothionein-1
-2.6-3.2	X02904	Glutathione S-transferase P subunit

Transcription factor

-25.2	U78102	Krox20 ó EGR-2(early growth response protein 2)
-5.2	X94246	Pax-8 protein
-2.7	M91802	Homeobox protein (Hox 1.11)

Hormone and signal transduction

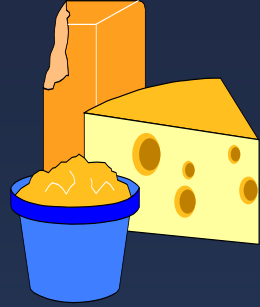
-117.5	S49491	Proenkephalin
~92.3 ⁺	J04488	Prostaglandin D synthetase
~47.3	D63772	Neuronal high affinity glutamate transporter
~8.6 ⁺	M12450	Vitamin D binding protein
-4.1	U57715	FGF receptor activating protein FRAG1
-2.8	U48596	MAP kinase kinase kinase 1 (MEKK1)
-2.3	L06096	Inositol trisphosphate receptor subtype 3 (IP3R-3)
-2.3	U53184	Estrogen-responsive uterine
-2.3	X59132	Secretin receptor
-2.2	D64045	Phosphatidylinositol 3-kinase p85 alpha subunit
-2.1	AF014009	Acidic calcium-independent phospholipase A2
-2	M91599	Fibroblast growth factor receptor subtype 4

Cellular cytoskeleton

~21.4 ⁺	X81448	Keratin 18
~12.2 ⁺	M93638	Keratin 5
~6.6 ⁺	AF013247	Beta-A4 crystallin
~3.8 ⁺	M59936	Connexin-31
-3.2	X67788	Ezrin p81
-2.3	X81449	Keratin 19

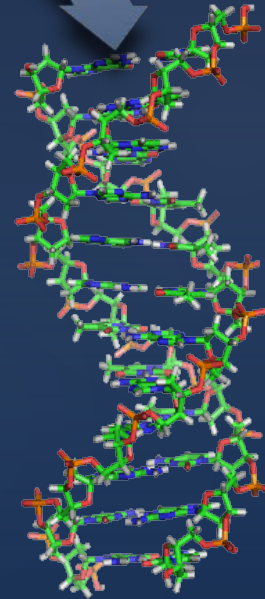
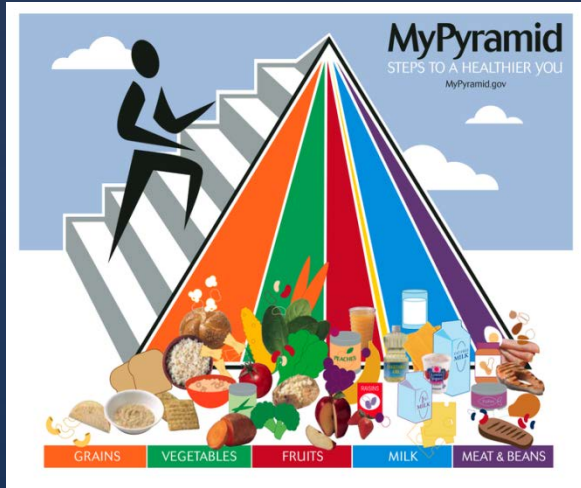
= corresponds to a transcript absent in the obese group (basal line).

Nutrigenomics and Nutrigenetics



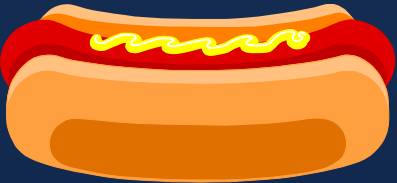
Dietary effects on gene expression

NUTRIGENOMICS

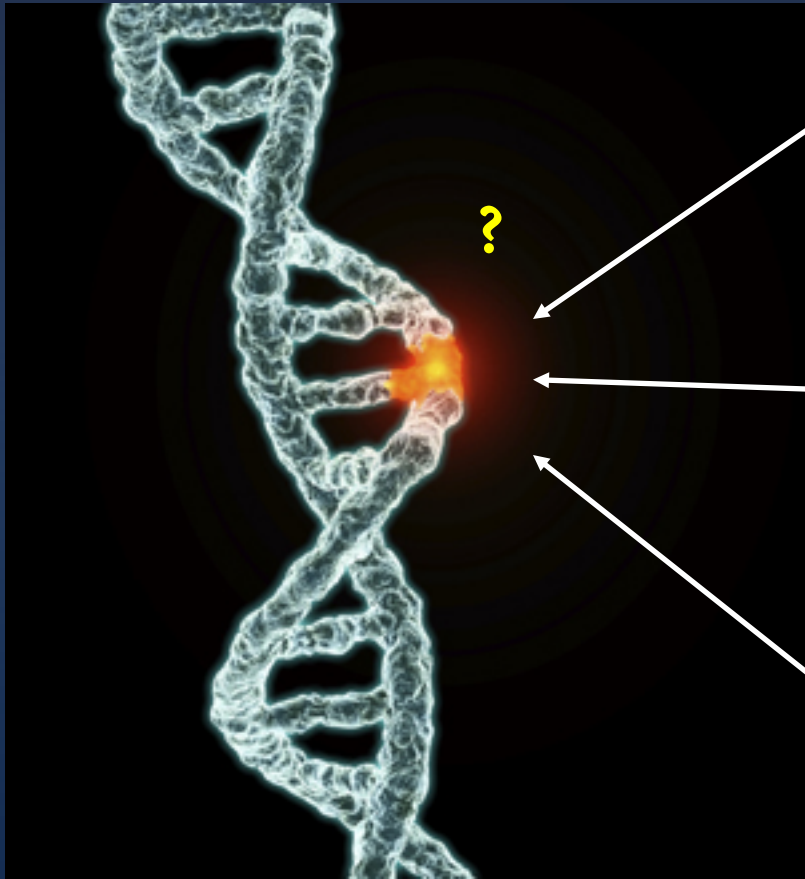


NUTRIGENETICS

Genotype influences the response related with nutrition and personalised metabolism

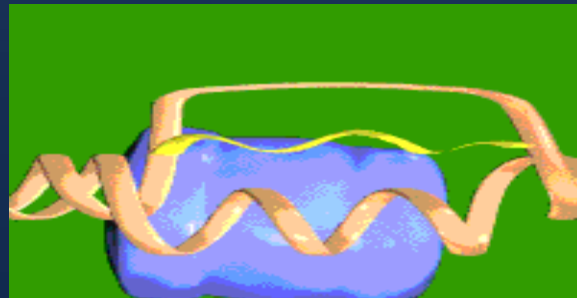


NUTRIGENETICS: Personalized nutrition based on genotype.

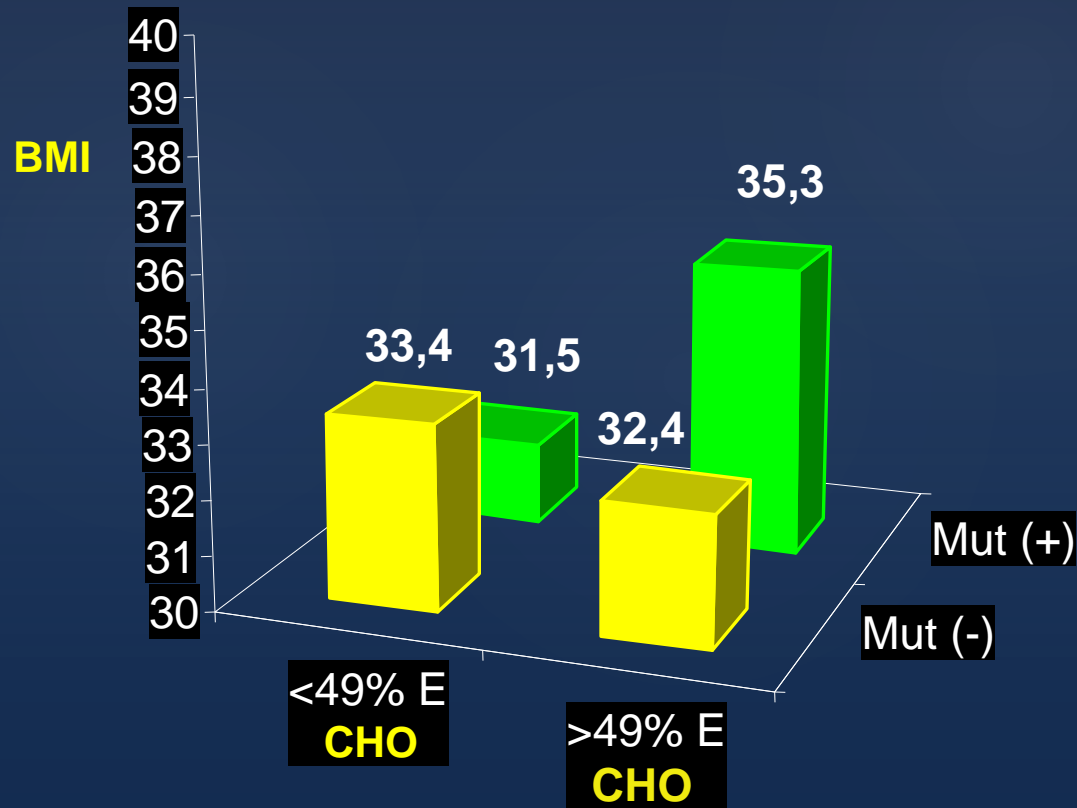


NUTRIGENOMICS is the study of molecular relationships between **nutrition** and the response of **genes**, with the aim of extrapolating how such subtle changes can affect **Human health**.

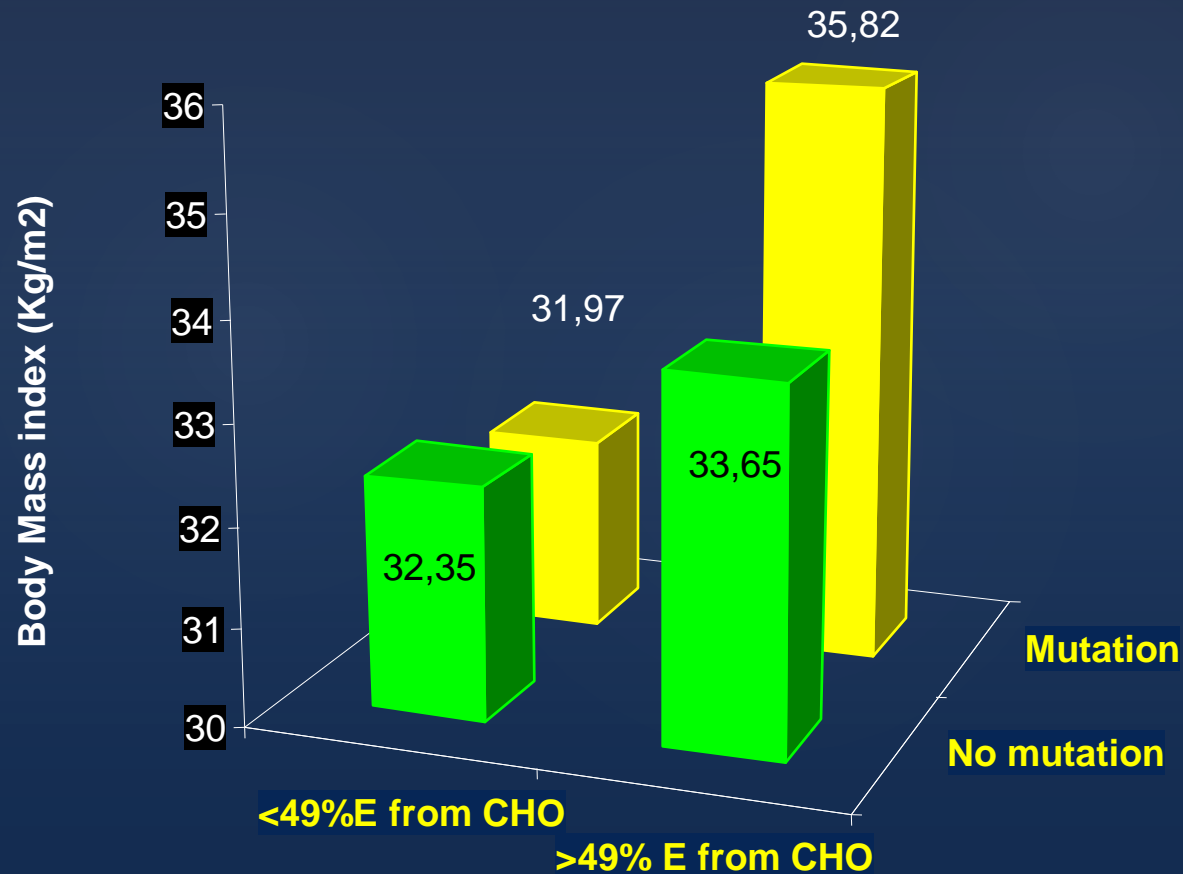
GENOTYPE & NUTRITION INTERACTIONS



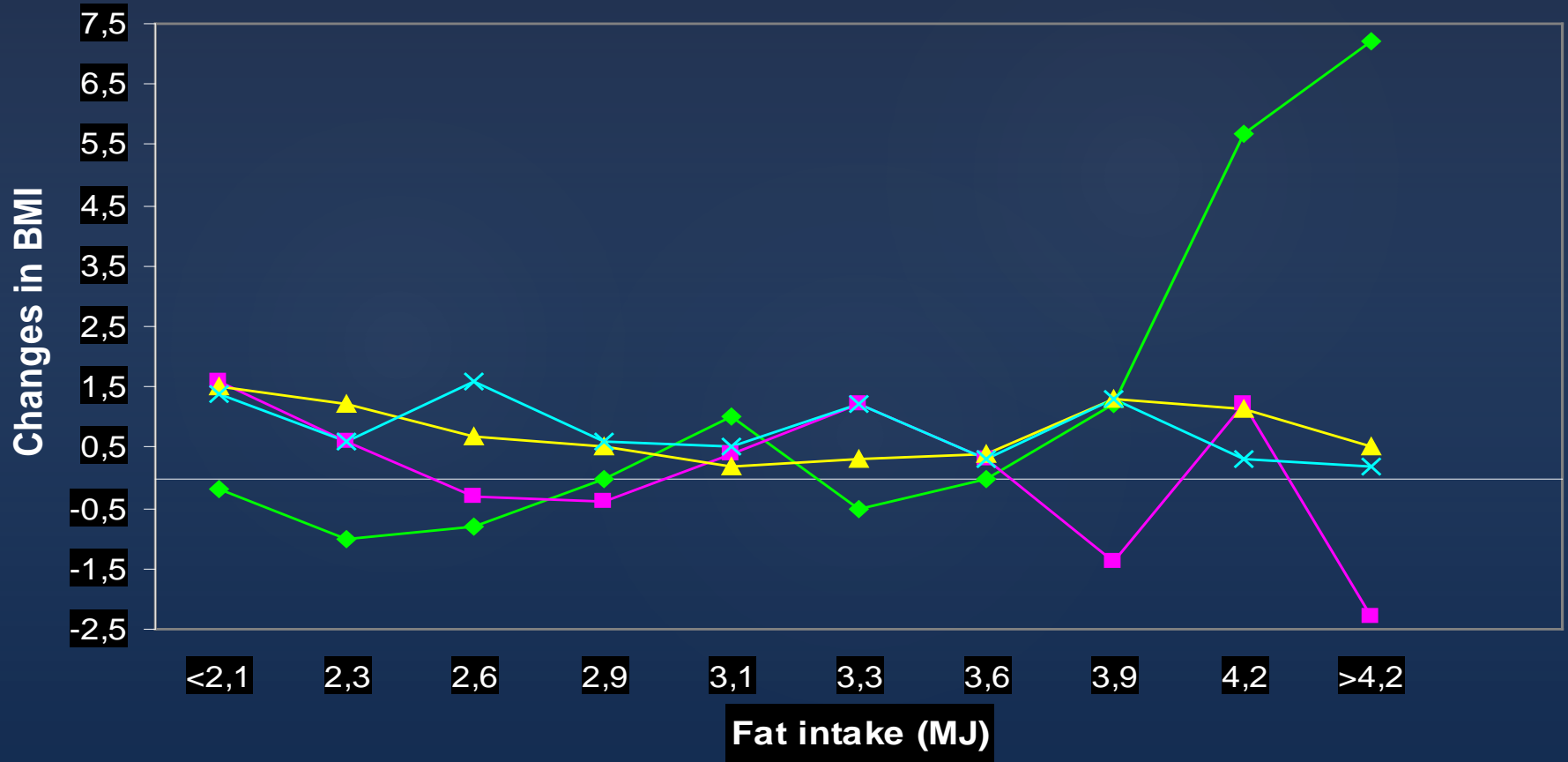
GENOTYPE & NUTRITION INTERACTIONS



NUTRIGENETICS: β 2AR POLYMORPHISM AT GLN27GLN

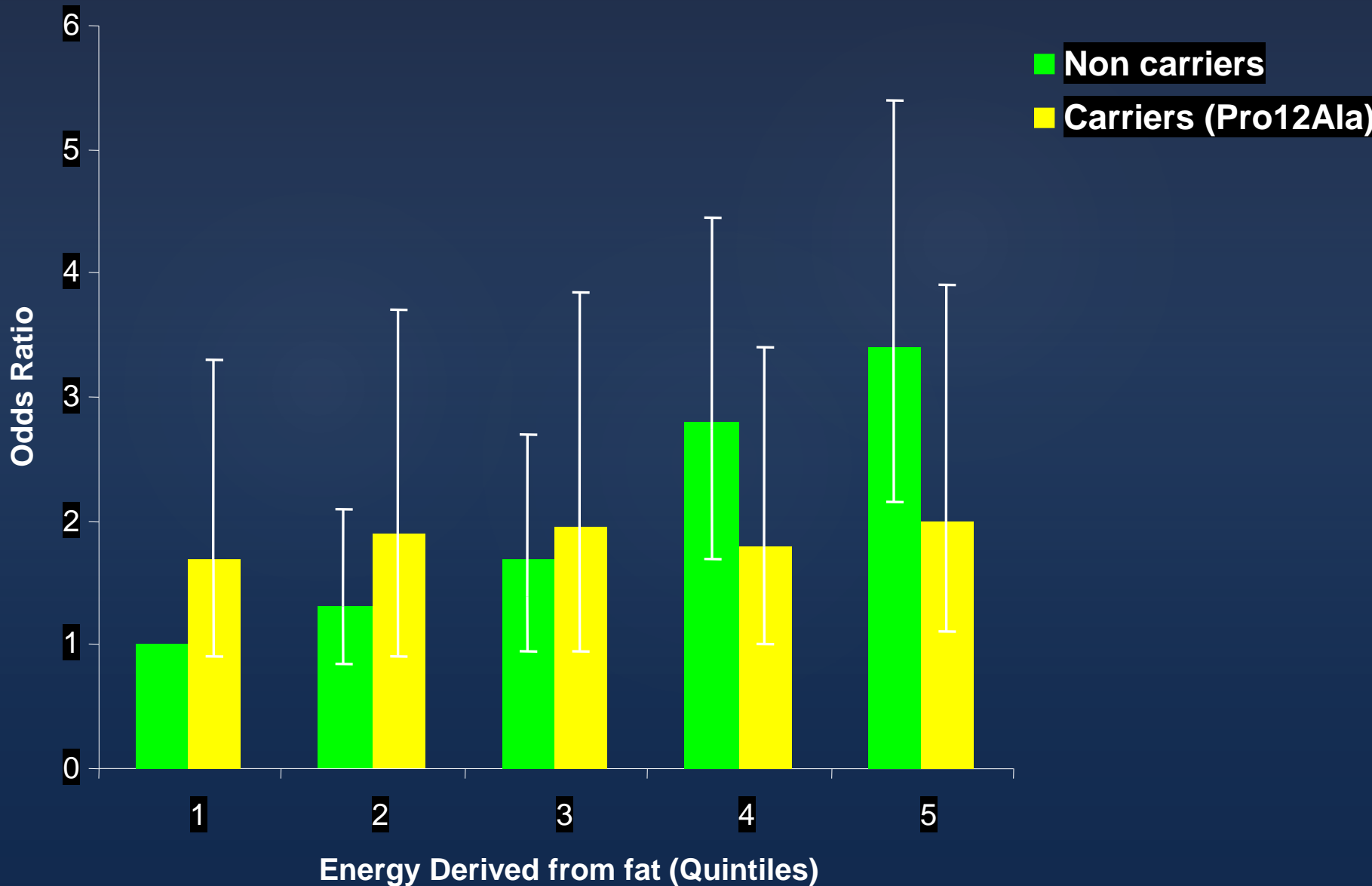


BMI, FAT INTAKE AND GENOTYPE INTERACTIONS

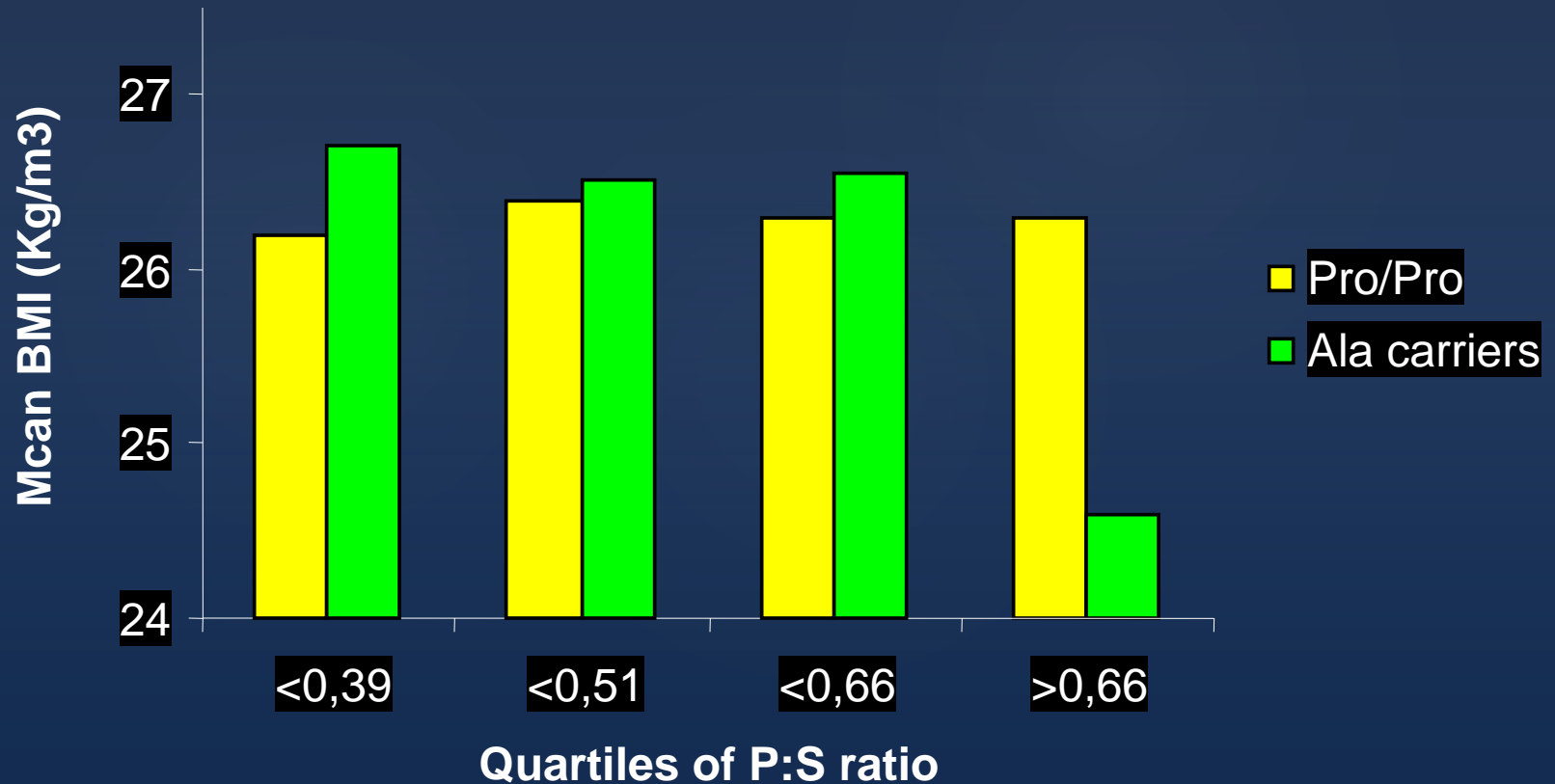


- ◆— Ow/Op Ow=overweight at baseline
- Ow/Np Nw=normal weight at baseline
- ▲— Nw/Op Op=obese parents
- ×— Nw/Np Np=normal weight parents

GENOTYPE X NUTRIENT (FAT) INTERACTIONS



GENOTYPE & NUTRITION INTERACTIONS



Dietary fatty acid distribution modifies obesity risk linked to the rs9939609 polymorphism of the fat mass and obesity-associated gene in a Spanish case-control study of children

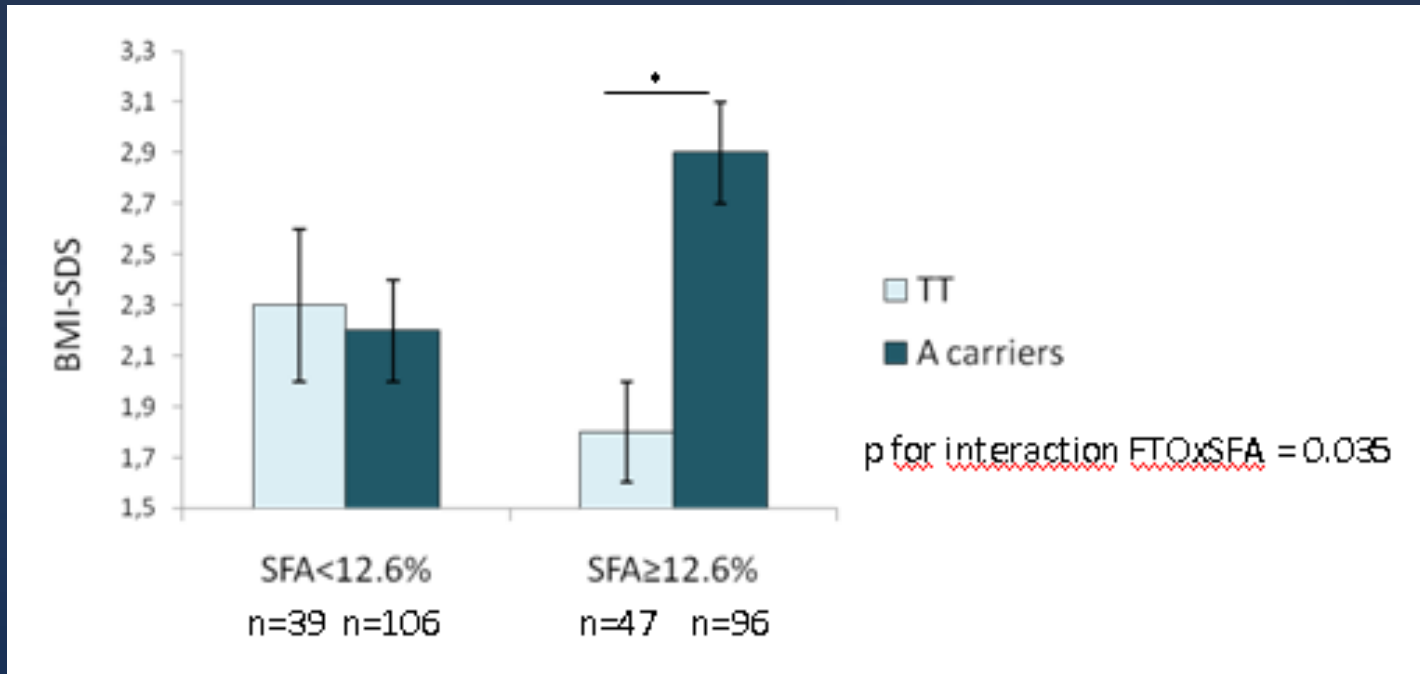
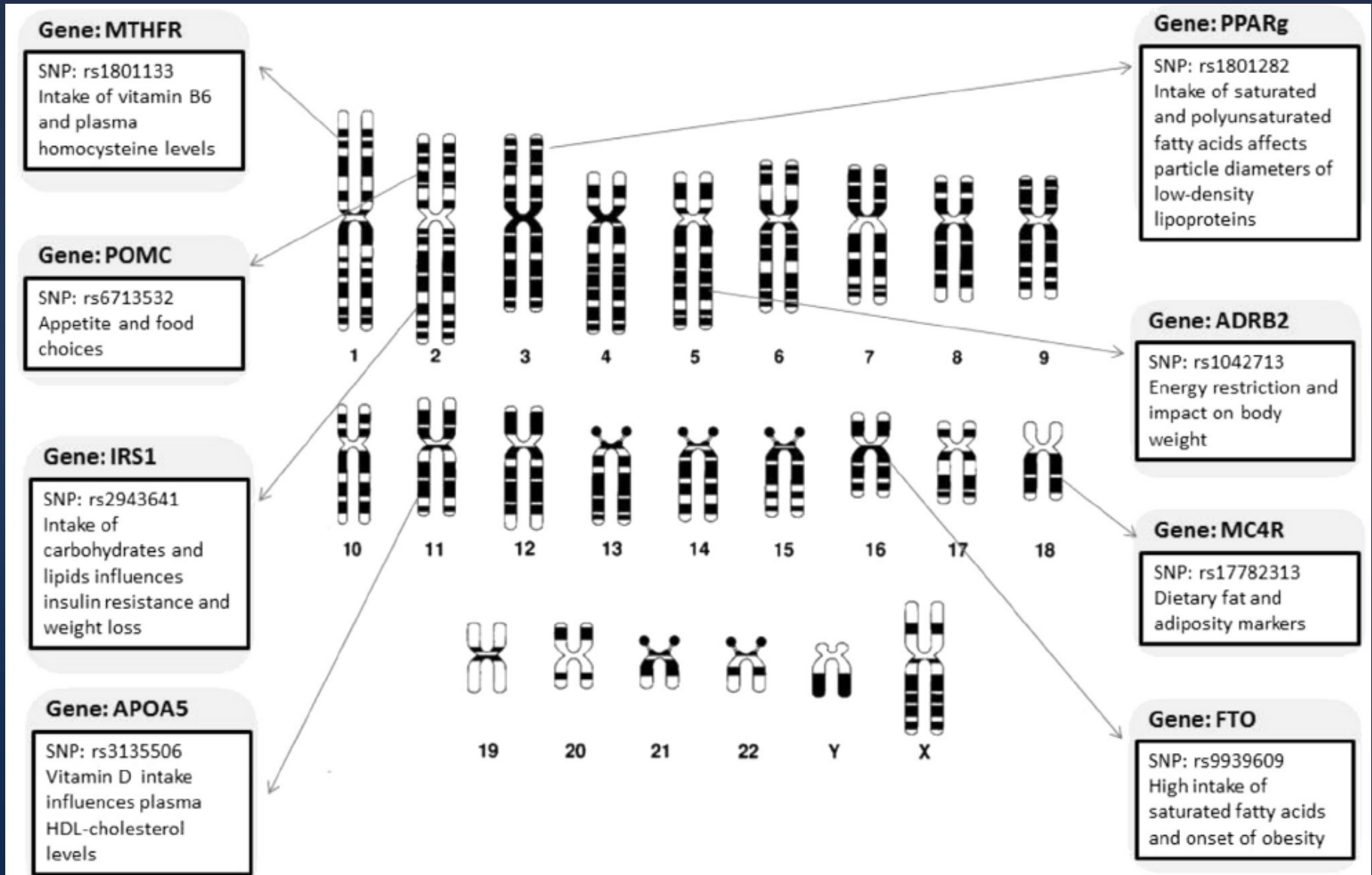
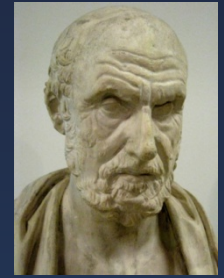


Fig. 2. BMI-standard deviation score (SDS) of children and adolescents according to SFA consumption (percentage of total energy, dichotomised by the median) and the presence of the fat mass and obesity associated (FTO) rs9939609 polymorphism in a dominant model. Values are means, with their standard errors represented by vertical bars.

GENE-NUTRIENT INTERACTIONS



Personalized Medicine and Nutrition



Hippocrates (Cos, 460 a. C. - Tesalia 370 a. C.) “...YOUR food is the basis of YOUR health”

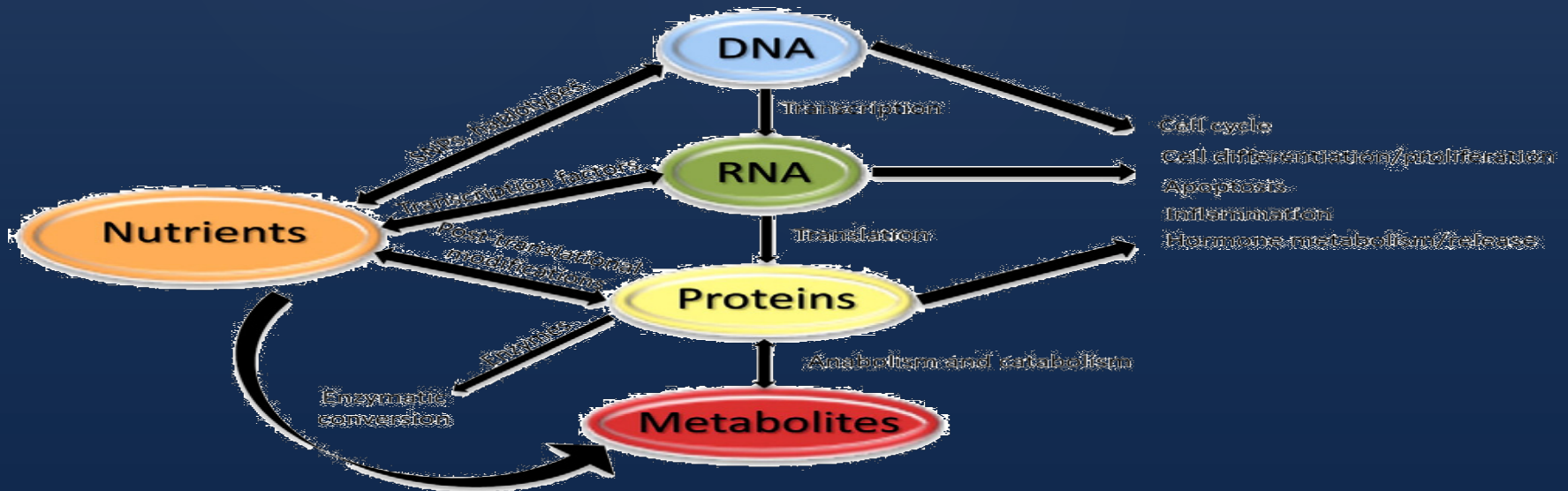
Galeno (Pérgamo, Greece, 130 - Roma, 200) “Personal attitudes and unique response to food”

C. Bernard. (s XIX) “No disease, but patients”

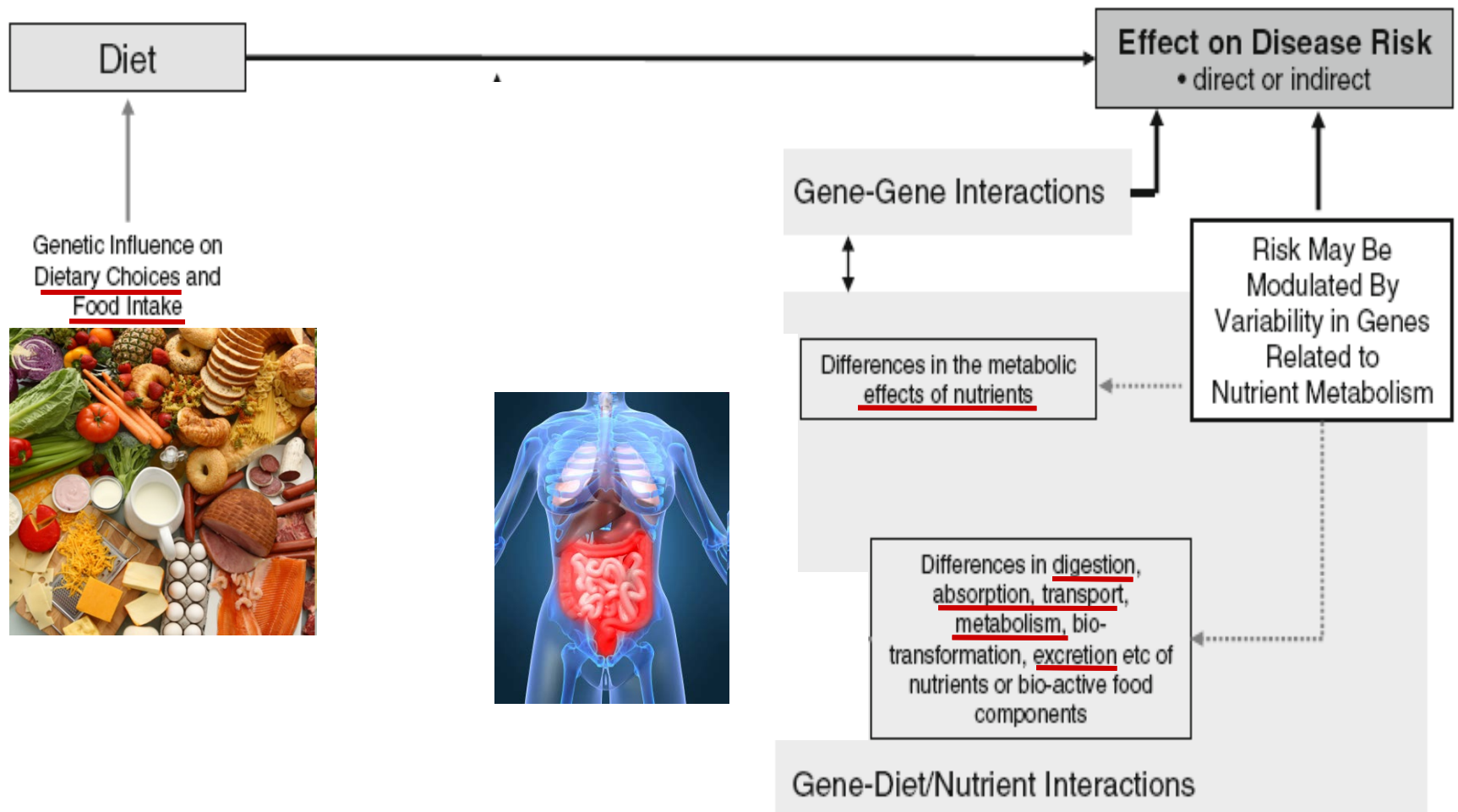
Mendel: (s XIX) Individualized trait transmission among generations

Garrod (early s XX) Nutritional outcomes depend on personal metabolism

Williams (1956): Personal variation in hormonal responses to food

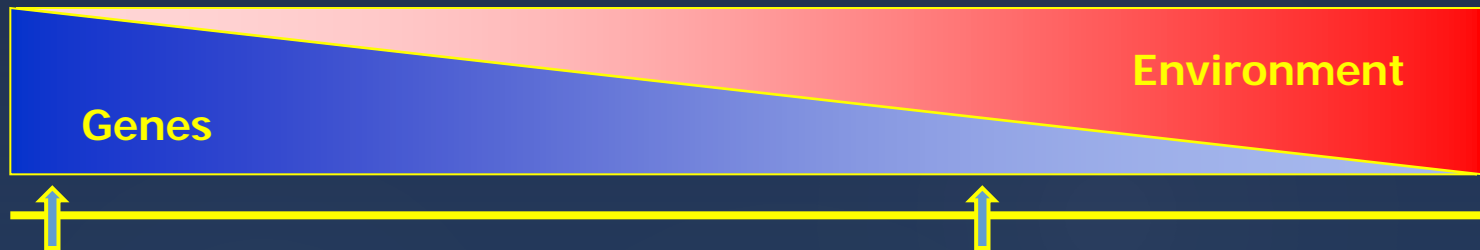


Personalization: Nutrition & Genetic Interactions



Possible interactions of diet with genetic variability to affect disease risk.

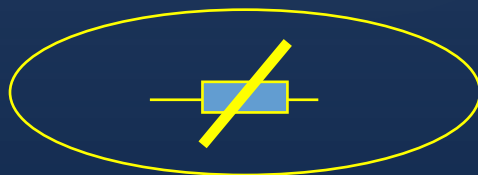
Genetics of Human Metabolism: gene and environment Interactions



Monogenic

- Rare cases
- Syndromes

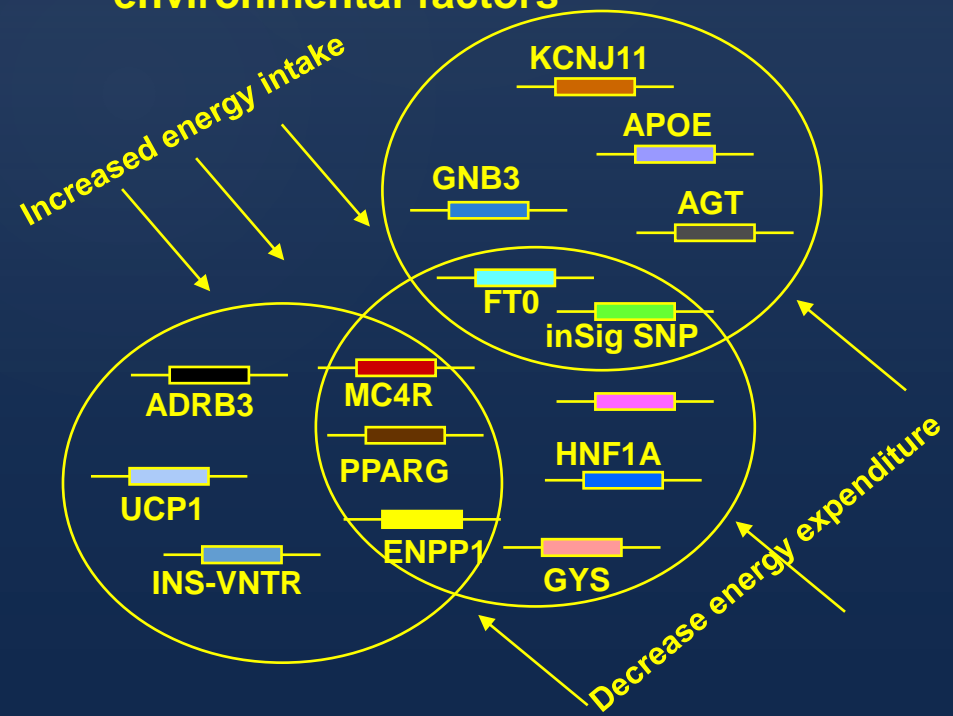
1 gene 1 disease



LEP, LEPR, POMC, PCSK1
SIM,,

Polygenic

Individual combination in interaction with environmental factors

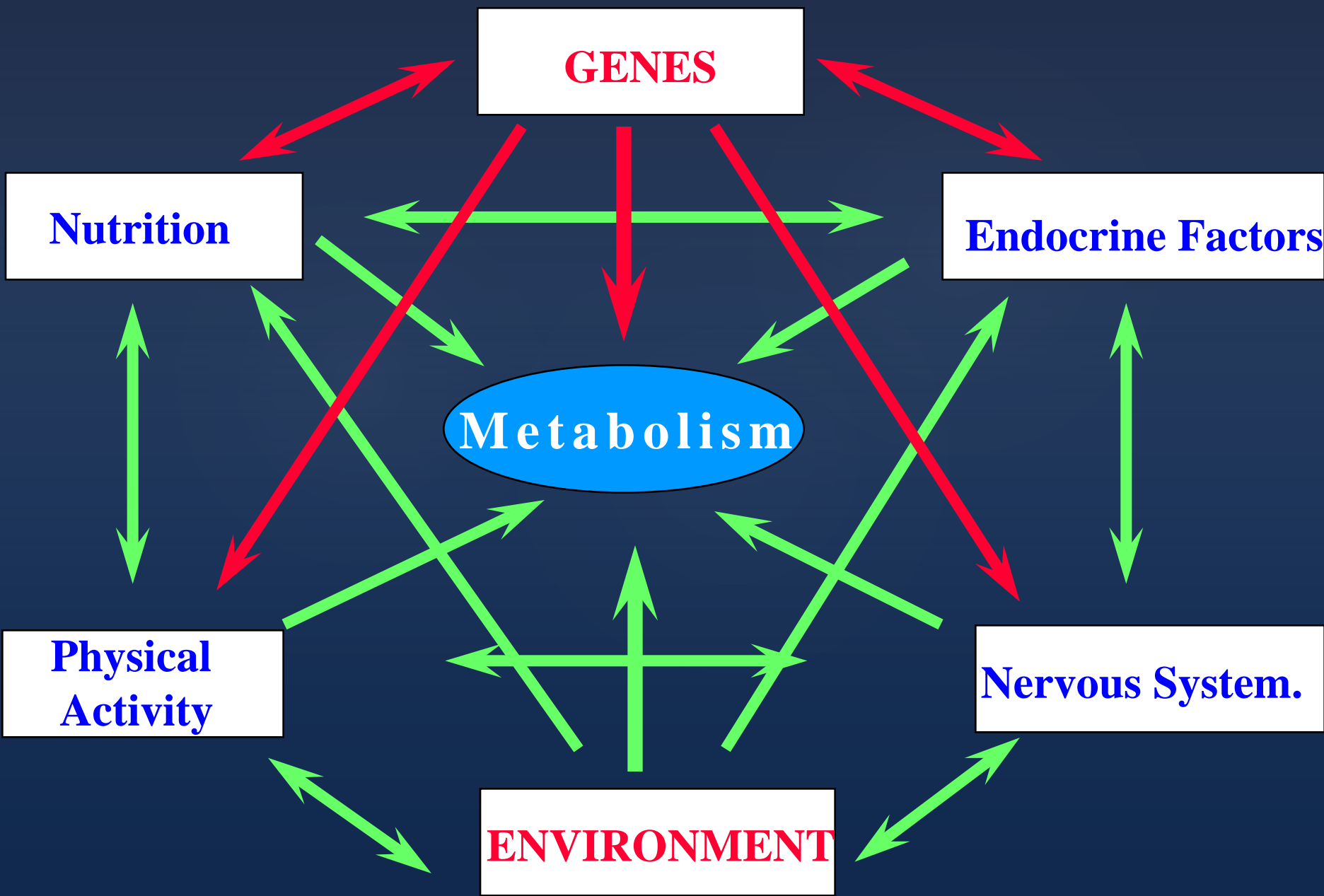


PREDISPOSITION (% RISK) → HAPLOTYPE X ENVIRONMENT

MONOGENIC DISEASES	POLYGENIC DISEASES
Celiac disease Lactose intolerance Familial hypercholesterolemia Phenylketonuria Galactosemia	Obesity Type 2 Diabetes Hyperlipidaemias Cardiovascular disease & Hypertension Osteoporosis Neurodegenerative diseases Cancer

- **Modifiable factors:**
lifestyle, alcohol, smoking, exercise, dietary habits. sleep
- **Exogenous factors :**
Toxins. pollutants, microorganisms, allergens

METABOLISM: ETHIOLOGICAL FACTORS



PERSONALIZACION: GENE RESEARCH

- **Genotype:** gene/alleles responsables for traits
- **Phenotype:** external manifestations of an observable character

Mendelian Syndromes



- Autosomal dominant
- Autosómico recessive
- X-linked

Animal models

- Genetically obese animals
- Transgenic Animals
- Q Trait Loci (QTL)

Association and Linkage Studies

- Candidate genes and GWAS
- Family segregation

MONOGENIC DISORDERS with OBESITY TRAITS

MIM number	Disorder	Locus
Autosomal Dominant		
100800	Achondroplasia (ACH)	4p16.3
122000	Posterior Polymorphous Corneal Dystrophy (PPCD)	20q11
176270	Prader-Willi Syndrome (PWS)	15q11.2-q12
181450	Schinz el syndrome/Ulnar-mammary syndrome (UMS)	12q23-q24.1
Autosomal Recessive		
	Bardet-Biedl Syndrome (BBS)	
209901	BBS1	11q13
209900	BBS2	16q21
600151	BBS3	3p13-p12
600374	BBS4	15q22.3-q23
216550	Cohen Syndrome (CHS1)	
X-LINKED		
301900	Borjeson-Forssman-Lehman Syndrome (BFLS)	Xq26-q27
303110	Choroideremia with deafness and obesity	Xq21
309585	Wilson-Turner Syndrome (WTS)	Xq21.1-q22
312870	Simpson-Golabi-Behmel (SGBS)	Xq26

GENETIC LINKAGE

Phenotype	Framingham		Canada		Norway	
	BMI		BMI/Skinfolds		BMI	
	n	r^2	n	r^2	n	r^2
Spouses	1163	0,19	3138	0,12	23936	0,12
Parent/child	4027	0,23	7194	0,20	43586	0,20
Siblings	992	0,28	3924	0,34	19157	0,24

BMI ASSOCIATIONS IN TWEENS

	NAS/NRC	Virginia	Sweden	England
Phenotype	BMI	IMC/Pliegues	BMI	BMI
n	4071	259	311	38
Monozigotes	0,81	0,79	0,70	0,61
Dizigotes	0,42	0,35	0,15	—
h^2	77%	85%	74%	

BMI ASSOCIATIONS between ADOPTEES & FAMILIES

	Denmark		Iowa		Montreal	
Relación	Biológico / Adoptee		Biológico / Adoptee		Biológico / Adoptee	
n	3651		357		553	
Parents	0,15	0,00	0,20	0,02	0,17	0,01
Siblings	0,23	0,14	—	—	0,13	0,07
h ²	34%		—		17%	

ANIMAL GENETIC MODELS

Type	<u>ANIMAL</u>			<u>HUMANS</u>	
	Chr	Loci	Inheritance	Chr	Gene Product
Diabetes (db)	4	Lepr	Recessive	1	leptina receptor
Fat (fat)	8	Cpe	Recessive	4	carboxipeptidasa E
Obese (ob)	6	Lep	Recessive	7	leptin
Tubby (tub)	7	Tub	Recessive	11	unknown
Agouti yellow	2	Ay	Dominant	20	Agouti protein



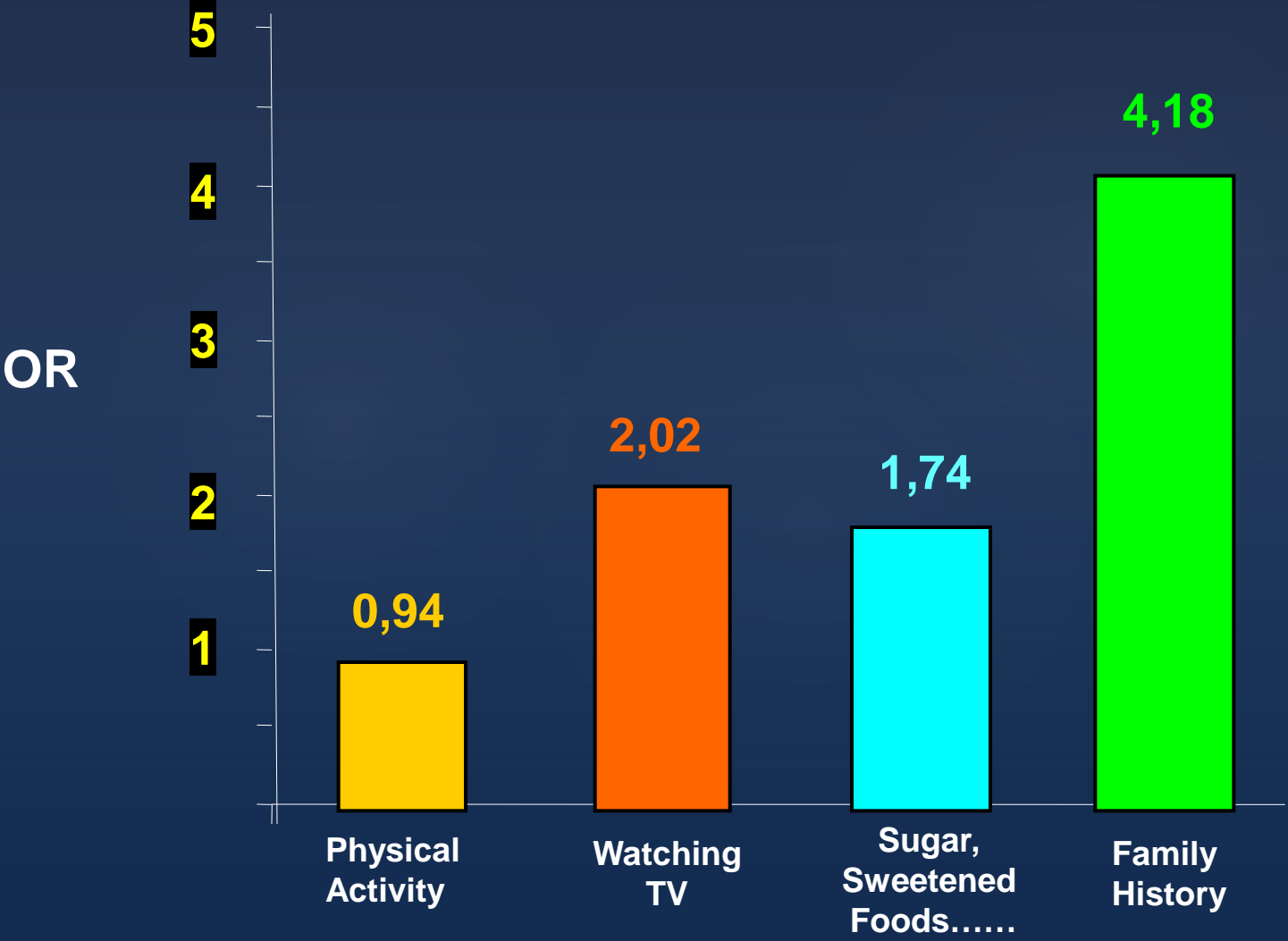
TRANSGENIC MODELS

Metabolic alterations

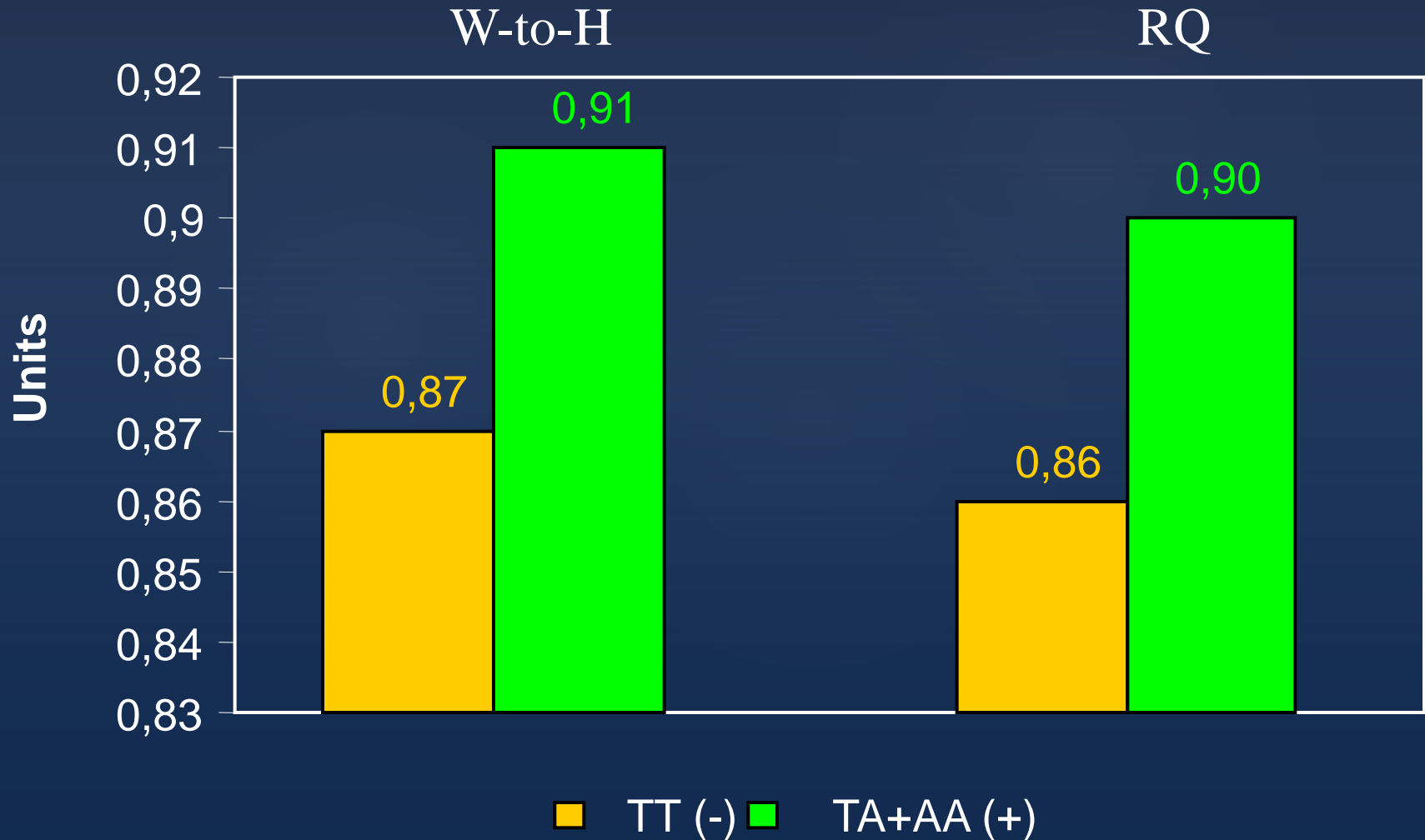
- **Knock-out de TNF- α (Glucose tolerance)**
- **Knock-out de c/EBP (Adipocyte differentiation)**
- **Knock-out de adrenalin (Thermoregulation)**
- **Knock-out de LPL (Lipid metabolism)**
- **Knock-out de BAT (Thermogenesis)**



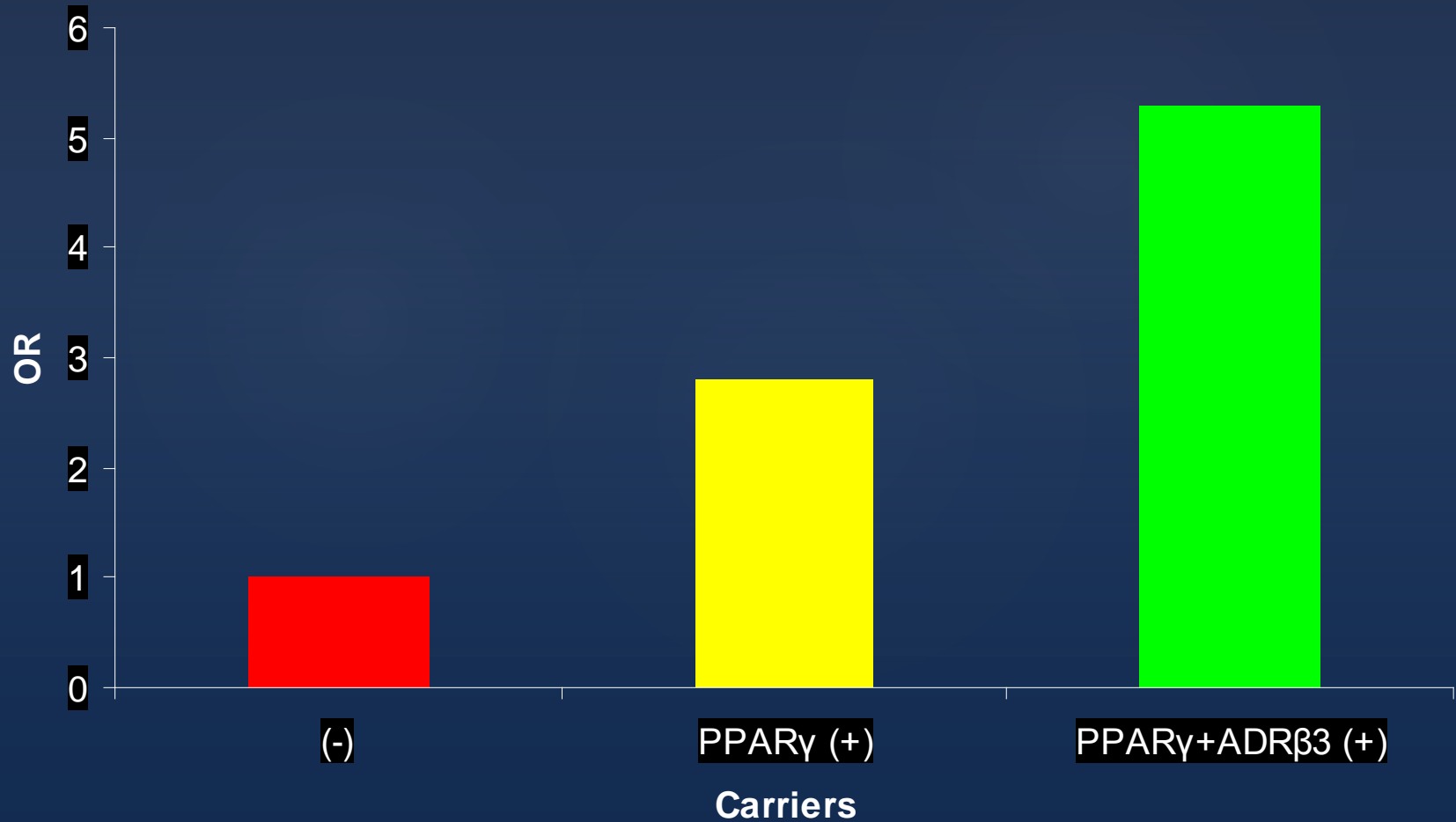
PREDICTOR FACTORS FOR CHILDHOOD OBESITY



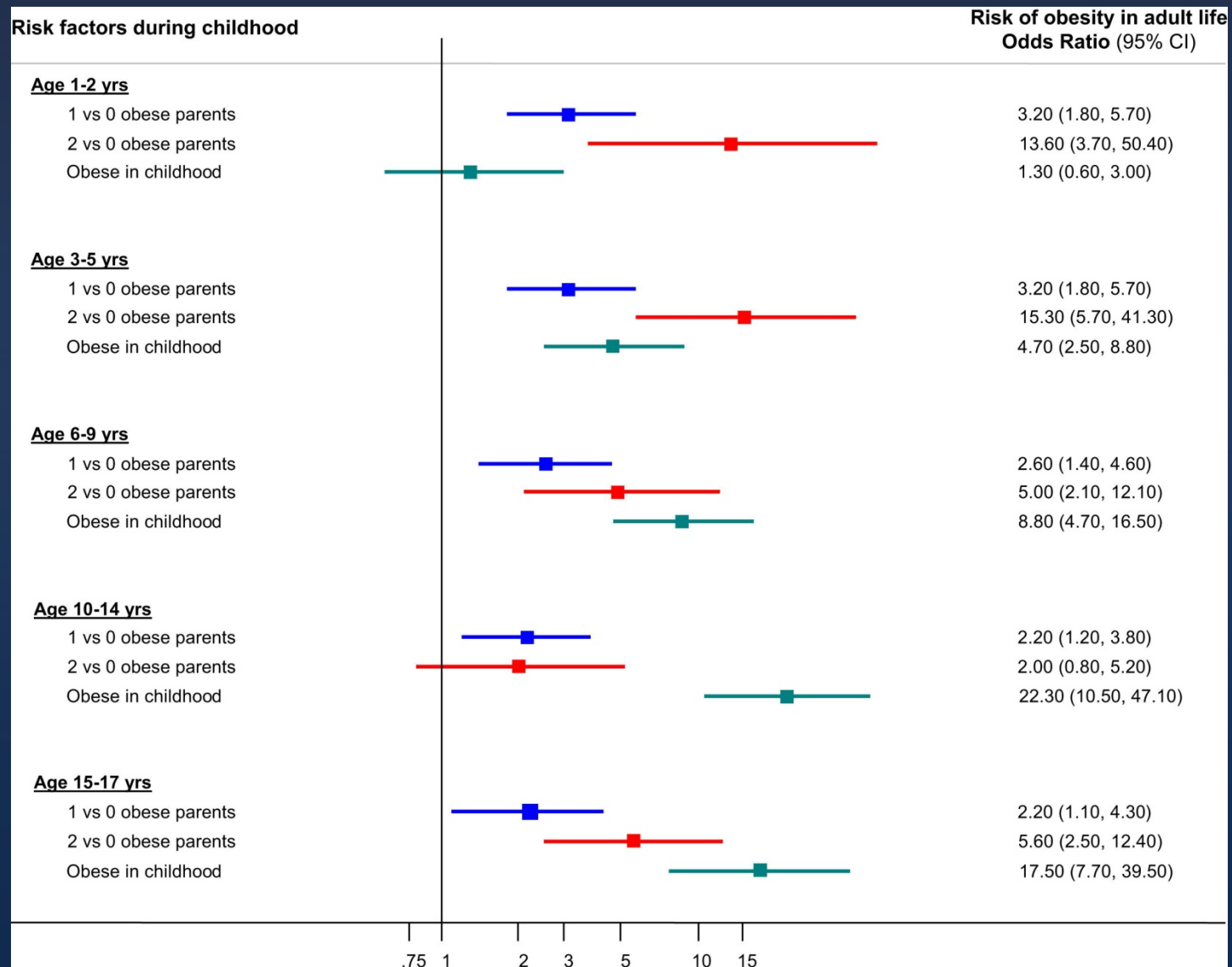
Trp64Arg MUTATION OF THE β_3 ADRENOCEPTOR



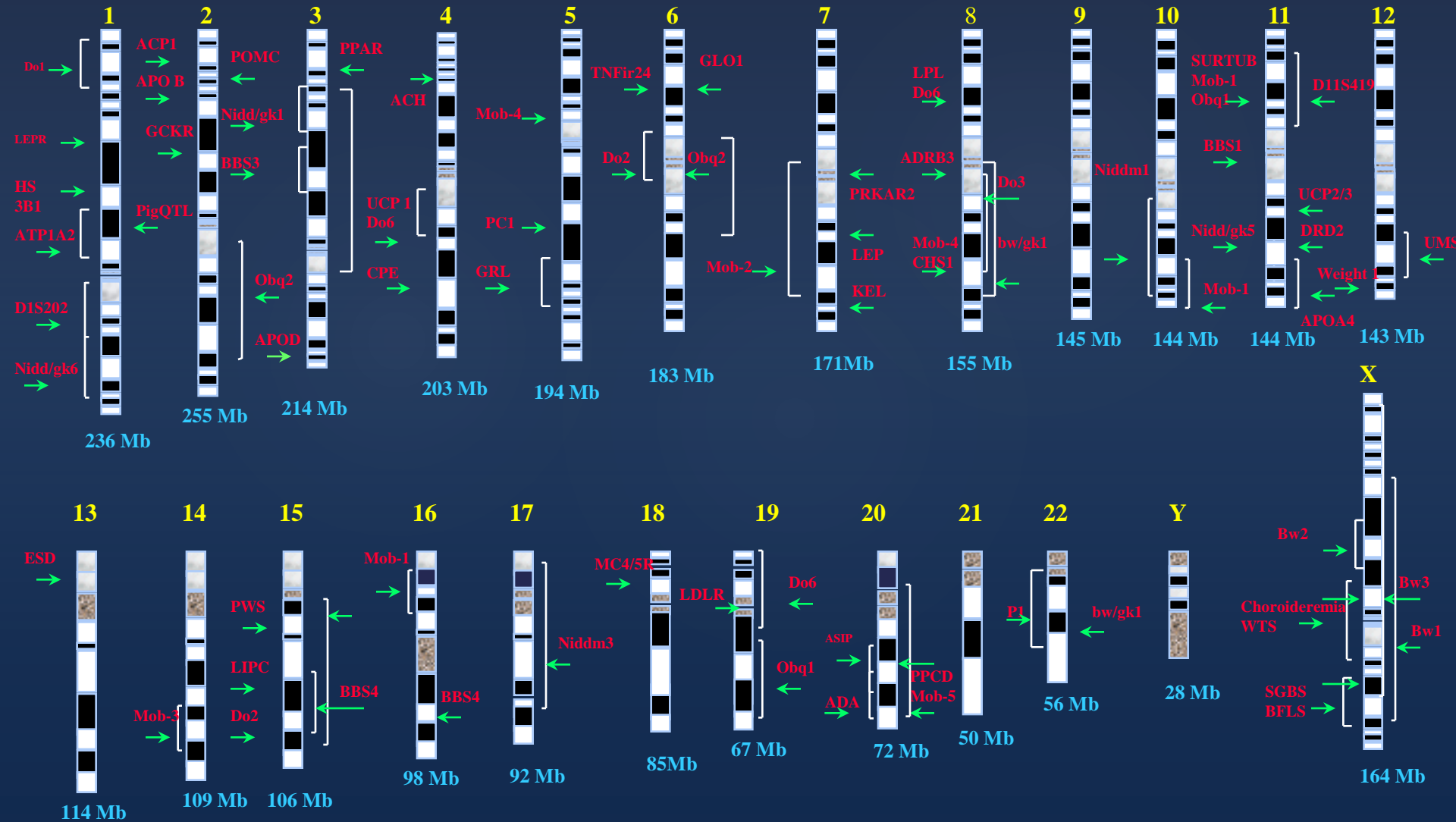
PPAR γ 2 x ADR β 3 INTERACTIONS



CHILDHOOD OVERWEIGHT AND THE RISK OF OBESITY IN ADULTHOOD



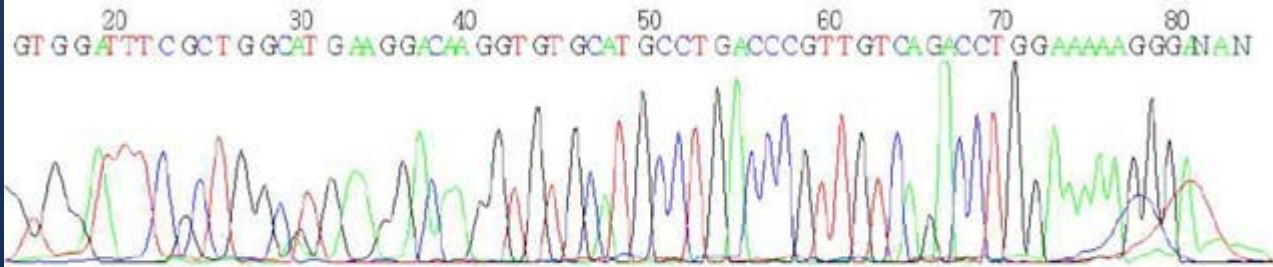
METABOLISM GENOME



LAST: FTO, MC4R, UCP, POMC, LEP, β AR, PPAR, AP2,..... TNF,...

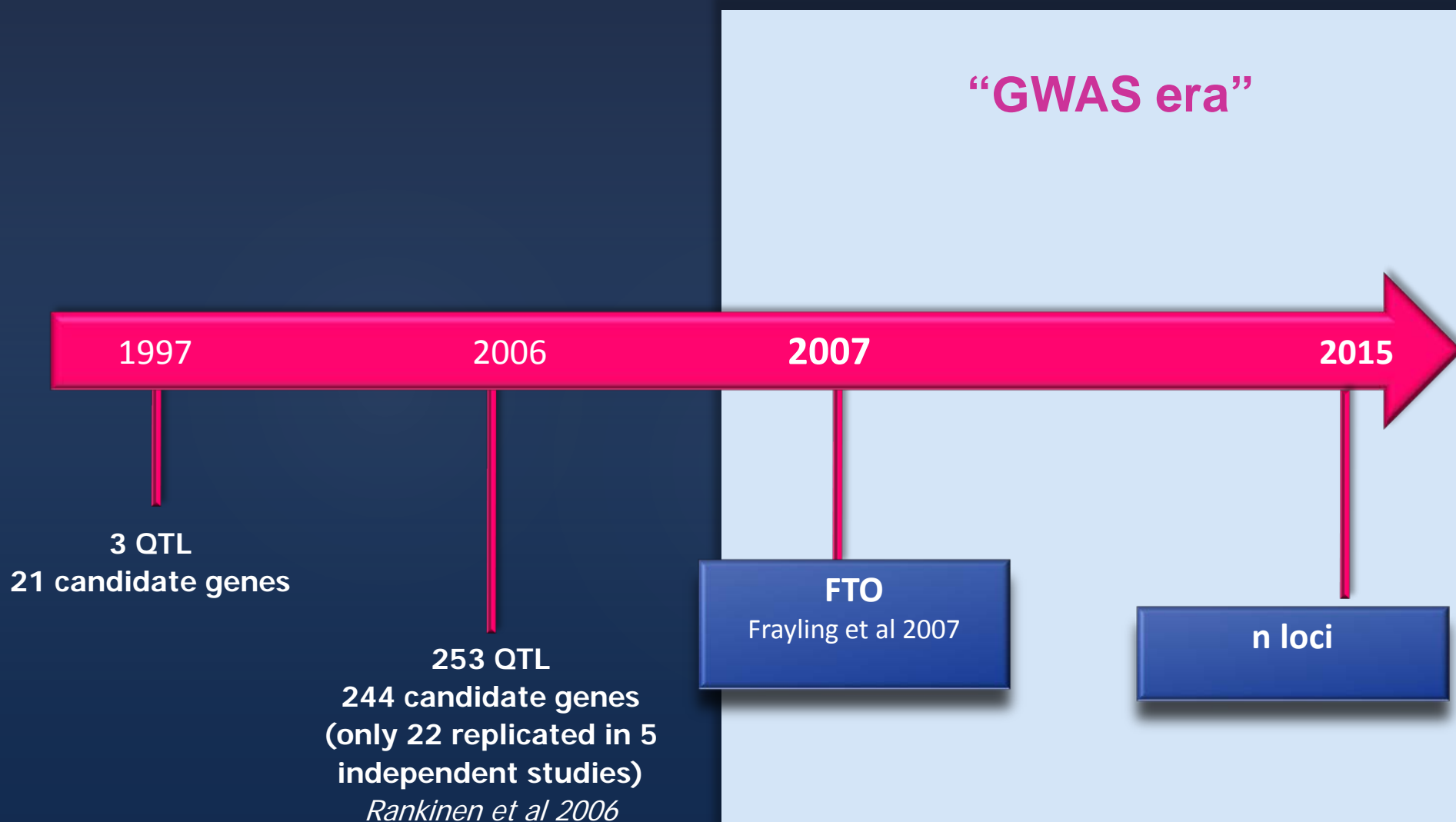
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GGCCTGCCGTGGCAGATCCCCAACGCCGGGCC
TCTC
CAGCA
CGAT
CGGA
ACAA
CGGATCTCTTGGCTCCAGCATCGATGAAGAAC
GATGAAGAACGCAGCGAAACGCGATATGTAA

Data acquisition OMICS & GWAS



Sequention microarrays

Milestones in Obesity genetic data acquisition



STRATEGIC APPROACHES IN GENETIC DATA ACQUISITION

CANDIDATE GENE STUDIES

Clinical cases (altered genes associated with disease "Healthy" no alteration)



Screening known gene



Associated SNPs to disease



Cellular/molecular studies
Physiology

GWAS

Genome-Wide Association Studies

Thousands of people



Wide genome scan



Genetic identification

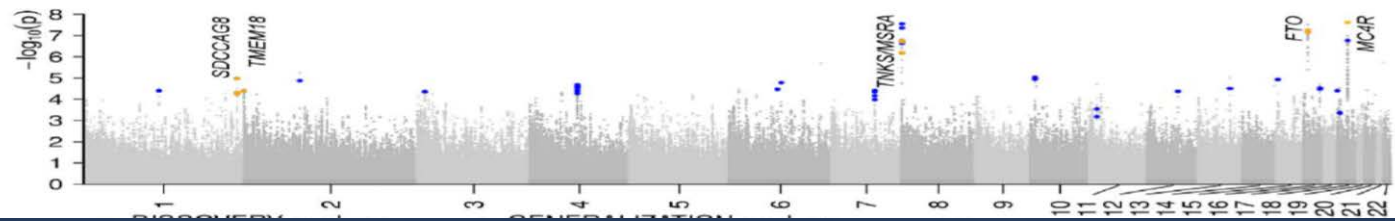


Biochemistry
Genetics
Comparative genomics

Cellular/molecular studies
Physiology

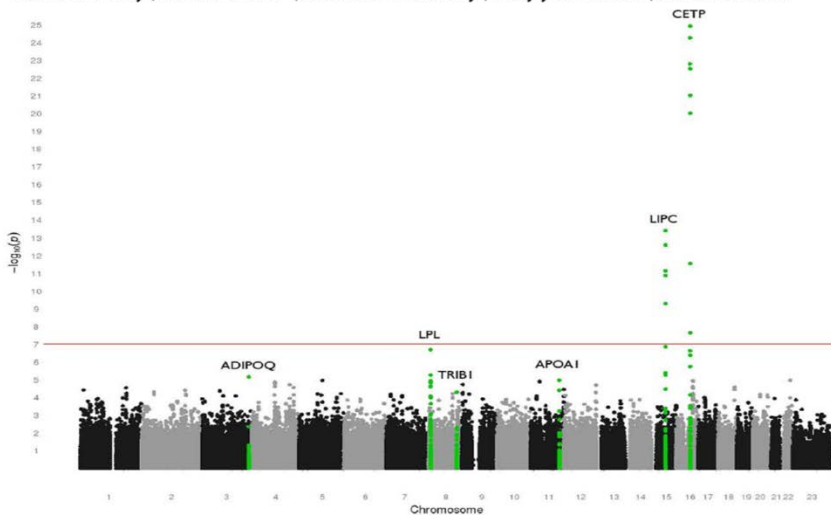
Two New Loci for Body-Weight Regulation Identified in a Joint Analysis of Genome-Wide Association Studies for Early-Onset Extreme Obesity in French and German Study Groups

André Scherag^{1,2*}, Christian Dina³, Anke Hinney², Vincent Vatin³, Susann Scherag², Carla I. G. Vogel²,



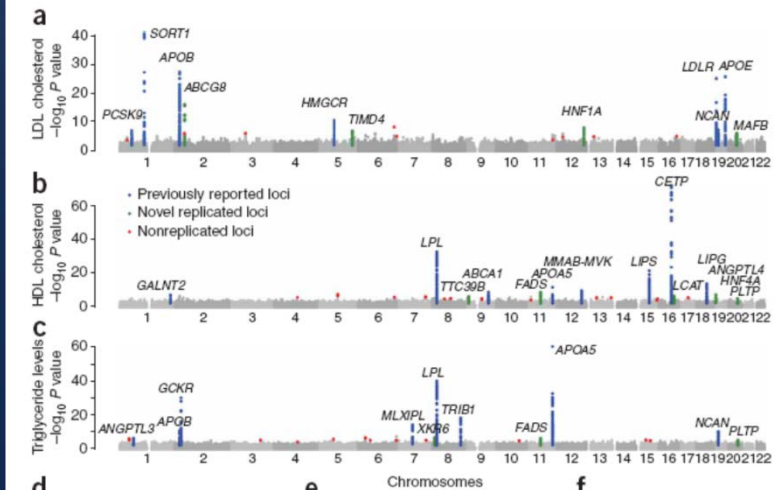
Knowledge-Driven Multi-Locus Analysis Reveals Gene-Gene Interactions Influencing HDL Cholesterol Level in Two Independent EMR-Linked Biobanks

Stephen D. Turner¹, Richard L. Berg², James G. Linneman², Peggy L. Peissig², Dana C. Crawford¹, Joshua C. Denny³, Dan M. Roden^{4,5}, Catherine A. McCarthy⁶, Marylyn D. Ritchie¹, Russell A. Wilke^{4*}



Common variants at 30 loci contribute to polygenic dyslipidemia

Sekar Kathiresan^{*1-5,37,38}, Cristen J Willer^{6,37}, Gina M Peloso^{4,7,37}, Serkalem Demissie^{4,7,37}, Kiran Musunuru^{1,2},



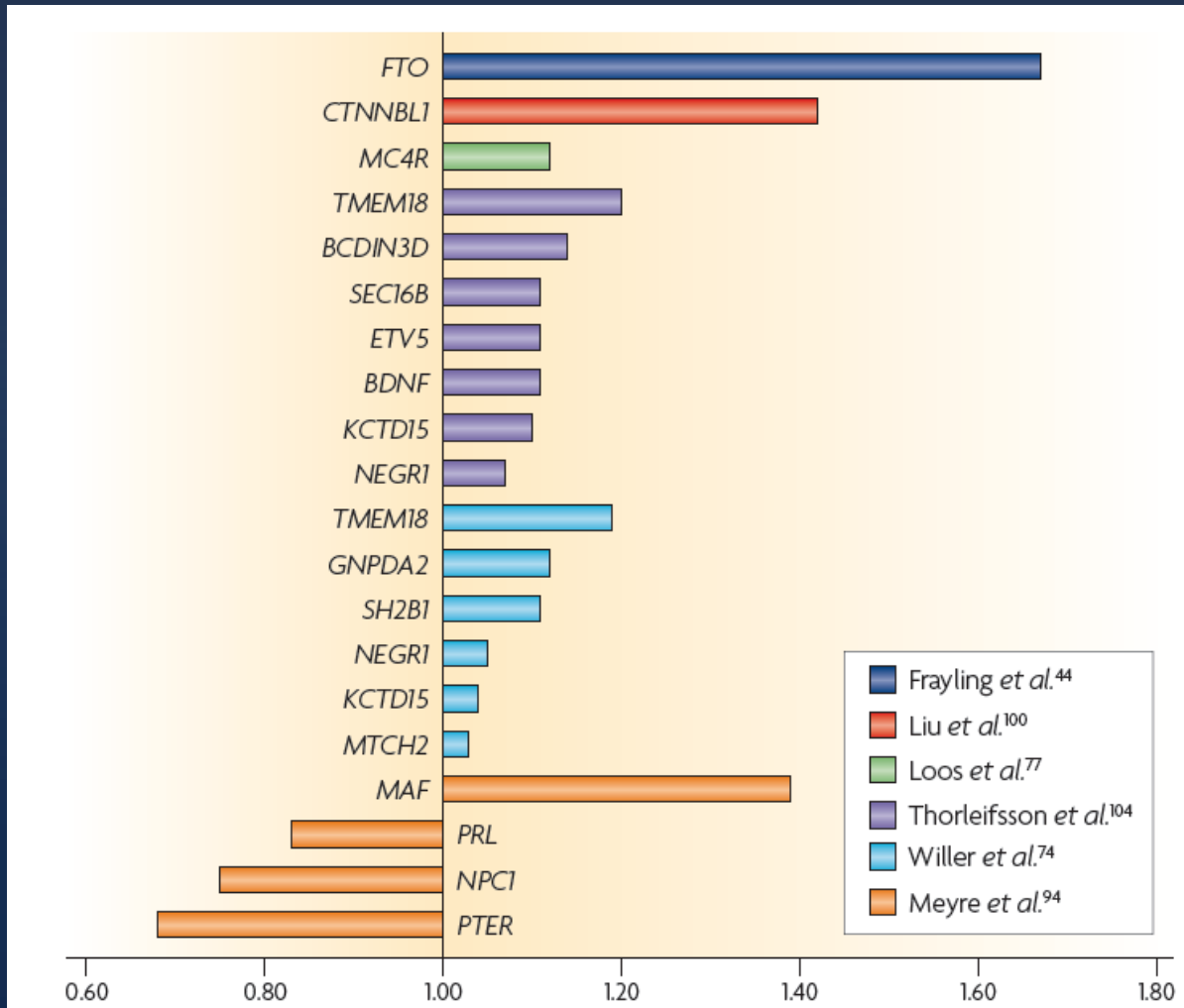
REVIEWS

The genetic contribution to non-syndromic human obesity

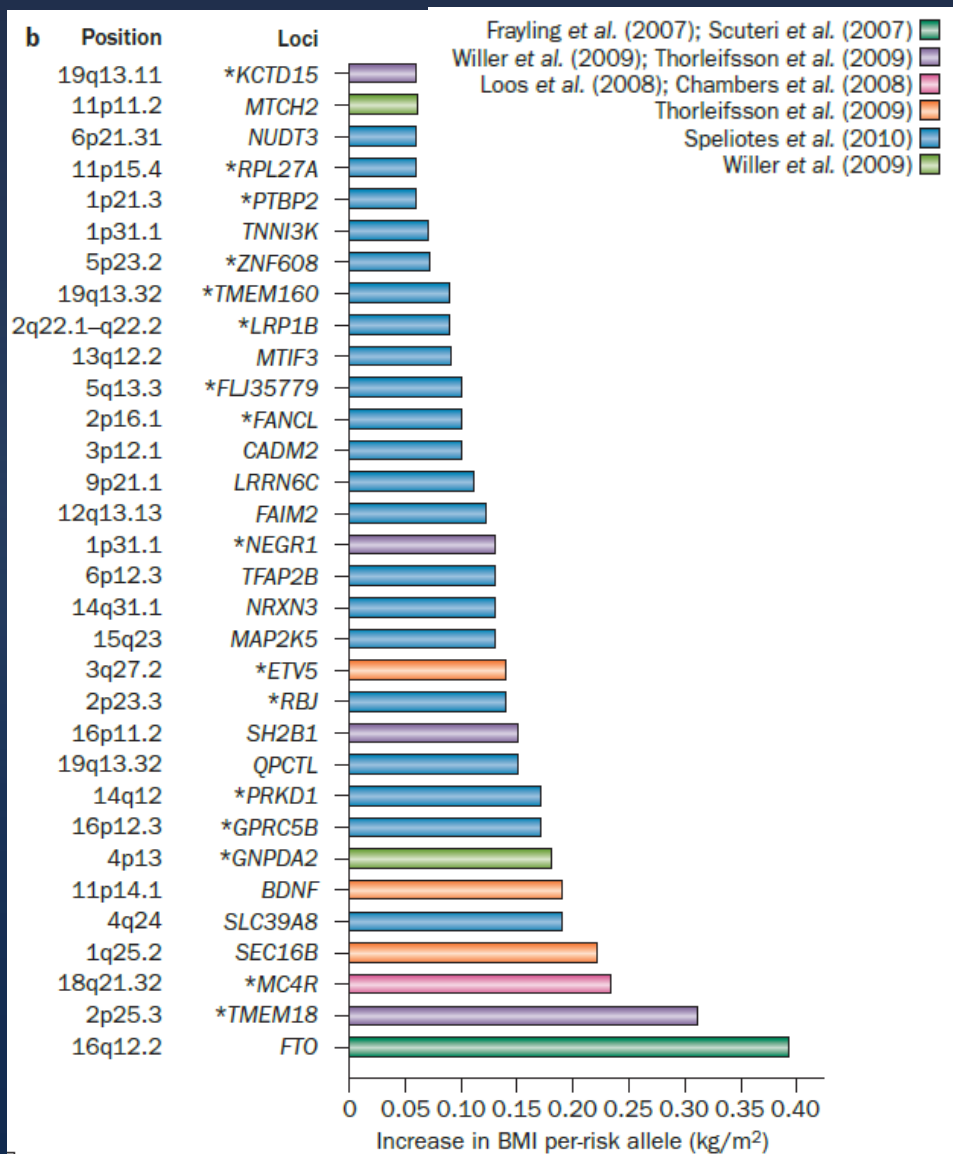
*Andrew J. Walley**, *Julian E. Asher** and *Philippe Froguel*†*

Abstract | The last few years have seen major advances in common non-syndromic obesity research, much of it the result of genetic studies. This Review outlines the competing hypotheses about the mechanisms underlying the genetic and physiological basis of obesity, and then examines the recent explosion of genetic association studies that have yielded insights into obesity, both at the candidate gene level and the genome-wide level. With obesity genetics now entering the post-genome-wide association scan era, the obvious question is how to improve the results obtained so far using single nucleotide polymorphism markers and how to move successfully into the other areas of genomic variation that may be associated with common obesity.

GENES ASSOCIATED with HUMAN OBESITY (GWAS)



EFFECT SIZES FOR GENETIC VARIANTS ASSOCIATED WITH BMI



*gene closest to the reported association



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8

Genetic determinants of common obesity and their value in prediction

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Keywords:

genome-wide association
obesity
body mass index (BMI)
prediction
personal genome profile

Genome-wide association studies (GWAS) have revolutionised the discovery of genes for common traits and diseases, including obesity-related traits. In less than four years time, 52 genetic loci were identified to be unequivocally associated with obesity-related traits. This vast success raised hope and expectations that genetic information would become soon an integral part of personalised medicine. However, these loci have only small effects on obesity-susceptibility and explain just a fraction of the total variance. As such, their accuracy to predict obesity is poor and not competitive with the predictive ability of traditional risk factors. Nevertheless, some of these loci are being used in commercially available personal genome tests to estimate individuals' lifetime risk of obesity. While proponents believe that personal genome profiling could have beneficial effects on behaviour, early reports do not support this hypothesis. To conclude, the most valuable contribution of GWAS-identified loci lies in their contribution to elucidating new physiological pathways that underlie obesity-susceptibility.

New genetic loci link adipose and insulin biology to body fat distribution

A list of authors and their affiliations appears at the end of the paper

Body fat distribution is a heritable trait and a well-established predictor of adverse metabolic outcomes, independent of overall adiposity. To increase our understanding of the genetic basis of body fat distribution and its molecular links to cardiometabolic traits, here we conduct genome-wide association meta-analyses of traits related to waist and hip circumferences in up to 224,459 individuals. We identify 49 loci (33 new) associated with waist-to-hip ratio adjusted for body mass index (BMI), and an additional 19 loci newly associated with related waist and hip circumference measures ($P < 5 \times 10^{-8}$). In total, 20 of the 49 waist-to-hip ratio adjusted for BMI loci show significant sexual dimorphism, 19 of which display a stronger effect in women. The identified loci were enriched for genes expressed in adipose tissue and for putative regulatory elements in adipocytes. Pathway analyses implicated adipogenesis, angiogenesis, transcriptional regulation and insulin resistance as processes affecting fat distribution, providing insight into potential pathophysiological mechanisms.

Genes enriched for WHRadjBMI-associated loci

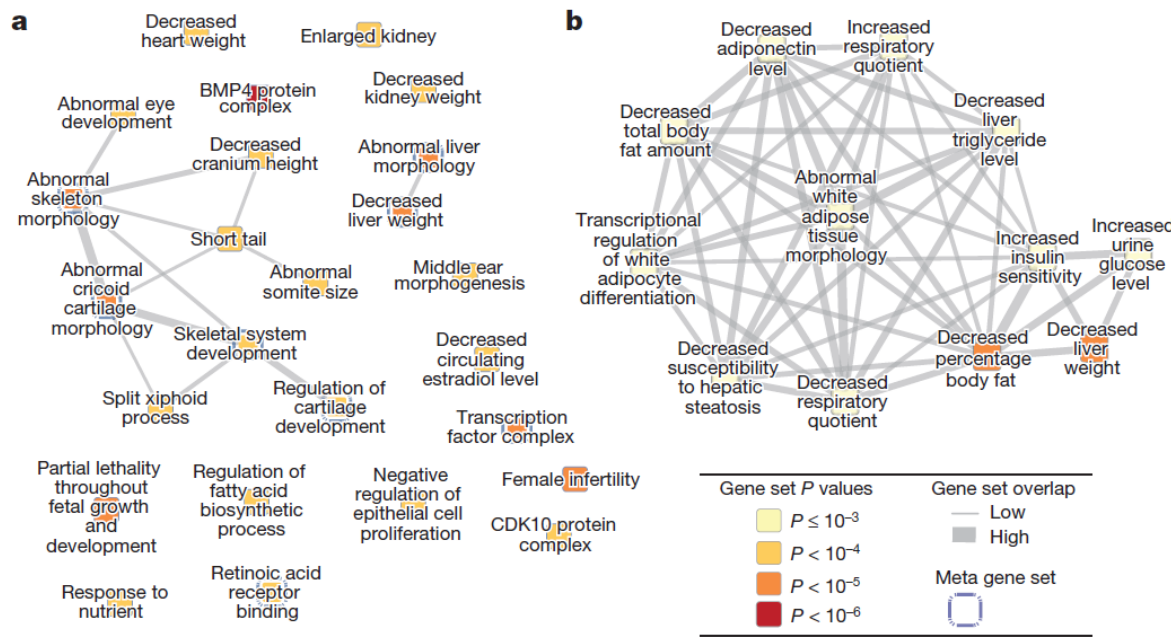
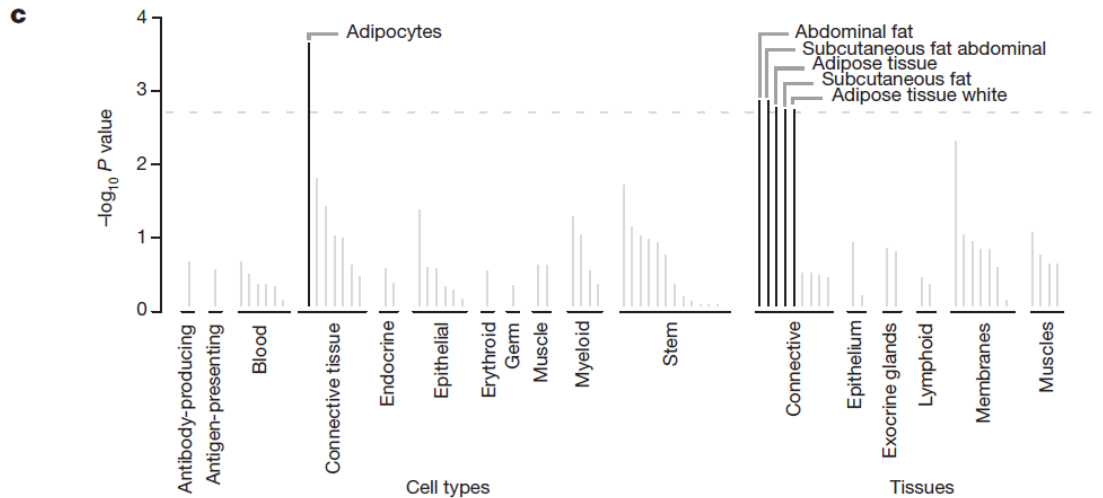


Figure 2 | Gene set enrichment and tissue expression of genes at WHRadjBMI-associated loci (GWAS-only $P < 10^{-5}$). **a**, Reconstituted gene sets found to be significantly enriched by DEPICT (FDR < 5%) are represented as nodes, with pairwise overlap denoted by the width of connecting lines and empirical enrichment P value indicated by colour intensity (darker is more significant). **b**, The ‘decreased liver weight’ meta-node, which consisted of 12 overlapping gene sets, including adiponectin signalling and insulin sensitivity. **c**, On the basis of expression patterns in 37,427 human microarray samples, annotations found to be significantly enriched by DEPICT are shown, grouped by type and significance.



Genetic studies of body mass index yield new insights for obesity biology

A list of authors and their affiliations appears at the end of the paper

Obesity is heritable and predisposes to many diseases. To understand the genetic basis of obesity better, here we conduct a genome-wide association study and Metabochip meta-analysis of body mass index (BMI), a measure commonly used to define obesity and assess adiposity, in up to 339,224 individuals. This analysis identifies 97 BMI-associated loci ($P < 5 \times 10^{-8}$), 56 of which are novel. Five loci demonstrate clear evidence of several independent association signals, and many loci have significant effects on other metabolic phenotypes. The 97 loci account for ~2.7% of BMI variation, and genome-wide estimates suggest that common variation accounts for >20% of BMI variation. Pathway analyses provide strong support for a role of the central nervous system in obesity susceptibility and implicate new genes and pathways, including those related to synaptic function, glutamate signalling, insulin secretion/action, energy metabolism, lipid biology and adipogenesis.

Genes enriched for BMI-associated loci

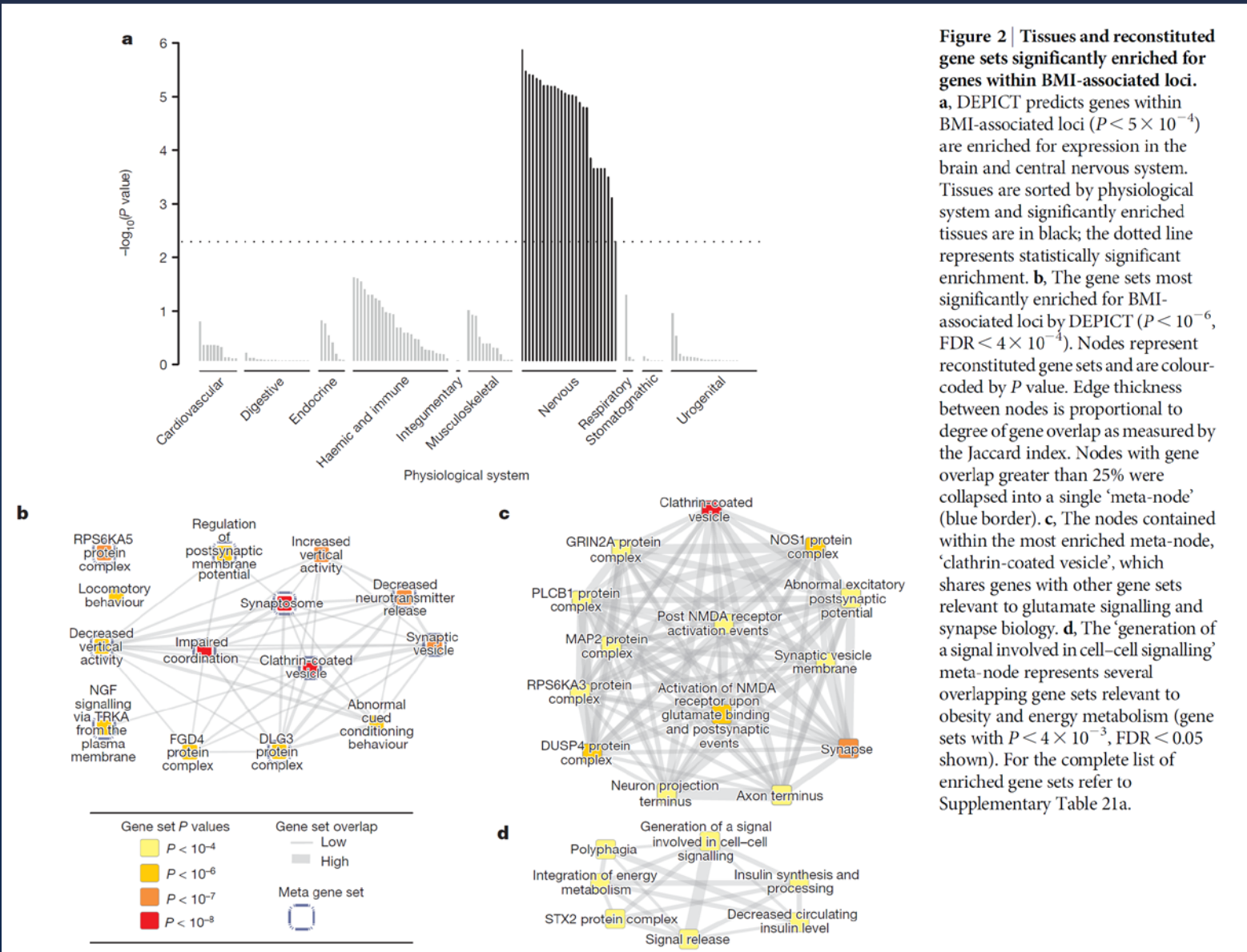
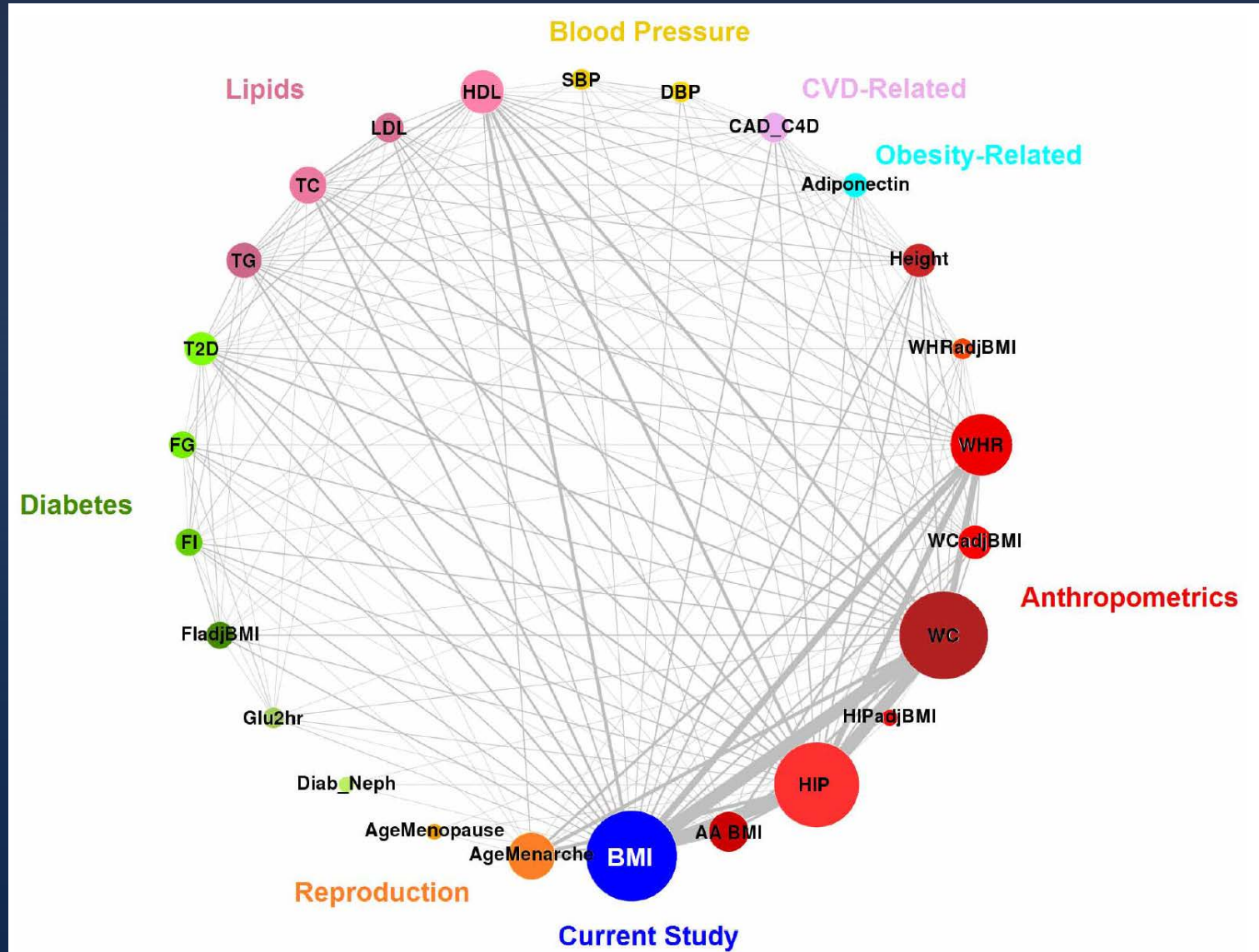


Figure 2 | Tissues and reconstituted gene sets significantly enriched for genes within BMI-associated loci. **a**, DEPICT predicts genes within BMI-associated loci ($P < 5 \times 10^{-4}$) are enriched for expression in the brain and central nervous system. Tissues are sorted by physiological system and significantly enriched tissues are in black; the dotted line represents statistically significant enrichment. **b**, The gene sets most significantly enriched for BMI-associated loci by DEPICT ($P < 10^{-6}$, $FDR < 4 \times 10^{-4}$). Nodes represent reconstituted gene sets and are colour-coded by P value. Edge thickness between nodes is proportional to degree of gene overlap as measured by the Jaccard index. Nodes with gene overlap greater than 25% were collapsed into a single 'meta-node' (blue border). **c**, The nodes contained within the most enriched meta-node, 'clathrin-coated vesicle', which shares genes with other gene sets relevant to glutamate signalling and synapse biology. **d**, The 'generation of a signal involved in cell-cell signalling' meta-node represents several overlapping gene sets relevant to obesity and energy metabolism (gene sets with $P < 4 \times 10^{-3}$, $FDR < 0.05$ shown). For the complete list of enriched gene sets refer to Supplementary Table 21a.

The 97 loci account for ~2,7% of BMI variation

The genetic overlap across traits at BMI susceptibility loci



A genetic risk tool for obesity predisposition assessment and personalized nutrition implementation based on macronutrient intake

Leticia Goni · Marta Cuervo · Fermín I. Milagro · J. Alfredo Martínez

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Abstract There is little evidence about genetic risk score (GRS)–diet interactions in order to provide personalized nutrition based on the genotype. The aim of the study was to assess the value of a GRS on obesity prediction and to further evaluate the interactions between the GRS and dietary intake on obesity. A total of 711 seekers of a Nutrigenetic Service were examined for anthropometric and body composition measurements and also for dietary habits and physical activity. Oral epithelial cells were collected for the identification of 16 SNPs (related with obesity or lipid metabolism) using DNA zip-coded beads. Genotypes were coded as 0, 1 or 2 according to the number of risk alleles, and the GRS was calculated by adding risk alleles with such a criterion. After being adjusted for gender, age, physical activity and energy intake, the GRS demonstrated that individuals carrying >7 risk alleles had in average 0.93 kg/m^2 of BMI, 1.69% of body fat mass, 1.94 cm of waist circumference and 0.01 waist-to-height ratio more than the individuals with ≤ 7 risk alleles. Significant interactions for GRS and the consumption of energy, total

protein, animal protein, vegetable protein, total fat, saturated fatty acids, polyunsaturated fatty acids, total carbohydrates, complex carbohydrates and fiber intake on adiposity traits were found after adjusted for confounders variables. The GRS confirmed that the high genetic risk group showed greater values of adiposity than the low risk group and demonstrated that macronutrient intake modifies the GRS association with adiposity traits.

Keywords Genetic risk score · Obesity · Adiposity · Gene–macronutrient interaction

Introduction

The prevalence of obesity is rising steadily not only in high-income countries but also in low-income countries. Indeed, it has been estimated that 1.12 billion adults will be obese by 2030 (Kelly et al. 2008). Consequently, the prevalence of obesity-associated metabolic diseases, such as type 2 diabetes, cardiovascular disease or certain can-

POLYMORPHISMS INCLUDED IN THE GENETIC RISK SCORE

Table 2 Genotype, minor allele frequency (MAF) and Hardy–Weinberg equilibrium calculations of the 16 SNPs included in the GRS

Gene	SNP	Major/ minor allele ^a	Major allele homozygote (%)	Heterozygote (%)	Minor allele homozygote (%)	MAF	HWE <i>p</i> value
<i>FTO</i>	rs9939609	T/A	218 (30.6)	351 (49.4)	142 (20.0)	0.45	0.973
<i>MC4R</i>	rs17782313	T/C	442 (62.2)	237 (33.3)	32 (4.5)	0.21	0.974
<i>MTHFR</i>	rs1801133	C/T	257 (36.2)	340 (47.8)	114 (16.0)	0.40	0.930
<i>PPARA</i>	rs1800206	C/G	591 (83.1)	116 (16.3)	3 (0.5)	0.09	0.507
<i>PPARG</i>	rs1801282	C/G	594 (82.5)	110 (15.5)	7 (1.0)	0.09	0.453
<i>APOA5</i>	rs662799	T/C	620 (87.2)	88 (12.4)	3 (0.4)	0.07	0.948
<i>APOE</i>	rs429358	T/C	574 (80.7)	129 (18.1)	8 (1.1)	0.10	0.804
<i>APOE</i>	rs7412	C/T	624 (87.8)	84 (11.8)	3 (0.4)	0.06	0.923
<i>LIPC</i>	rs1800588	C/T	406 (57.1)	250 (36.3)	47 (6.6)	0.24	0.489
<i>PLINI</i>	rs894160	G/A	378 (53.2)	282 (39.7)	51 (7.2)	0.27	0.872
<i>NOS3</i>	rs1799983	G/T	286 (40.2)	326 (45.8)	99 (13.9)	0.37	0.692
<i>GCKR</i>	rs1260326	C/T	208 (29.2)	367 (50.9)	141 (19.8)	0.45	0.465
<i>LPL</i>	rs328	C/G	510 (71.7)	189 (26.6)	12 (1.7)	0.15	0.244
<i>CELSR2</i>	rs12740374	G/T	440 (61.9)	241 (33.9)	30 (4.2)	0.21	0.676
<i>CETP</i>	rs1800777	G/A	681 (95.8)	28 (3.9)	2 (0.3)	0.02	0.005
<i>LIPG</i>	rs4939883	C/T	508 (71.4)	179 (25.2)	24 (3.4)	0.16	0.100

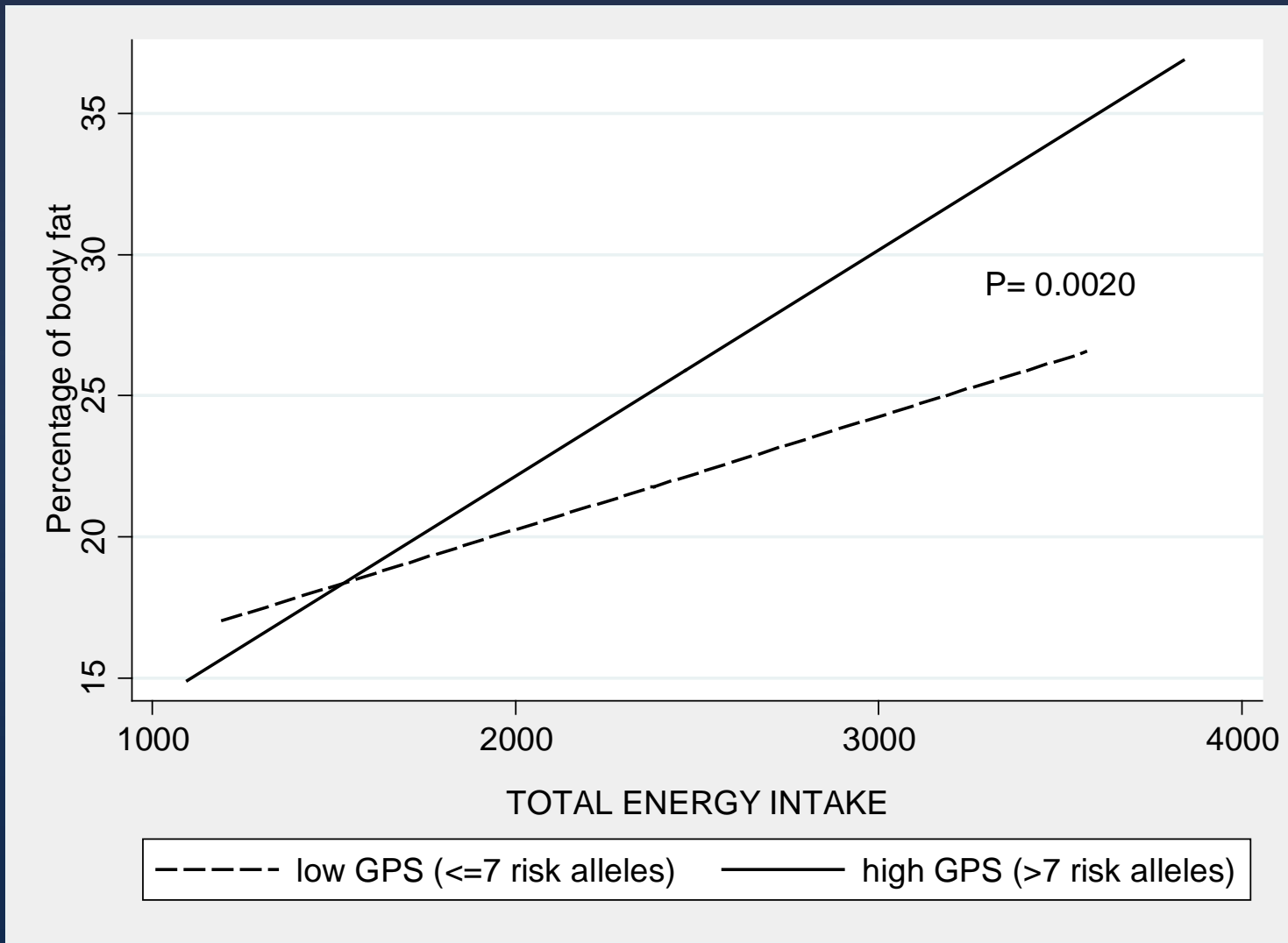
SNP single nucleotide polymorphism, MAF minor allele frequency, HWE *p* value hardy–weinberg equilibrium *p* value

^a According to Hap-Map CEU for European population

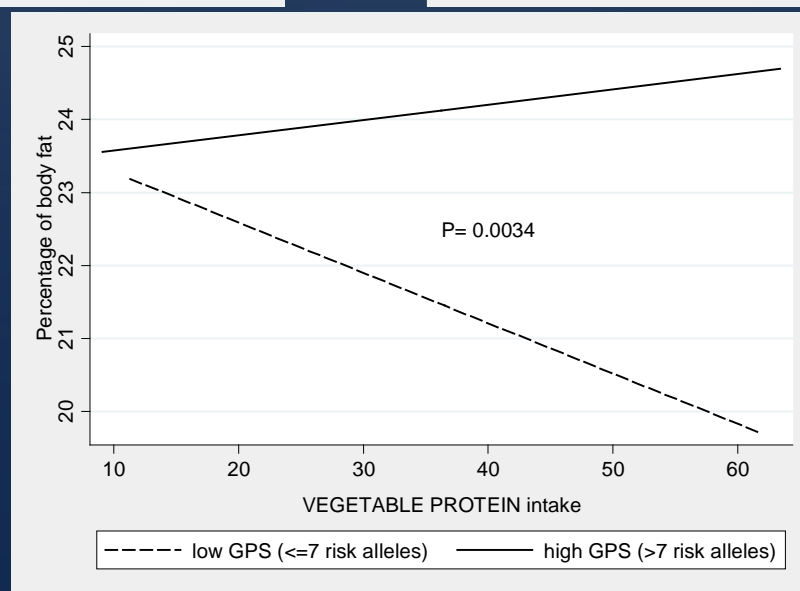
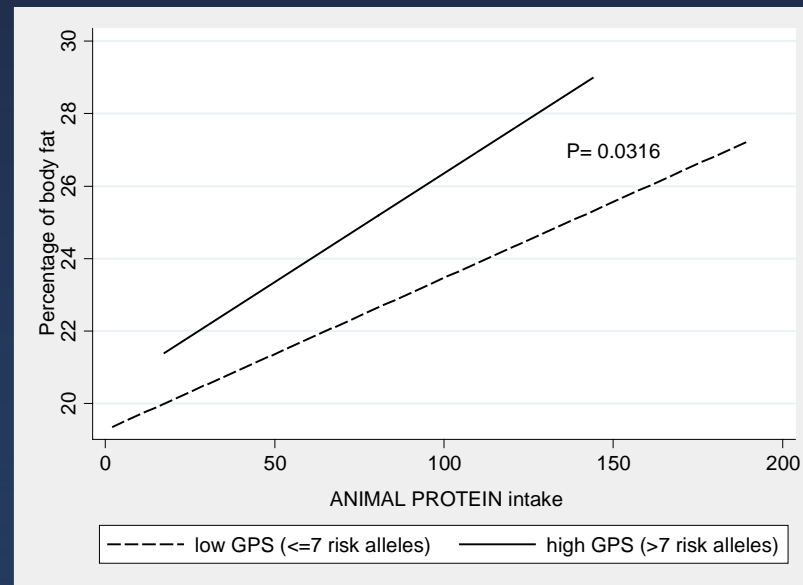
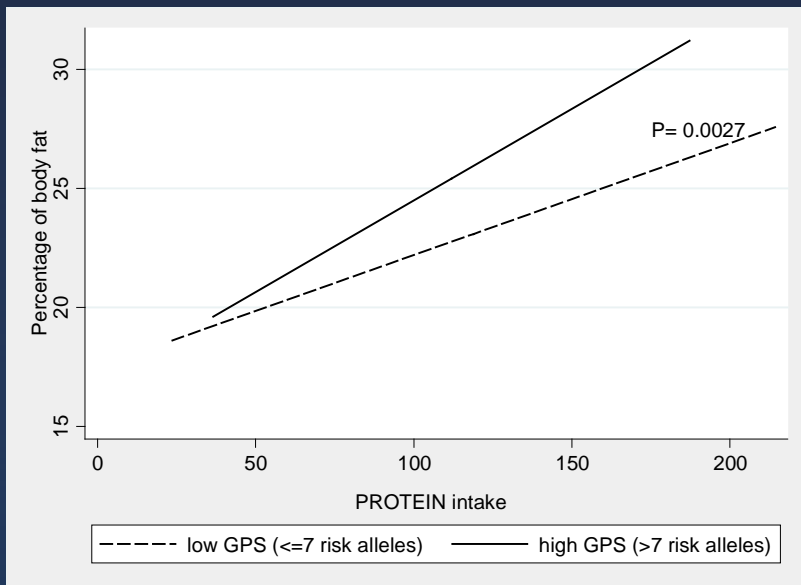
ASSOCIATION BETWEEN THE GENETIC RISK SCORE AND ANTHROPOMETRIC VARIABLES

	Linear regression coefficients				Logistic regression coefficients			
	Model 1		Model 2		Model 1		Model 2	
	B (95 % CI)	<i>p</i> value	B (95 % CI)	<i>p</i> value	OR (95 % CI)	<i>p</i> value	OR (95 % CI)	<i>p</i> value
BMI (kg/m²)								
≤7 risk alleles	0 (ref.)		0 (ref.)		1 (ref.)		1 (ref.)	
>7 risk alleles	1.02 (0.17–1.87)	0.019	0.93 (0.17–1.68)	0.016	1.41 (1.04–1.93)	0.031	1.42 (1.02–1.99)	0.038
Percentage of BFM								
≤7 risk alleles	0 (ref.)		0 (ref.)		1 (ref.)		1 (ref.)	
>7 risk alleles	1.81 (0.59–3.03)	0.004	1.69 (0.58–2.80)	0.003	1.72 (1.22–2.42)	0.002	1.72 (1.19–2.48)	0.004
Waist circumference (cm)								
≤7 risk alleles	0 (ref.)		0 (ref.)		1 (ref.)		1 (ref.)	
>7 risk alleles	2.14 (0.08–4.21)	0.042	1.94 (0.12–3.75)	0.036	1.54 (1.04–2.29)	0.032	1.57 (1.02–2.40)	0.039
Waist-to-hip ratio								
≤7 risk alleles	0 (ref.)		0 (ref.)		1 (ref.)		1 (ref.)	
>7 risk alleles	0.00 (–0.01–0.002)	0.445	0.00 (–0.01–0.01)	0.480	1.15 (0.82–1.61)	0.401	1.14 (0.81–1.61)	0.454
Waist-to-height ratio								
≤7 risk alleles	0 (ref.)		0 (ref.)		1 (ref.)		1 (ref.)	
>7 risk alleles	0.01 (0.00–0.03)	0.036	0.01 (0.00–0.02)	0.029	1.39 (0.95–2.02)	0.089	1.41 (0.94–2.10)	0.096
Model 1: Adjusted for gender and age								
Model 2: Adjusted for gender, age, physical activity and energy intake								
<i>BMI</i> body mass index, <i>BFM</i> body fat mass, <i>95 % CI</i> 95 % confidence interval, <i>OR</i> odds ratio								

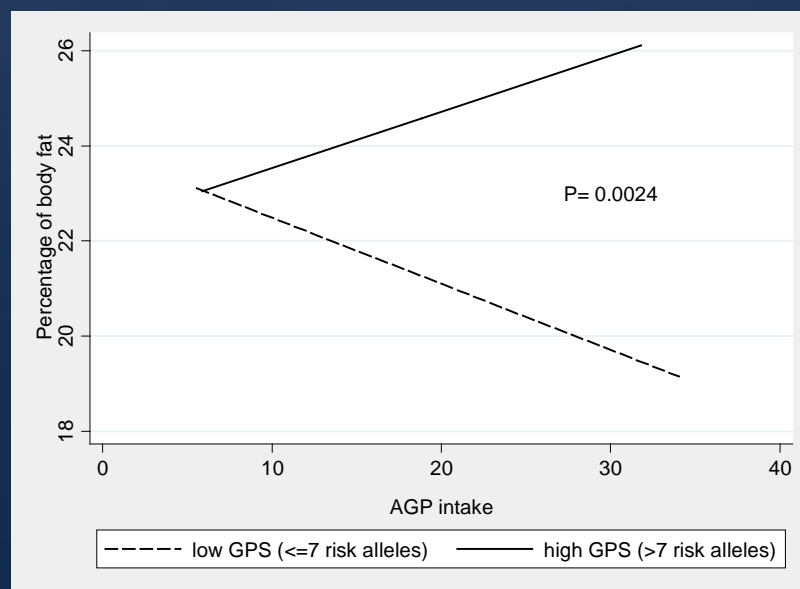
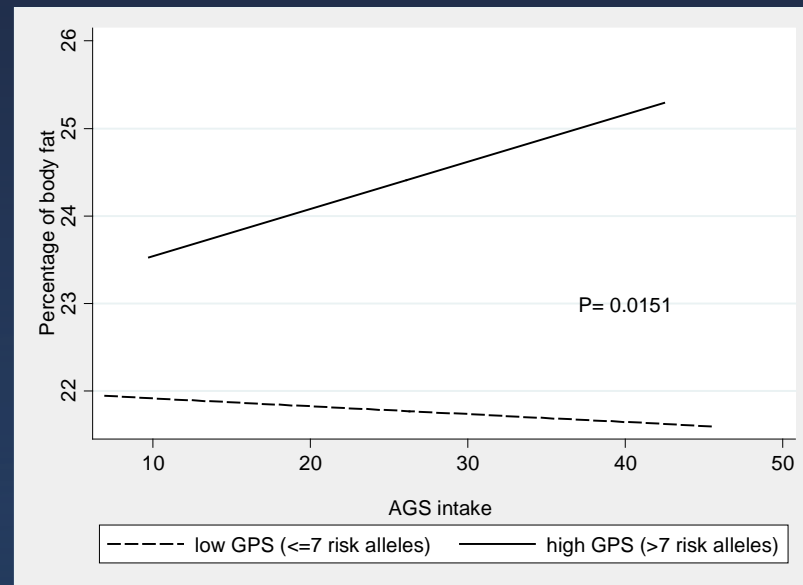
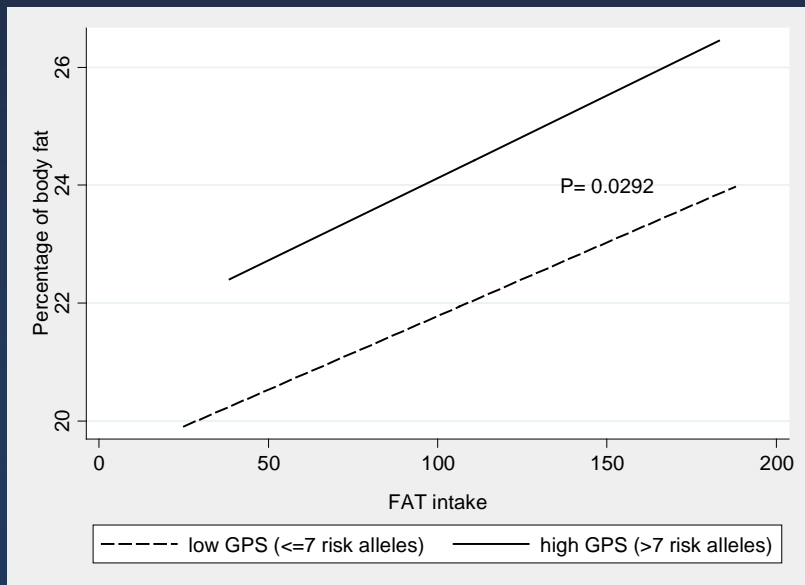
INTERACTION BETWEEN THE GENETIC RISK SCORE AND ENERGY INTAKE



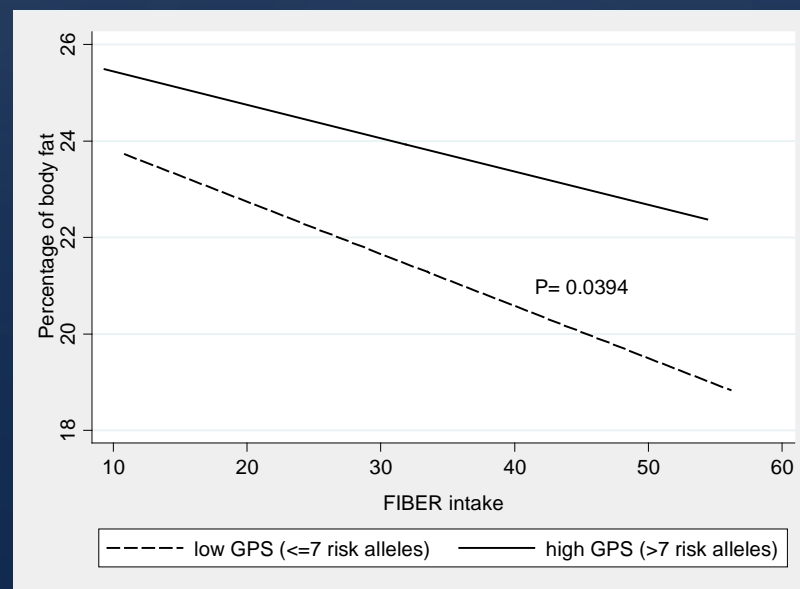
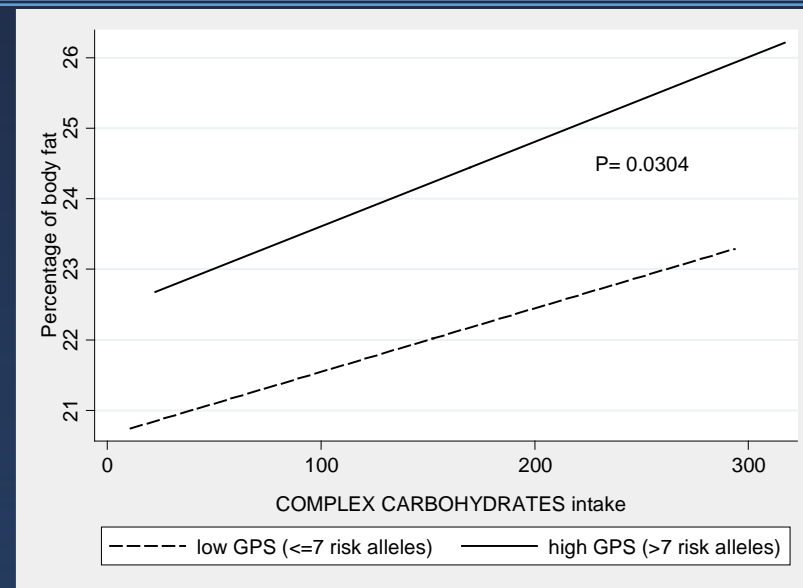
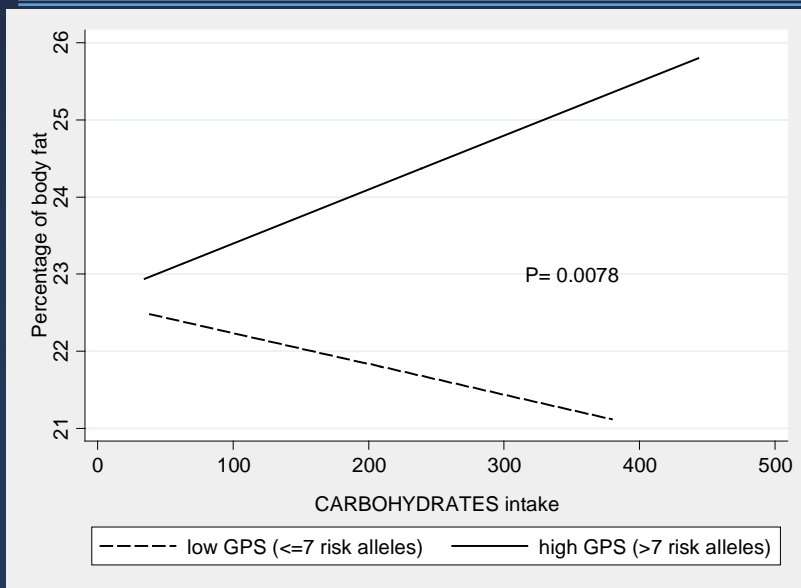
INTERACTION BETWEEN THE GENETIC RISK SCORE AND PROTEIN INTAKE



INTERACTION BETWEEN THE GENETIC RISK SCORE AND DIETARY FAT INTAKE



INTERACTION BETWEEN THE GENETIC RISK SCORE AND CARBOHYDRATE AND FIBER INTAKE



GENE-NUTRIENT INTERACTIONS IN DETERMINING WEIGHT RELATED PHENOTYPES

Authors and reference	Phenotype	Studied population	Description of the gene-diet interaction
Smith <i>et al.</i> ⁶⁰	Waist and hip circumference, BMI	Caribbean-origin Hispanics (N.=920, aged 45-74 y) living in the Boston area	The PLIN 11482G > A (rs894160) polymorphism interacted with complex carbohydrate intake in determining obesity-related measures. When complex carbohydrate intake was low (<144 g/d), waist circumference was larger in PLIN 11482G > A carriers. Conversely, when complex carbohydrate intake was high waist and hip circumferences were less in PLIN 11482G > A carriers.
Richardson <i>et al.</i> ⁶⁴	Waist circumference and BMI	Two populations of European ancestry (Framingham and GOLDN participants)	PLIN4 (rs8887) interacted with dietary PUFA in determining anthropometric traits and this acts in part through creation of a microRNA-522 regulatory site. The association data indicate for rs8887 minor allele carriers that elevated intake of PUFA n-3 resulted in decreasing anthropometrics compared to non-carriers
Zillikens <i>et al.</i> ⁶²	BMI	4575 elderly men and women in the population-based Rotterdam Study	SIRT1 genetic variants interacted with intakes of fat, vitamin E, calcium, and milk on BMI. The most relevant was the interaction between vitamin E intake and rs146756. This SNP was associated with BMI in the lowest tertile, but no association was observed in the higher tertiles.
Junyent <i>et al.</i> ⁶⁵	Waist circumference and BMI	936 participants in the GOLDN Study.	The ADAM17_135708A>G polymorphism interacted with n-6 PUFA intake in determining obesity. When n-6 PUFA intake was the association of the A allele with higher BMI disappeared.
Sonestedt <i>et al.</i> ⁶⁴	BMI	4839 participants in the population-based Malmö Diet and Cancer Study	FTO (rs9939609) polymorphism interacted with fat and carbohydrate intake in determining BMI. High-fat and low-carbohydrate diets accentuated the susceptibility to obesity in carriers of the risk-allele.
Luan <i>et al.</i> ⁶⁵	BMI	592 non-diabetic participants in the Isle of Ely Study	The Pro12Ala polymorphism in the PPARG gene interacted with the PUFA:SFA ratio on BMI. When this ratio was low, the BMI in Ala carriers was greater than that in Pro homozygotes, but when the ratio was high, the opposite was seen
Memisoglu <i>et al.</i> ⁶⁶	BMI	2141 participants in the Nurses' Health Study	The Pro12Ala polymorphism in the PPARG gene interacted with total fat intake on BMI. Among Pro/Pro individuals, those in the highest quintile of total fat intake, had significantly higher BMI compared with those in the lowest quintile, whereas among 12Ala-carriers there was no significant trend.
Lamri <i>et al.</i> ⁶⁷	BMI	4679 participants in the French general population, the D.E.S.I.R. cohort	The Pro12Ala polymorphism in the PPARG gene interacted with total fat intake on BMI. AlaAla individuals had a higher BMI than Pro carriers among high fat consumers.
Phillips <i>et al.</i> ⁶⁸	BMI, waist circumference	1754 participants in the LIPGENE-SU.VI.MAX Study	The FTO (rs9939609) polymorphism interacted with SFA intake in determining BMI and waist circumference. High SFA intake accentuated the associations in carriers of the risk-allele (A).
Robitaille <i>et al.</i> ⁶⁹	Waist circumference	632 men from Canada	The PPARalpha-L162V polymorphism interacted with total fat or saturated fat intake in determining waist circumference. Fat intake was directly related to waist circumference only in L162L homozygotes
Miyaki <i>et al.</i> ⁷⁰	Obesity	295 healthy Japanese men	The Trp64Arg polymorphism in the ADRB3 gene interacted with total energy intake in determining obesity risk. The Arg64-allele was associated with greater obesity risk only in the highest energy intake quartile

GENE-NUTRIENT INTERACTIONS IN RELATION TO CENTRAL OBESITY RELATED TRAITS

Reference	Gene	SNP	Population	Sex	No. of subjects	Energy or nutrient	Results
Robitaille et al. (2003) ⁴³	<i>PPARG</i>	rs1801282	French Canadian	F and M	720	TF and SFA	The higher the TF intake, the greater the WC in P12/P12 homozygotes
Robitaille et al. (2007) ⁴⁴	<i>CPT1A</i>	rs17610395	French Canadian	F and M	351	TF	The higher the TF intake, the greater the WC in A275/A275 homozygotes
Robitaille et al. (2007) ⁴⁴	<i>CPT1B</i>	rs470017	French Canadian	F and M	351	TF	The higher the TF intake, the greater the WC in E531/K531 heterozygotes
Song et al. (2007) ⁴⁵	<i>IL6R</i>	rs8192284	Japanese	M	285	Energy	The higher the energy intake, the greater the WC in T allele carriers (TT and TG)
Smith et al. (2008) ⁴⁶	<i>PLIN</i>	rs894160	Puerto Rican	F and M	920	Complex CH	The lower the complex CH intake, the greater the WC in A allele carriers
Smith et al. (2008) ⁴⁶	<i>PLIN</i>	rs894160	Puerto Rican	F and M	921	Complex CH	The higher the complex CH intake, the lower the WC in A allele carriers
Phillips et al. (2009) ⁴⁷	<i>STAT3</i>	rs8069645, rs744166, rs1053005, rs2293152, rs2306580	French	F and M	1,754	SFA	The higher the SFA intake, the greater the WC in subjects carrying >2 risk alleles
Phillips et al. (2010) ⁴⁸	<i>IL6, LTA, TNF-alpha</i>	rs1800797, rs1800629, rs915654	French	F and M	1,754	SFA/PUFA plasma concentrations	The lower the SFA/PUFA plasma concentrations, the greater the WC in risk genotype carriers
Phillips et al. (2010) ⁴⁹	<i>ACC2</i>	rs4766587	French	F and M	464	PUFA	The higher the PUFA intake, the greater the WC in AA homozygotes
Dedoussis et al. (2011) ⁵⁰	<i>PPARG</i>	rs1801282	Greek (young)	F	1,332	MUFA	The higher the MUFA intake, the lower the WC in P12/P12 homozygotes
Mattei et al. (2011) ⁵¹	<i>APOA1</i>	rs670	Puerto Rican	F and M	821	TF	The lower the TF intake, the lower the WC in common allele homozygotes
Phillips et al. (2012) ⁵²	<i>FTO</i>	rs9939609	French	F and M	1,754	SFA	The higher the SFA intake, the greater the WC in A allele carriers

Abbreviations: CH, carbohydrates; F, female; M, male; MUFA, monounsaturated fatty acids; PUFA, polyunsaturated fatty acids; SFA, saturated fatty acids; SFA/PUFA, saturated fatty acids to polyunsaturated fatty acids ratio; SNP, single-nucleotide polymorphism; TF, total fat; WC, waist circumference.

PERSONALIZED APPROACHES AGAINST OBESITY

Nutritional and Diet Theraphy

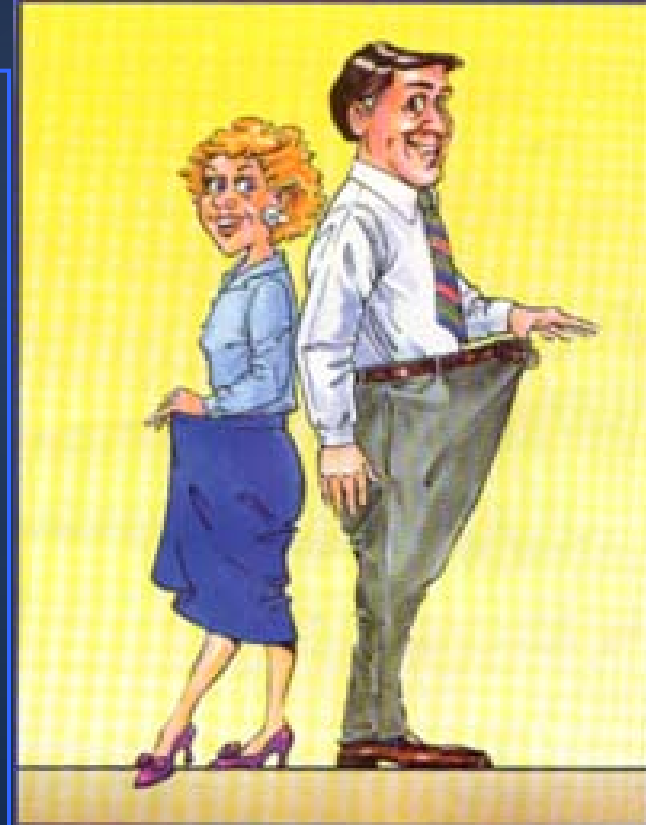
Drugs Treatments

Physical Activity Programmes

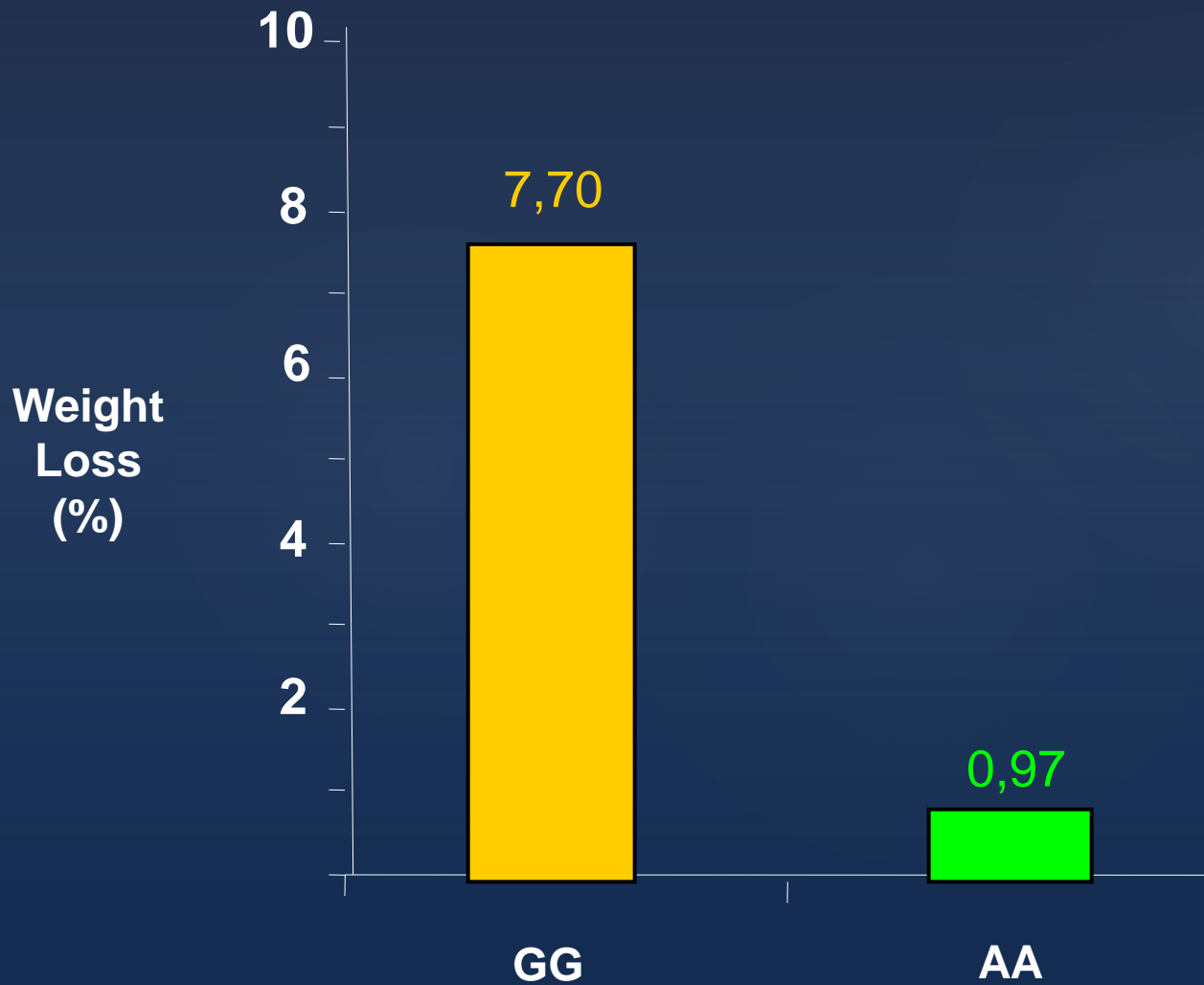
Bariatric Surgery

Others: Personalized.....

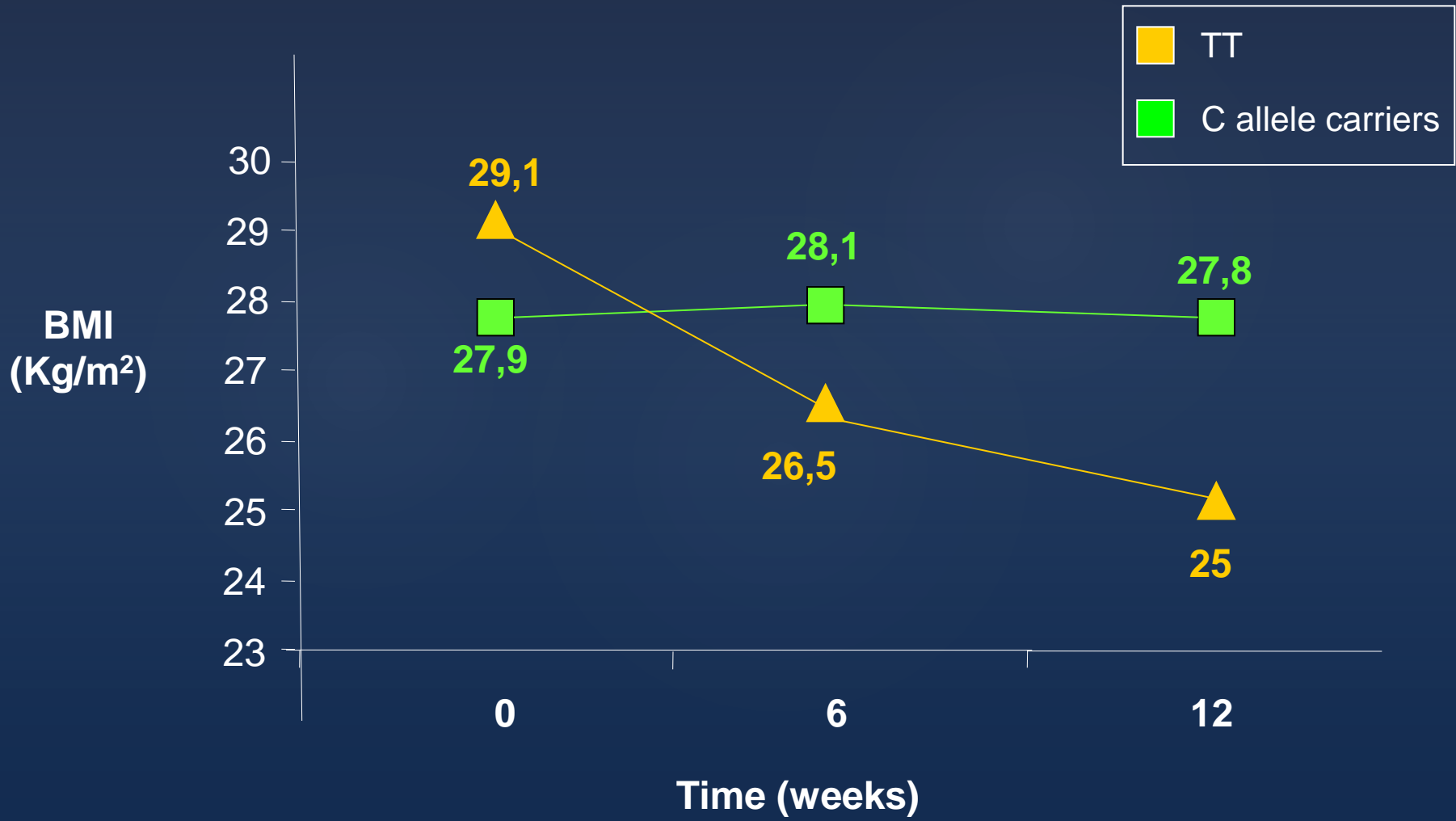
.....Nutrition



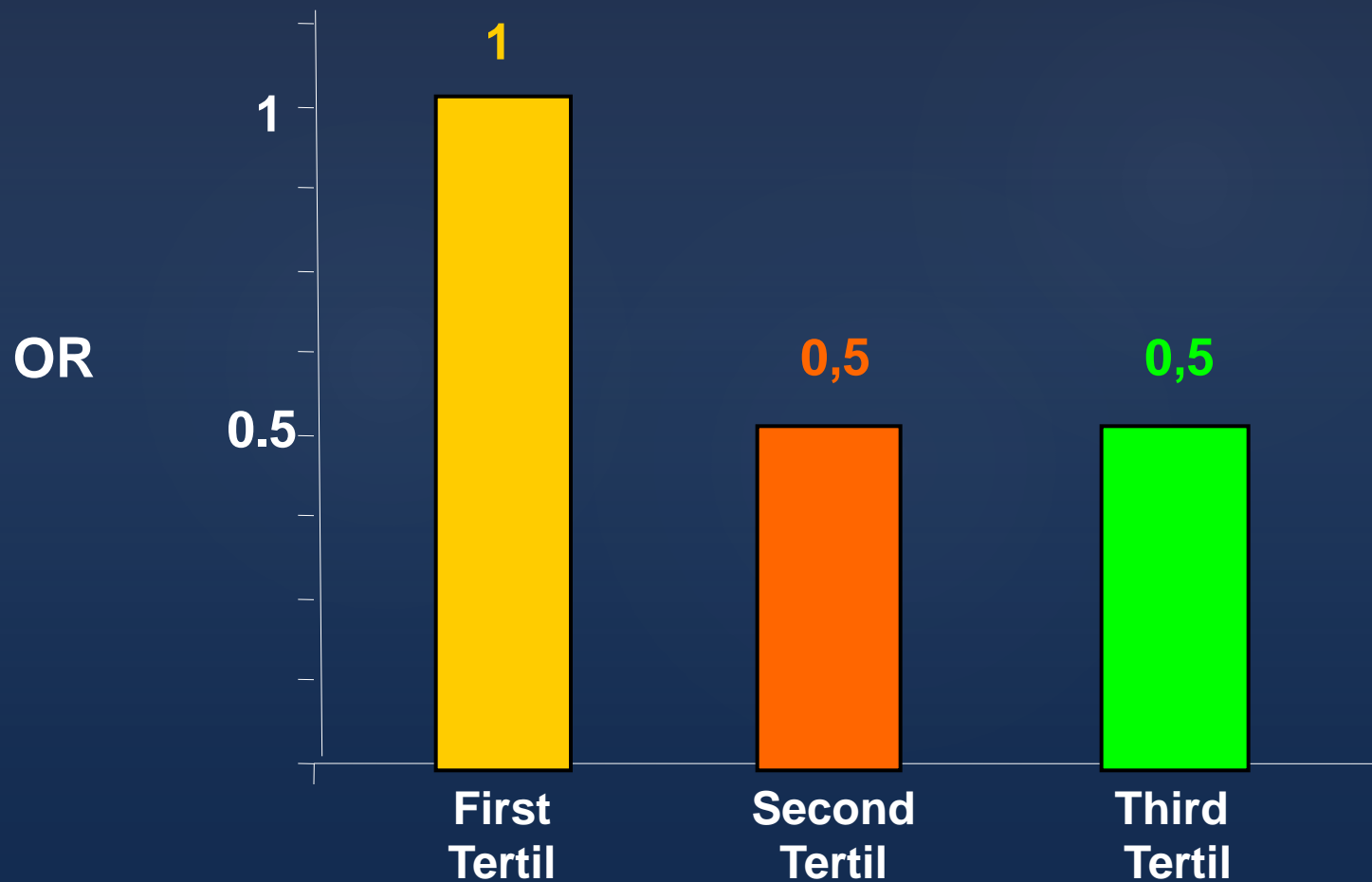
PERILIPIN GENE AND WEIGHT LOSS



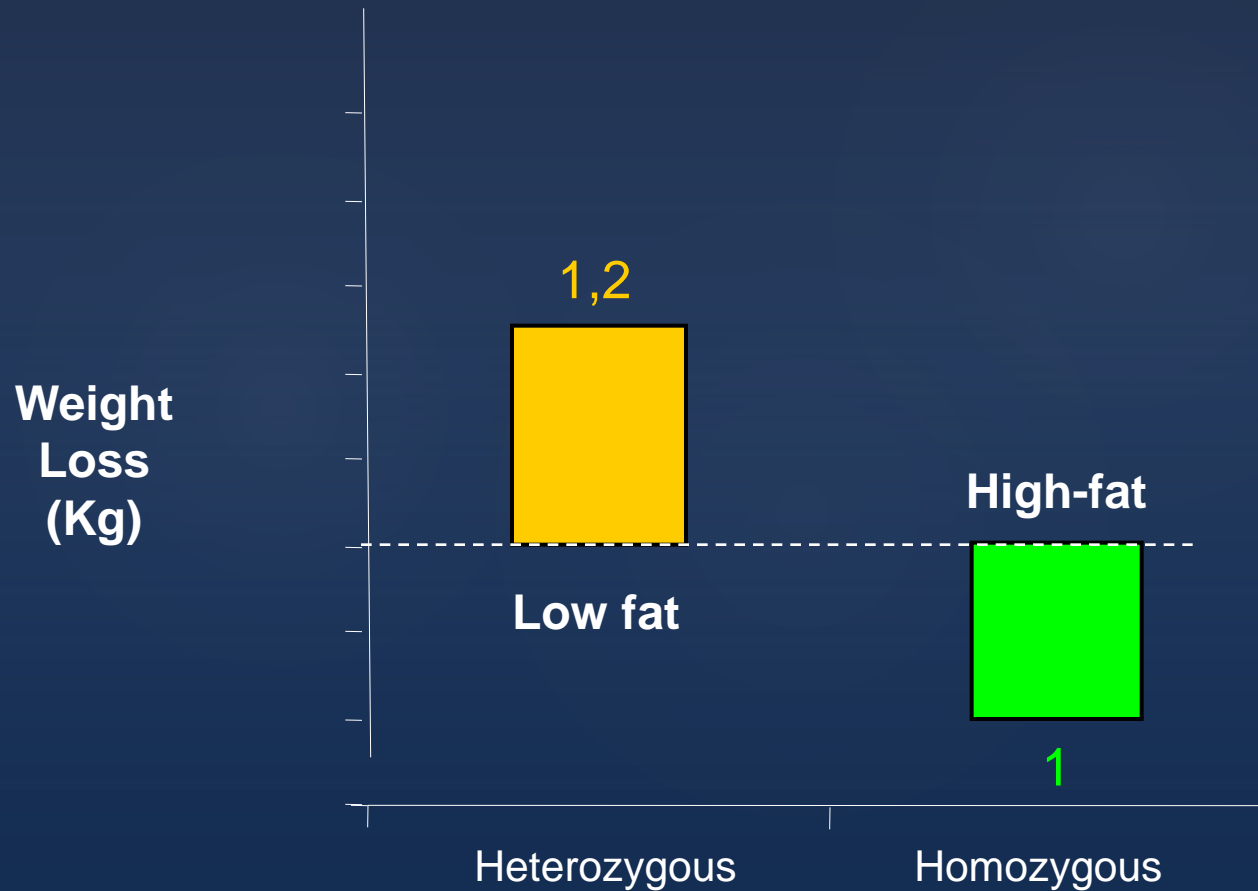
POLYMORPHISM IN THE APOLIPOPROTEIN A5 GENE



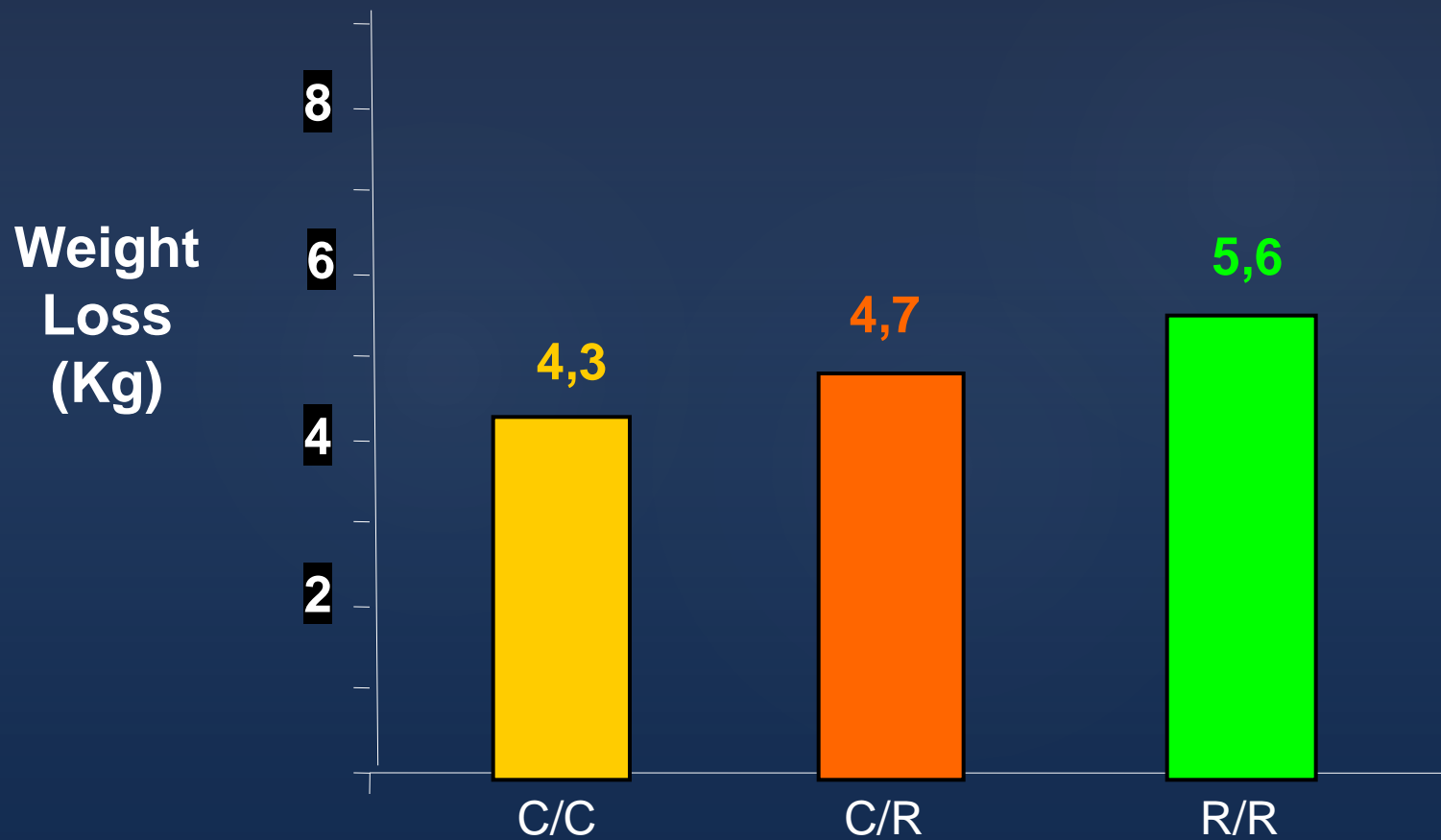
LIPC – 514>CT POLYMORPHISM AND FIBRE INTAKE (TERTILES)



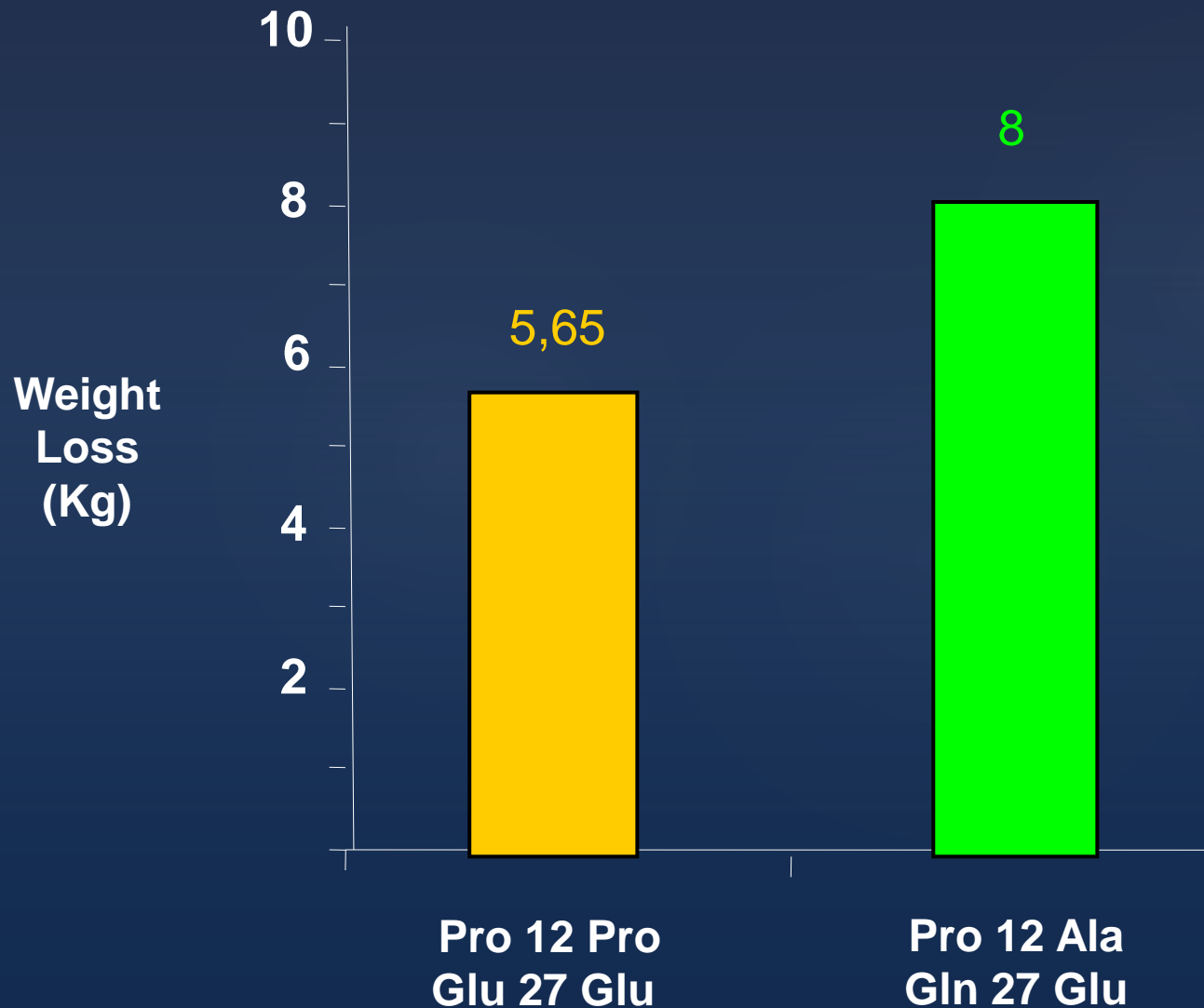
ADIPOQ – 11377 C>G POLIMORPHISM INFLUENCE ON WEIGHT LOSS



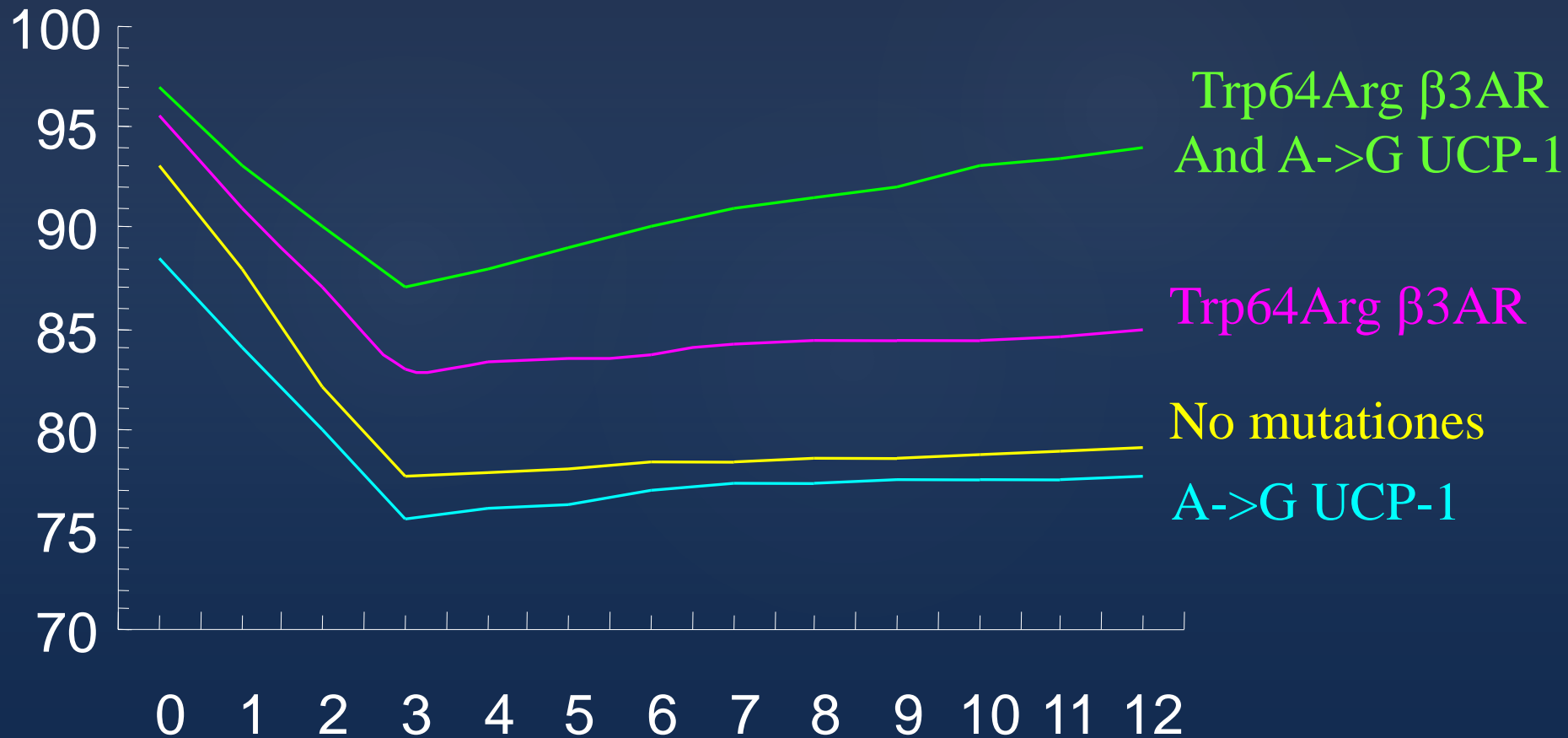
UCP₃ HAPLOTYPES IMPACT ON WEIGHT LOSS



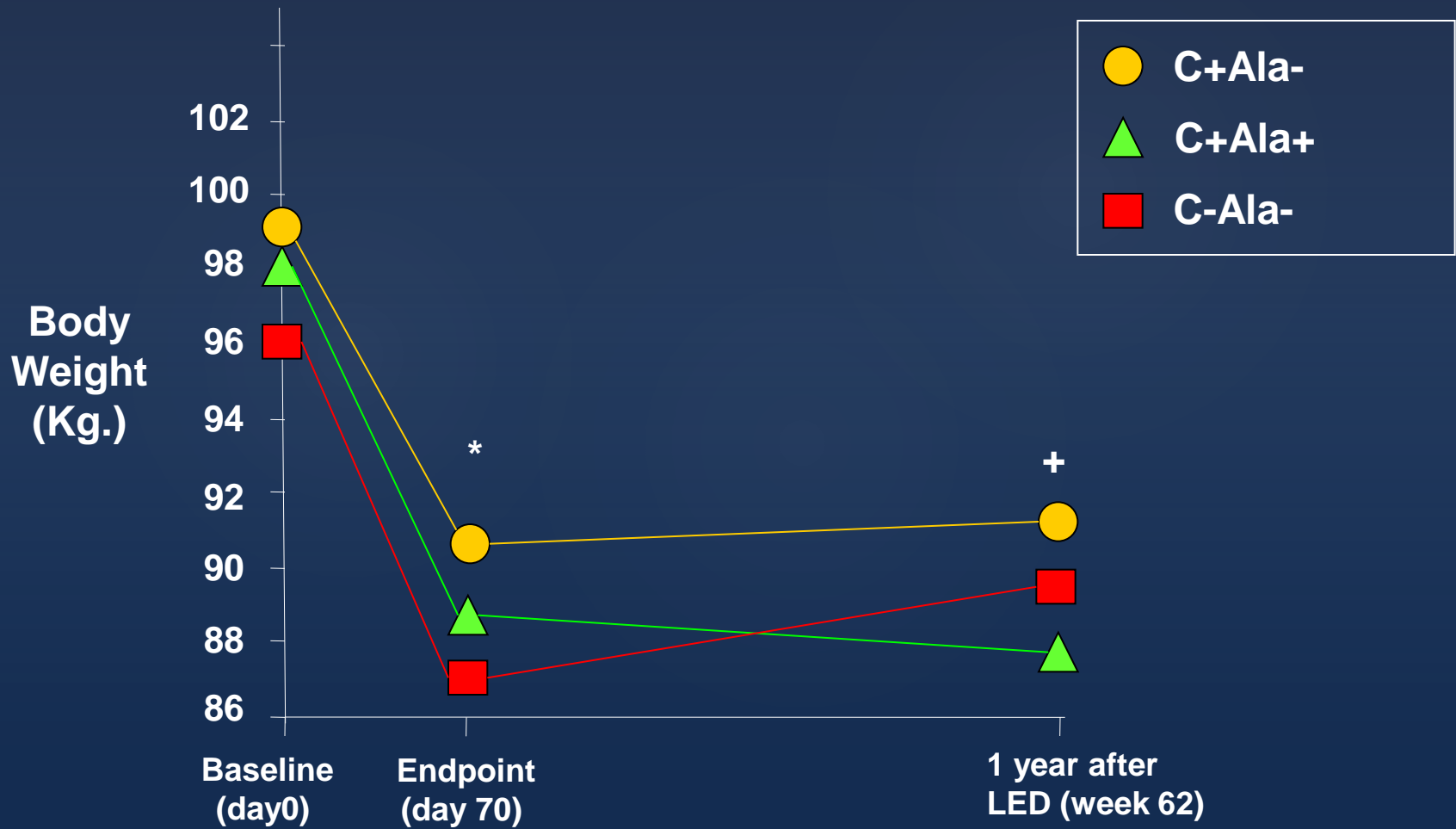
PPAR x ADRB2 interaction



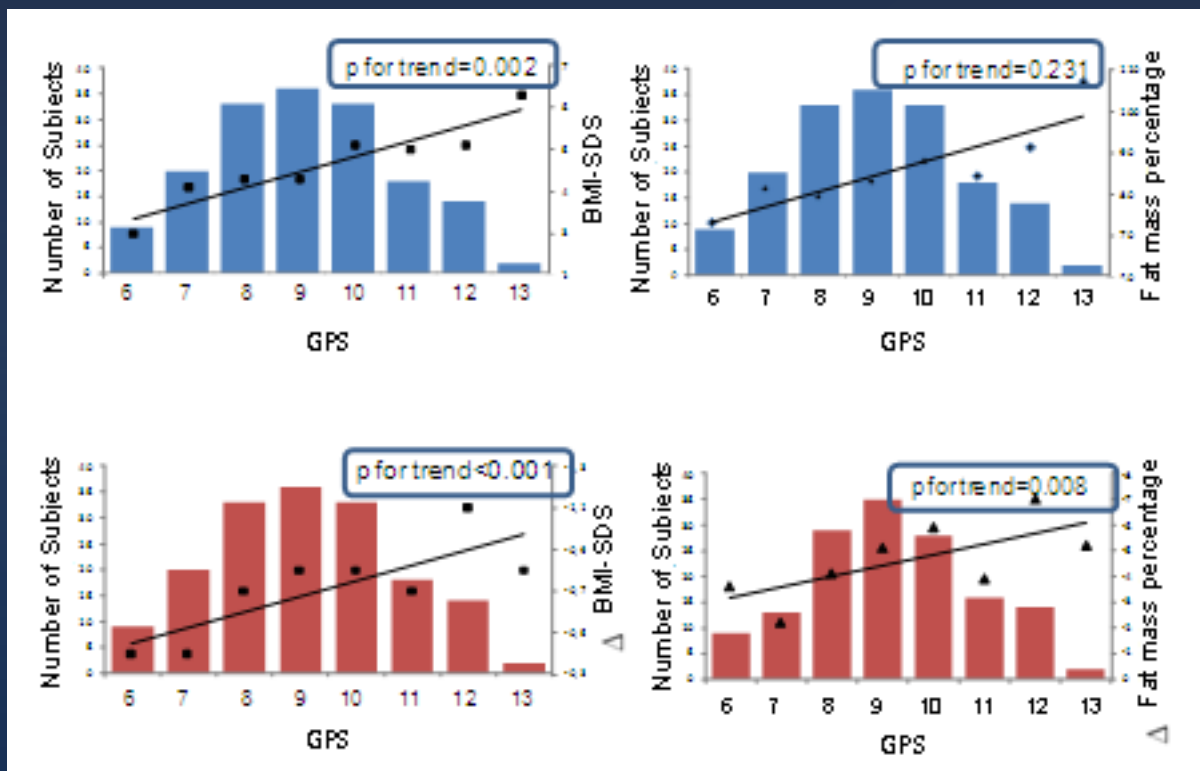
WEIGHT CHANGES AND GENOTYPE



BODY WEIGHT REDUCTION AND GENETIC VARIANTS: IL-6 AND PPAR- Γ 2



Obesity Susceptibility Loci on Body Mass Index and Weight Loss in Spanish Adolescents after a Lifestyle Intervention



Supplementary Figure 2 (online): Distribution of the Genetic Predisposition Score (GPS), trend and cumulative effects on BMI-SDS and fat mass percentage in the adolescent population A.) At baseline and B.) After 10 weeks of multidisciplinary intervention. Left axis: Prevalence. Right axis: A) BMI-SDS or Fat mass percentage (baseline) and B) BMI-SDS or Fat mass percentage variation (after the intervention).

Original Paper

Gene-Gene Interplay and Gene-Diet Interactions Involving the *MTNR1B* rs10830963 Variant with Body Weight Loss

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J. Alfredo Martínez^{a–d}

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Key Words

MTNR1B · *FTO* · *MC4R* · Obesity · Body weight loss · Gene-gene interplay · Gene-diet interaction

Abstract

Background/Aims: Investigation of the genetic makeup may facilitate the implementation of more personalized nutritional interventions. The aims were to examine whether the rs10830963 *MTNR1B* polymorphism affects weight loss in response to a hypocaloric diet and to find potential gene-gene interplays and gene-diet interactions. **Methods:** 167 subjects enrolled in a personalized nutritional intervention for weight loss (3–6 weeks) were examined for anthropometric measurements, dietary habits and physical activity at baseline and at the first follow-up visit. Three polymorphisms, which have previously been associated with body weight regulation, rs10830963 (*MTNR1B*), rs9939609 (*FTO*) and rs17782313 (*MC4R*), were analyzed using the Luminex® 100/200™ System. **Results:** After adjusting for covariates, females with the rs10830963 CG/GG genotype showed lower weight loss than those with the CC genotype. In the total population, carriers of variant alleles of both *FTO* and *MC4R* showed a significant association with *MTNR1B* and weight loss outcome. Moreover, among women, higher total protein and animal protein intakes were associated with a lower weight loss in G allele carriers of the *MTNR1B* variant. **Conclusions:** Our data evidenced that rs10830963 *MTNR1B* polymorphism could be associated with individual differences in weight loss induced by a hypocaloric diet. This association was influenced by *FTO* and *MC4R* loci and modified by baseline protein intake.

ASSOCIATION BETWEEN *MTNR1B* GENETIC VARIANT AND CHANGES IN WEIGHT AND BMI

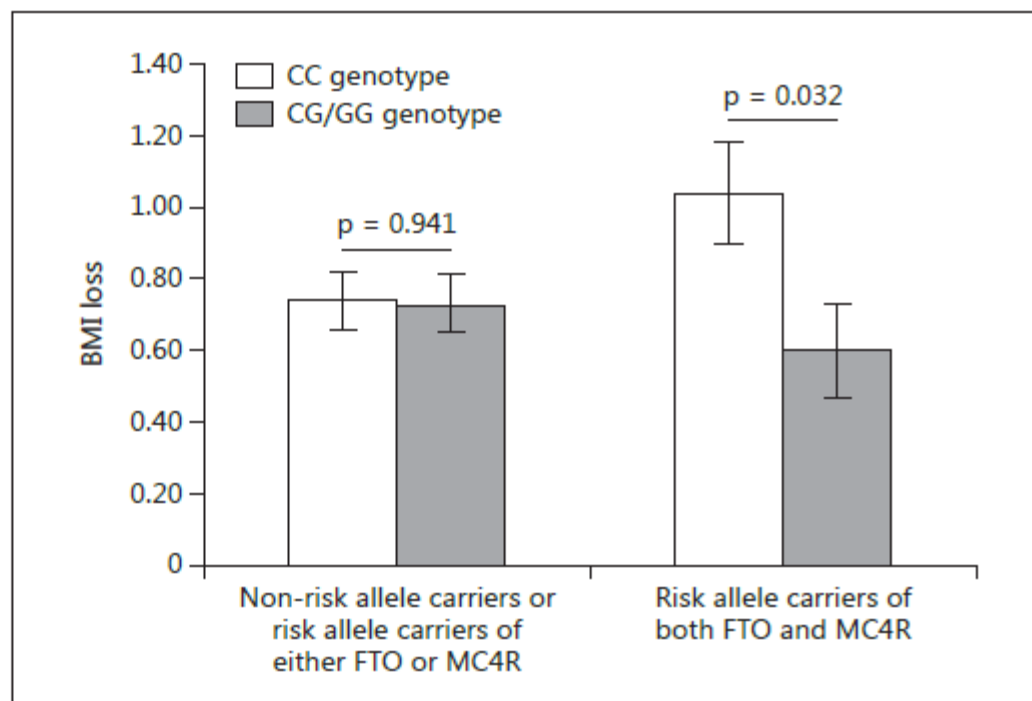
Table 2. Linear regression coefficients for the association between *MTNR1B* and anthropometric variables after weight loss intervention

	Δ weight		Δ BMI	
	B (95% CI)	p	B (95% CI)	p
<i>All</i>				
CC	0 (ref.)		0 (ref.)	
CG/GG	-0.11 (-0.64, 0.42)	0.686	-0.08 (-0.27, 0.11)	0.391
<i>Males</i>				
CC	0 (ref.)		0 (ref.)	
CG/GG	0.73 (-1.05, 2.51)	0.409	0.24 (-0.30, 0.79)	0.368
<i>Females</i>				
CC	0 (ref.)		0 (ref.)	
CG/GG	-0.55 (-1.07, -0.03)	0.040	-0.23 (-0.45, -0.03)	0.027

Adjusted for gender, age, energy restriction, time between visits 1 and 2, FTO and MC4R variants and baseline value of the appropriate anthropometric variable.

INFLUENCE OF *FTO* AND *MC4R* POLYMORPHISMS ON THE ASSOCIATION OF *MTNR1B* POLYMORPHISM AND BMI LOSS

Fig. 1. Influence of obesity loci on the association of *MTNR1B* and BMI loss in the total population. Adjusted for age, energy restriction, time between visits and BMI at baseline.



INTERACTION BETWEEN *MTRN1B* POLYMORPHISM AND PROTEIN INTAKE AT BASELINE

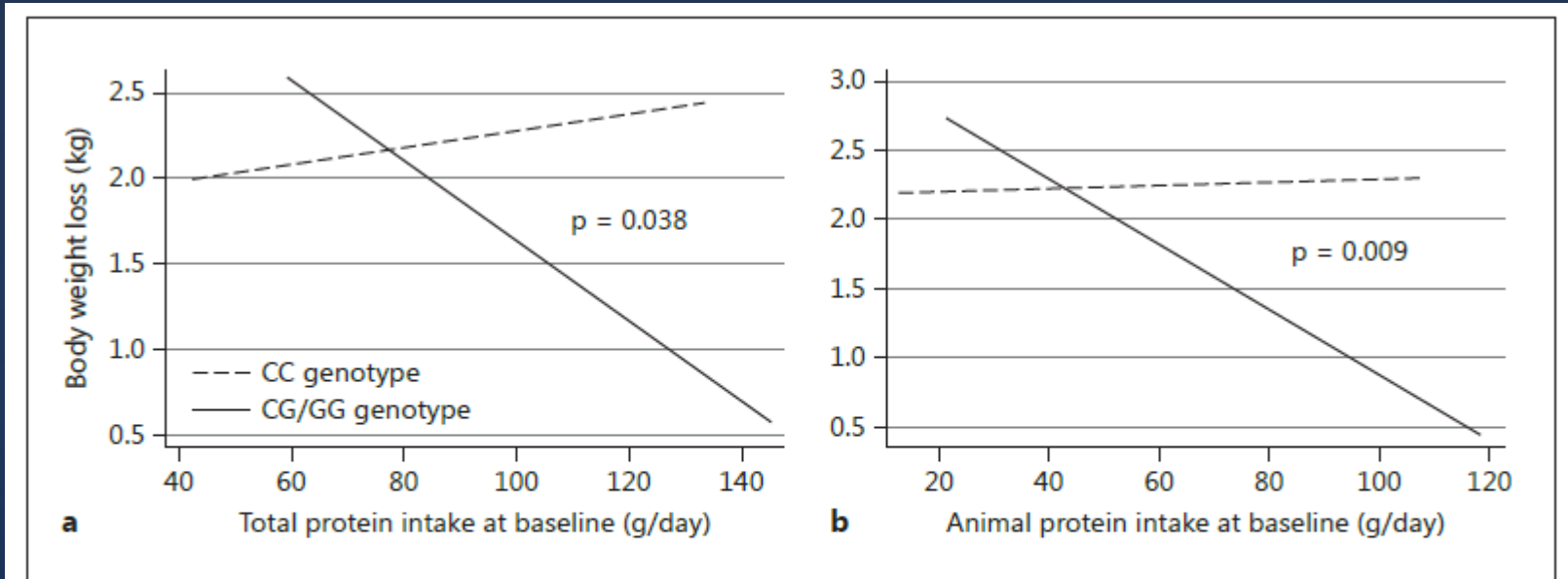


Fig. 2. Interaction between *MTRN1B* and total protein intake at baseline (**a**) and animal protein intake at baseline (**b**) and its effect on body weight loss among women. Adjusted for age, energy restriction, time between visits, *FTO*, *MC4R* and body weight at baseline.

BRIEF REPORT

Inflammatory State and Stress Condition in Weight-lowering
Lys109Arg LEPR Gene Polymorphism Carriers

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Received for publication November 24, 2008; accepted March 2, 2009 (ARCMED-D-08-00537).

Background and Aims. Carrying variants on the leptin receptor gene (LEPR) may have an impact on inflammatory and stress markers. Thus, the aim of the study was to analyze the role of the *Lys109Arg* LEPR gene polymorphism on inflammatory (leptin and IL-6) and stress (cortisol) markers in obese subjects who followed a hypocaloric diet designed to lose weight.

Methods. One hundred and seventy (80 females/90 males) Caucasian subjects (body mass index: 30.8 ± 2.4 kg/m²), were genotyped for the *Lys109Arg* polymorphism by a PCR/RFLP procedure. Anthropometric measurements were assessed and blood samples were drawn in all the volunteers before and after an 8-week energy-restricted diet (-30% E). Plasma levels of leptin as well as interleukin-6 (IL-6) as proinflammatory markers and circulating cortisol concentrations as a stress hormone were measured.

Results. Weight loss ($-6.1 \pm 2.7\%$; $p < 0.001$) induced significant changes in anthropometric and biochemical determinations. The AA genotype group showed a higher fat mass loss as well as greater total cholesterol decrease compared with the minor allele carriers. Moreover, the G allele carriers were associated with a higher basal risk of inflammation (OR = 2.5; $p = 0.042$) and stress (OR = 3.3; $p = 0.011$), which were reduced after weight lowering ($p > 0.05$).

Conclusions. The Arg allele carriers of the *Lys109Arg* LEPR gene polymorphism were associated with an increased proinflammatory state and stress condition at baseline. These obesity-related markers were importantly decreased after following a hypocaloric diet. © 2009 IMSS. Published by Elsevier Inc.

Key Words: *Lys109Arg*, Leptin receptor polymorphism, IL-6, Cortisol, Obesity.



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International Diabetes Federation

Enhanced short-term improvement of insulin response to a low-caloric diet in obese carriers the Gly482Ser variant of the PGC-1 α gene

Estibaliz Goyenechea, Ana B. Crujeiras, Itziar Abete, Dolores Parra, J. Alfredo Martínez*

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Polymorphism

Weight-loss

Weight regulation

ABSTRACT

Aim: The Gly482Ser missense mutation of the transcriptional coactivator, peroxisome proliferator-activated receptor- γ coactivator-1 α (PGC-1 α) has been involved in insulin function impairments, with conflicting results. The current study investigated the relationships of carrying this polymorphism with insulin resistance (IR) during a short-term weight-loss and the subsequent weight follow-up.

Methods: The Gly482Ser was genotyped in 180 Spanish volunteers [body mass index: 31.4 ± 3.2 kg/m²; age: 35 ± 5 years]. Specific phenotypical measurements were determined at baseline, following an 8-week low-calorie diet (LCD) as well as after 6-month and 1-year of follow-up.

Results: At baseline the Ser482Ser genotype was associated with higher HOMA-IR and insulin concentrations than the other genotypes ($p < 0.05$), which was accompanied by an increased higher risk of IR (OR: 2.97; 95% CI: 1.24–7.15). After following the LCD, such increased risk of insulin insensitivity in Ser482Ser carriers was toned down ($p > 0.05$). This outcome was sustained after 6-month and 1-year of follow-up ($p > 0.05$).

Conclusions: These data show an increased risk of IR in obese carrying the rs8192673 Ser482Ser genotype. This risk was markedly reduced by an energy-restricted diet, which was sustained 6 months and 1 year after the diet therapy. This observation allows identifying obese subjects who might personally profit most from an energy-restrictive treatment concerning insulin response and lead to more individualized prognostic and therapeutic decisions.

Weight regain after slimming induced by an energy-restricted diet depends on interleukin-6 and peroxisome-proliferator-activated-receptor- γ 2 gene polymorphisms

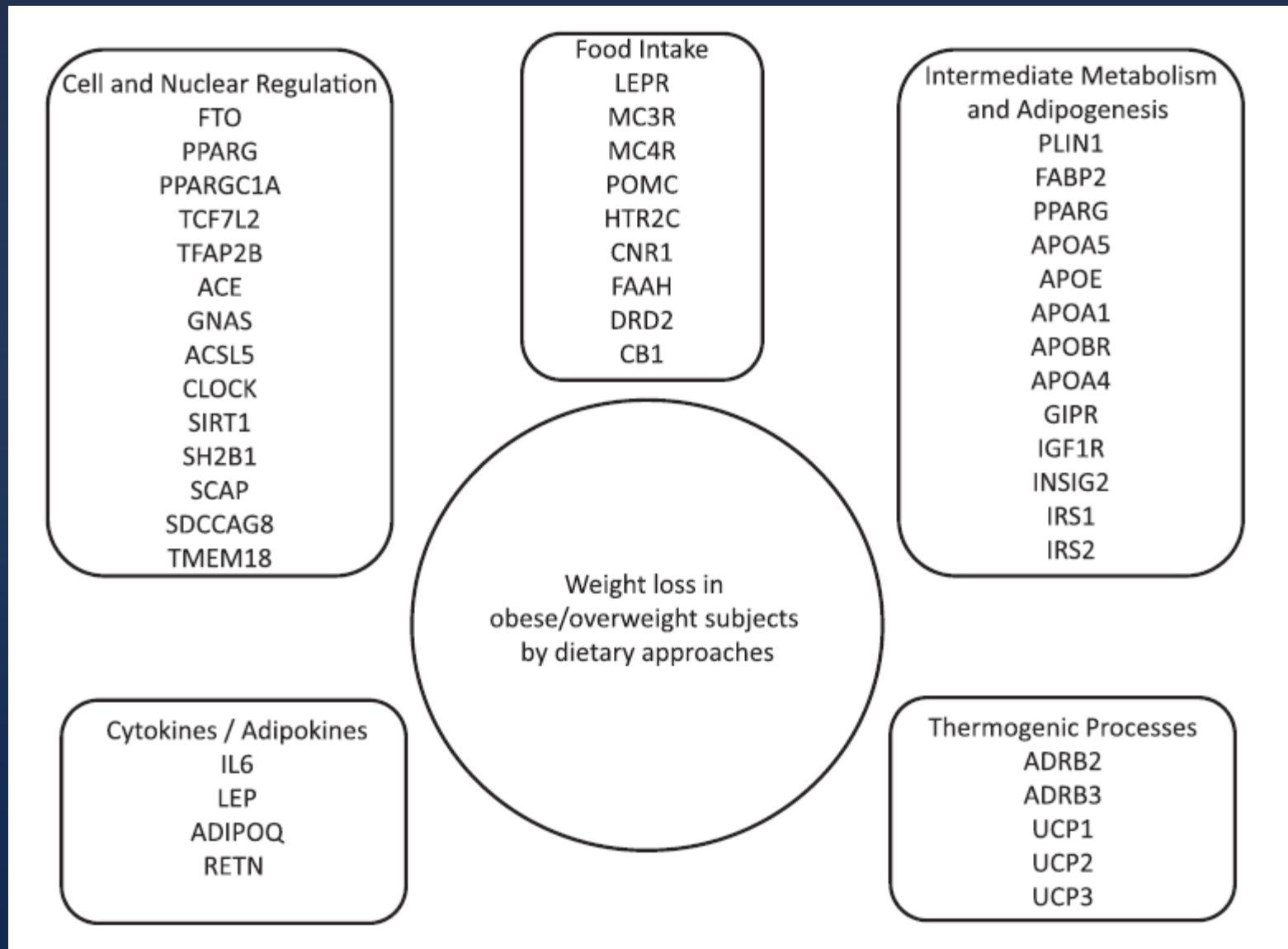
Estibaliz Goyenechea, M. Dolores Parra and J. Alfredo Martínez*

Department of Physiology and Nutrition, University of Navarra, Irunlarrea 1, 31008 Pamplona, Spain

(Received 28 February 2006 – Revised 24 May 2006 – Accepted 7 June 2006)

Weight-loss maintenance after following an energy-restricted diet is a major problem that a number of studies are trying to characterise. The aim of the present study was to investigate the role of IL-6 -174G > C and PPAR- γ 2 Pro12Ala variants on weight regulation in obese subjects receiving a low-energy diet and at 1 year after the acute slimming period. Sixty-seven volunteers (age 34.7 (SD 7.0) years; BMI 35.8 (SD 4.8) kg/m²) were enrolled in a 10-week dietary intervention and were contacted again 1 year after the end of this period. Body composition was measured at three times during the study. Also, PPAR- γ 2 Pro12Ala and IL-6 -174G > C polymorphisms were analysed in the participants. No statistical differences were observed depending on the genetic variants at baseline for anthropometric variables, or after the intervention. However, the C allele of the -174G > C IL-6 gene polymorphism was more frequently observed ($P=0.032$) in subjects with successful weight maintenance (< 10 % weight regain). In fact, the C allele partially protected against weight regain (odds ratio 0.24; $P=0.049$), while the conjoint presence of both gene variants (C + and Ala +) further improved the ability for weight maintenance (odds ratio 0.19; $P=0.043$). The present study demonstrates that the C allele of the -174G > C polymorphism gives protection against regain of weight lost. Moreover, the presence of the Ala allele of the PPAR γ -2 together with the C allele strengthens this protection. These findings support a role for these polymorphisms on weight regulation and suggest a synergetic effect of both variants on weight maintenance after following a diet to lose weight.

GENES IN WHICH THERE ARE POLYMORPHISMS RELATED TO BODY WEIGHT LOSS



Personalization for weight management

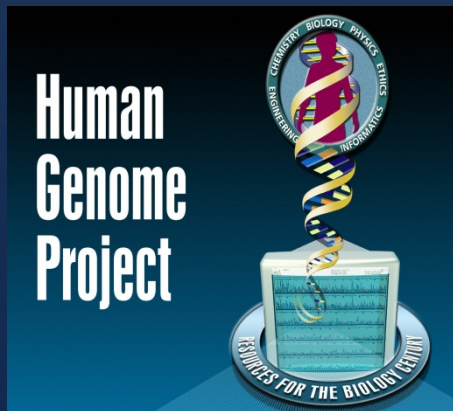


Background

Personalised nutrition: the concept?

“Personalised nutrition is the tailoring of dietary advice to suit an individual based on their genetic make-up.”

2000

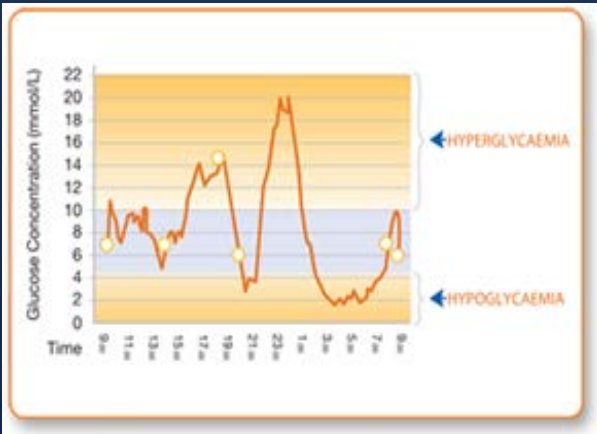


Phenotyping devices

Continuous glucose monitoring system



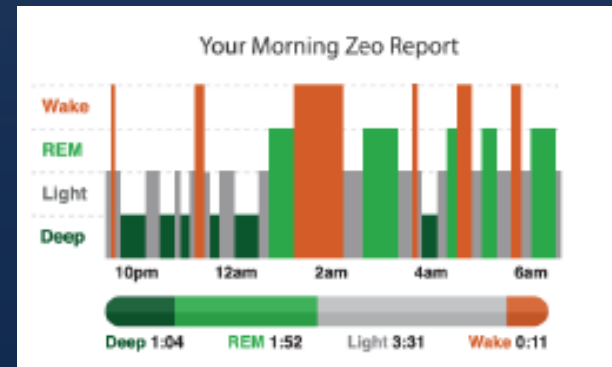
Sensor tail 5 mm



Direct Life Activity Monitor



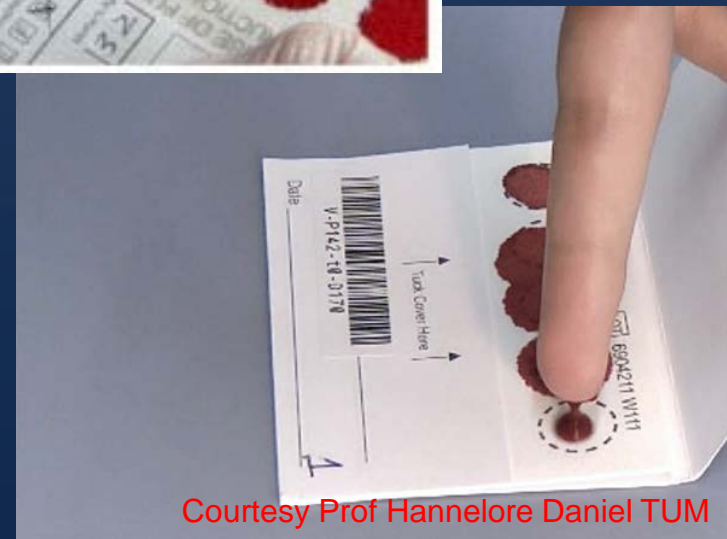
The Zeo sleep Manager (Oram)



GPS: Biochemical and Genetic analysis



30 – 100 μ l
per spot

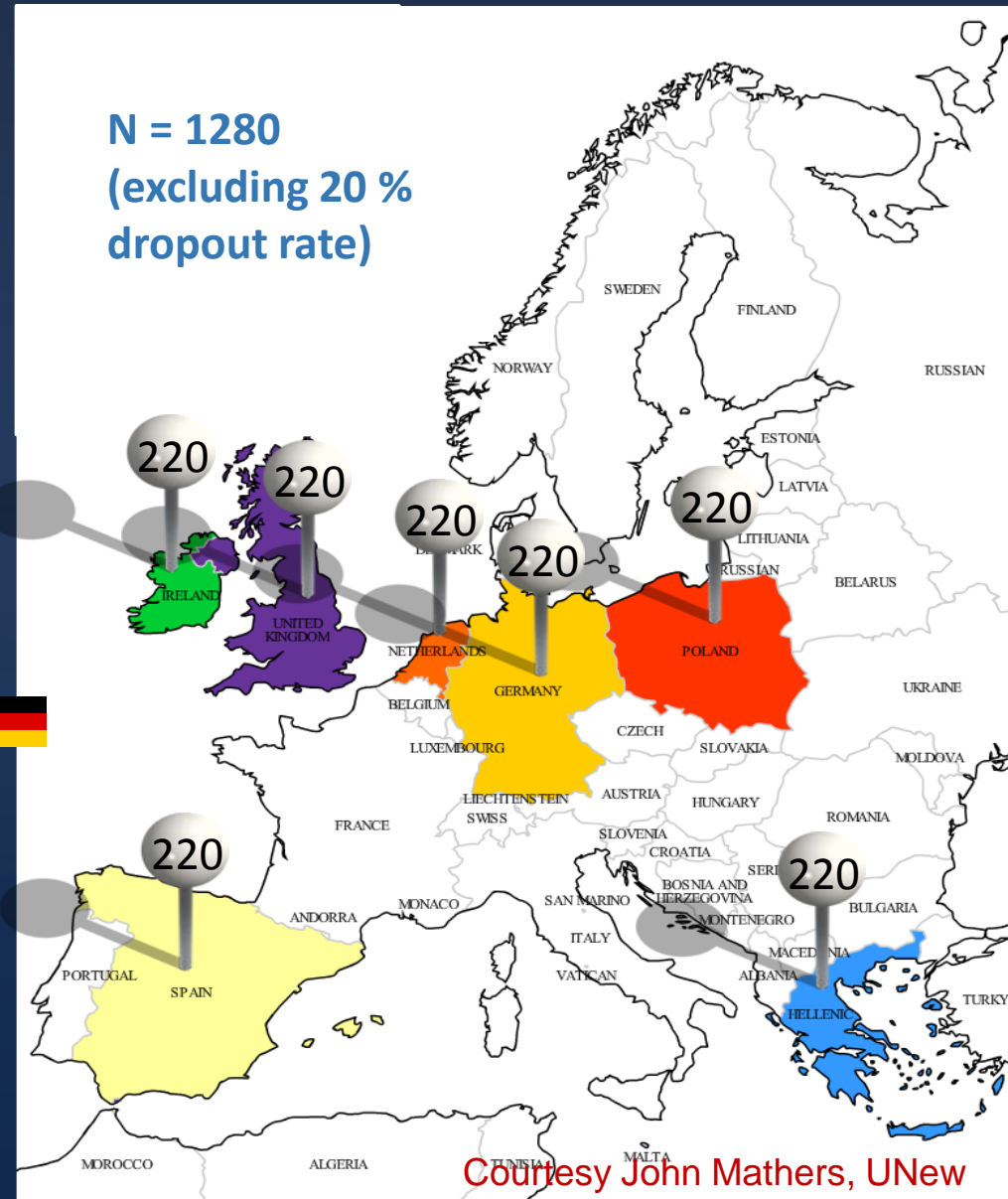


Courtesy Prof Hannelore Daniel TUM



FOOD4ME: Recruiting centres for Study

1. **University College Dublin (Ireland)** 
2. **Maastricht University (The Netherlands)** 
3. **University of Navarra (Spain)** 
4. **University of Reading (UK)** 
5. **National Food and Nutrition Institute Warsaw (Poland)** 
6. **Harokopio University Athens (Athens)** 
7. **Technische Universitaet Muenchen (Germany)** 



Objectives

- ↳ To explore the **scientific, business and consumer** aspects of personalised nutrition
- ↳ To determine whether dietary advice based on a person's genes, could deliver consumer benefits



ETHICAL ISSUES!

Appetite 66 (2013) 67–74



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Research report

Factors influencing European consumer uptake of personalised nutrition. Results of a qualitative analysis [☆]



Barbara Stewart-Knox ^a, Sharron Kuznesof ^b, Jenny Robinson ^a, Audrey Rankin ^a, Karen Orr ^a, Maresa Duffy ^a, Rui Poínhos ^c, Maria Daniel Vaz de Almeida ^c, Anna Macready ^d, Caroline Gallagher ^e, Aleksandra Berezowska ^f, Arnout R.H. Fischer ^f, Santiago Navas-Carretero ^g, Martina Riemer ^h, Iwona Traczyk ⁱ, Ingrid M.F. Gjelstad ^j, Christina Mavrogianni ^k, Lynn J. Frewer ^{b,*}

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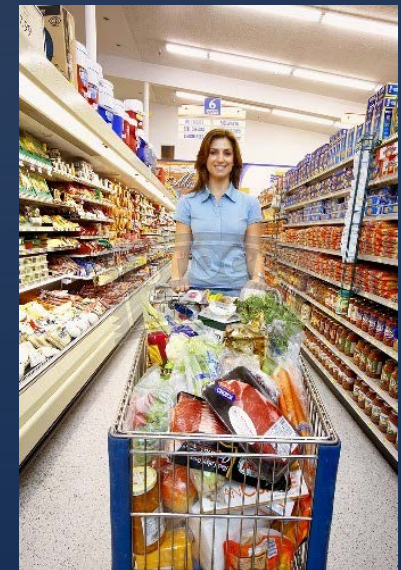
Acceptance

Focus group

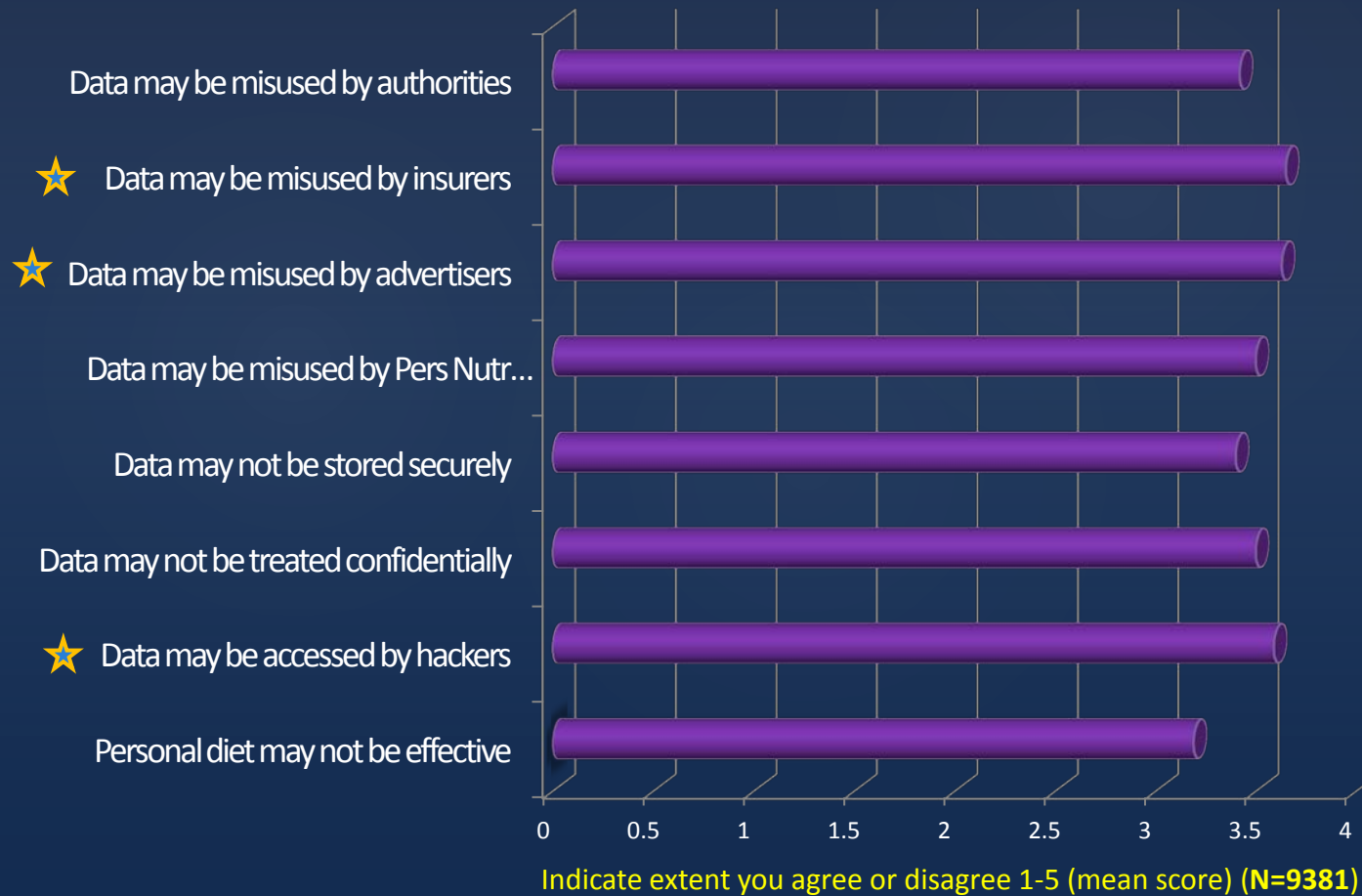
Food4Me

ABSTRACT

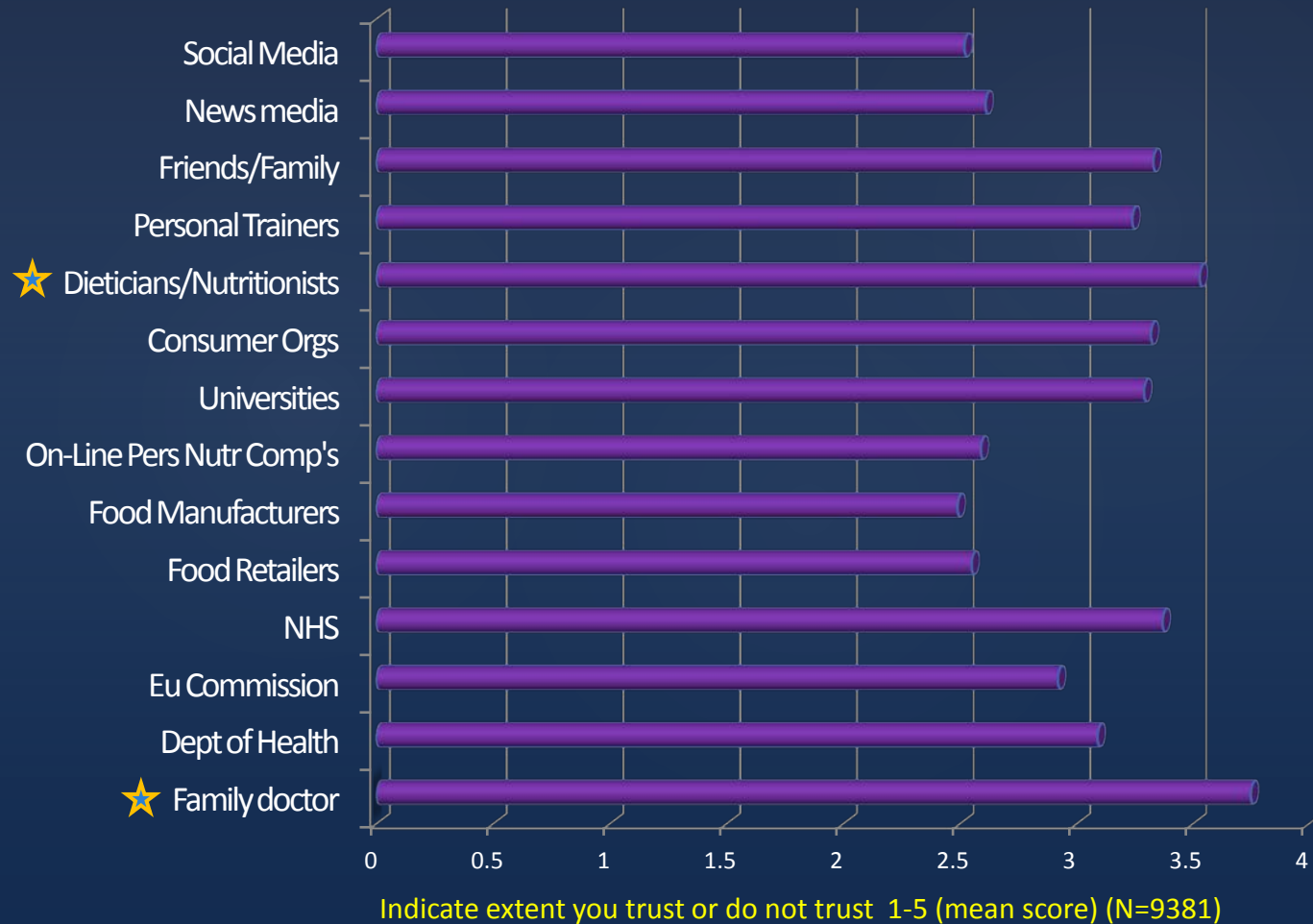
The aim of this research was to explore consumer perceptions of personalised nutrition and to compare these across three different levels of “medicalization”: lifestyle assessment (no blood sampling); phenotypic assessment (blood sampling); genomic assessment (blood and buccal sampling). The protocol was developed from two pilot focus groups conducted in the UK. Two focus groups (one comprising only “older” individuals between 30 and 60 years old, the other of adults 18–65 yrs of age) were run in the UK, Spain, the Netherlands, Poland, Portugal, Ireland, Greece and Germany ($N = 16$). The analysis (guided using grounded theory) suggested that personalised nutrition was perceived in terms of benefit to health and fitness and that convenience was an important driver of uptake. Negative attitudes were associated with internet delivery but not with personalised nutrition *per se*. Barriers to uptake were linked to broader technological issues associated with data protection, trust in regulator and service providers. Services that required a fee were expected to be of better quality and more secure. An efficacious, transparent and trustworthy regulatory framework for personalised nutrition is required to alleviate consumer concern. In addition, developing trust in service providers is important if such services to be successful. © 2013 Elsevier Ltd. All rights reserved.



WHAT WORRIES THE PUBLIC ABOUT PERSONALISED NUTRITION?



WHO DO THE PUBLIC TRUST TO PROVIDE PERSONALISED NUTRITION?



Position of the Academy of Nutrition and Dietetics: Nutritional Genomics

ABSTRACT

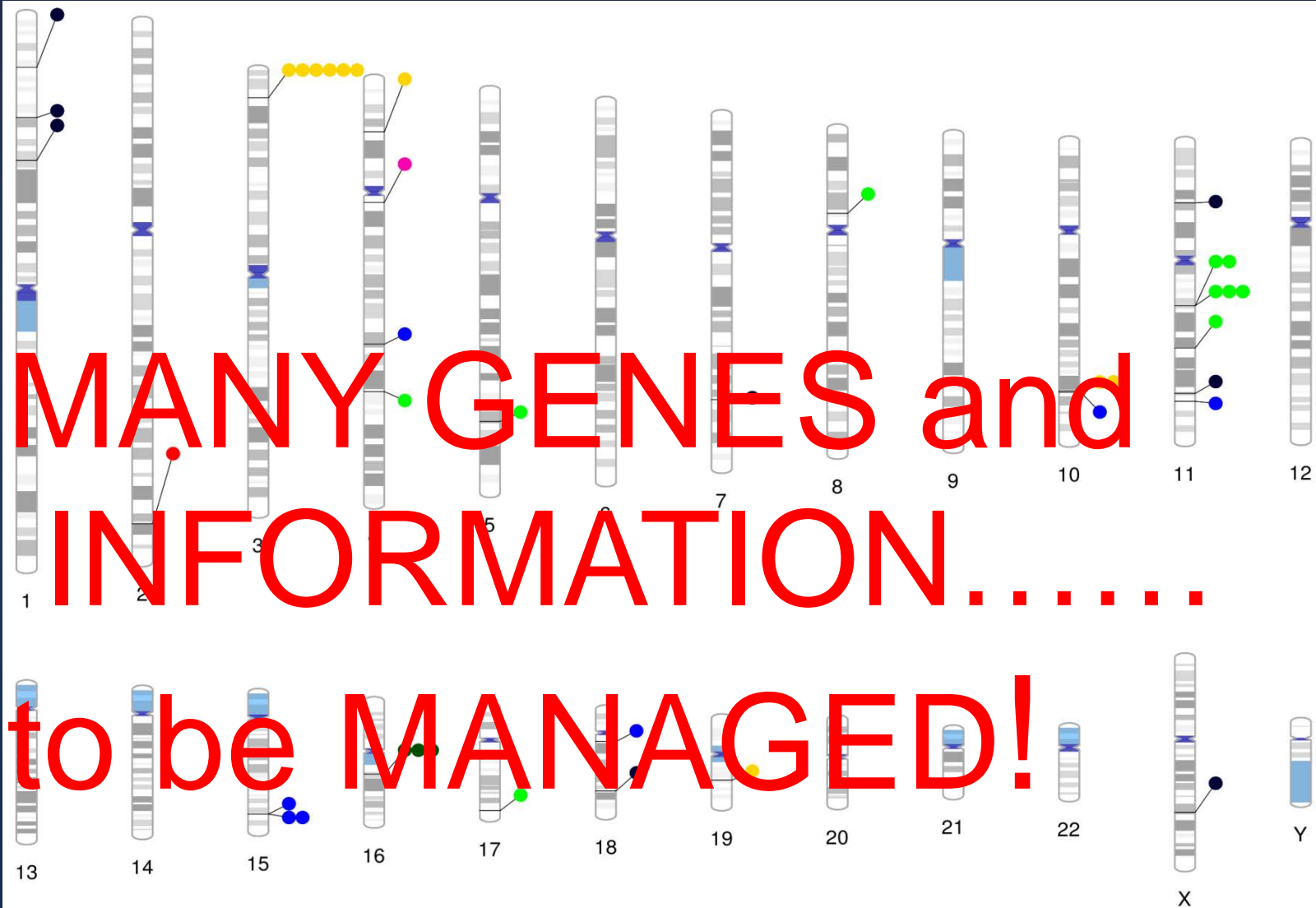
It is the position of the Academy of Nutrition and Dietetics that nutritional genomics provides insight into how diet and genotype interactions affect phenotype. The practical application of nutritional genomics for complex chronic disease is an emerging science and the use of nutrigenetic testing to provide dietary advice is not ready for routine dietetics practice. Registered dietitian nutritionists need basic competency in genetics as a foundation for understanding nutritional genomics; proficiency requires advanced knowledge and skills. Unlike single-gene defects in which a mutation in a single gene results in a specific disorder, most chronic diseases, such as cardiovascular disease, diabetes, and cancer are multigenetic and multifactorial and therefore genetic mutations are only partially predictive of disease risk. Family history, biochemical parameters, and the presence of risk factors in individuals are relevant tools for personalizing dietary interventions. Direct-to-consumer genetic testing is not closely regulated in the United States and may not be accompanied by access to health care practitioners. Applying nutritional genomics in clinical practice through the use of genetic testing requires that registered dietitian nutritionists understand, interpret, and communicate complex test results in which the actual risk of developing a disease may not be known. The practical application of nutritional genomics in dietetics practice will require an evidence-based approach to validate that personalized recommendations result in health benefits to individuals and do not cause harm.

J Acad Nutr Diet. 2014;114:299-312.

POSITION STATEMENT

It is the position of the Academy of Nutrition and Dietetics that nutritional genomics provides insight into how diet and genotype interactions affect phenotype. The practical application of nutritional genomics for complex chronic disease is an emerging science and the use of nutrigenetic testing to provide dietary advice is not ready for routine dietetics practice. Registered dietitian nutritionists need basic competency in genetics as a foundation for understanding nutritional genomics; proficiency requires advanced knowledge and skills.

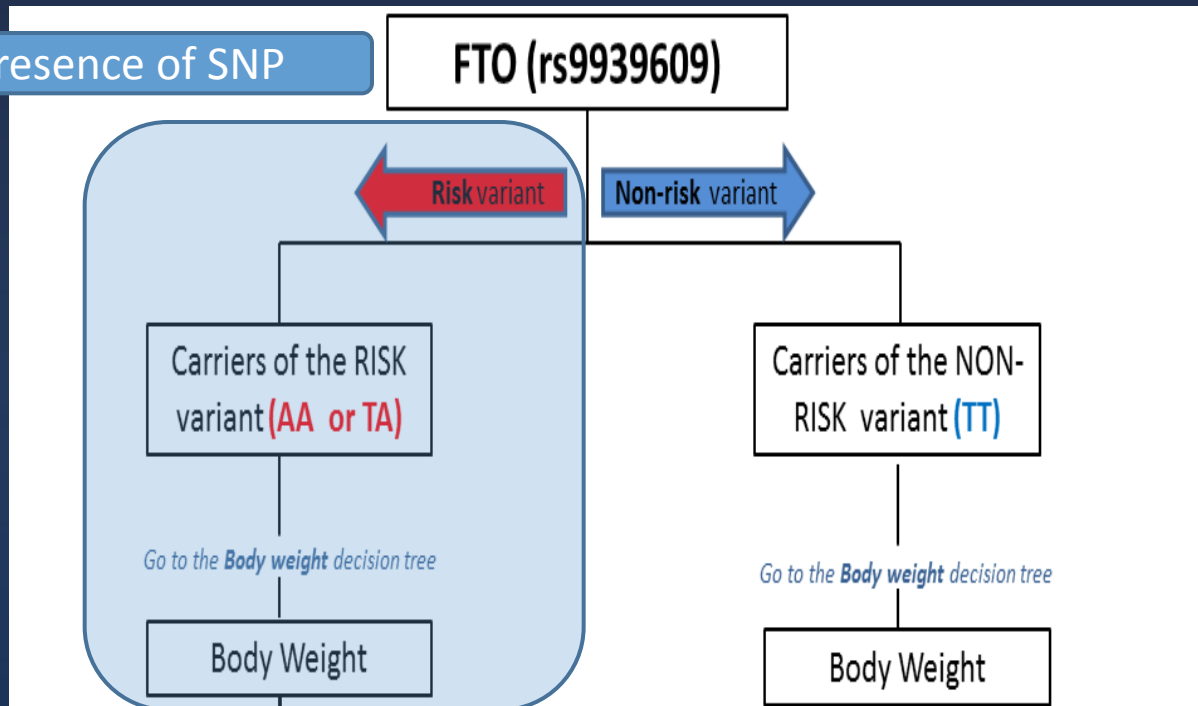
KARYOGRAM DEPICTING LOCI THAT HAVE BEEN ASSOCIATED WITH BODY WEIGHT LOSS IN RESPONSE TO A NUTRITIONAL INTERVENTION



- Energy expenditure
- Adipogenesis
- Cell and nuclear regulation
- Circadian system
- Energy intake
- Lipid metabolism
- Carbohydrate metabolism

BODY WEIGHT: *FTO* SNP

1 Check the presence of SNP



BODY WEIGHT: *FTO* SNP

FTO (rs9939609)

Carriers of the **Risk Variant (AA or TA)**

Body weight

2 Check BMI

Check BMI

Overweight /Obese (BMI >25 kg.m²)

3 Check WC

Normal Waist Circumference (Females <88 cm; Males <102cm)

4 Check PA

Check Physical Activity level?

Sedentary **Lightly Active** **Active**

5 Check Glucose levels

Check Glucose levels?

Check Glucose levels?

6 Check Cholesterol levels

<6.1 **6.1 to 7.0** **>7.0** **<6.1** **6.1 to 7.0** **>7.0**

Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels?

Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8	Message No	<	5	5 to 8	>8		
L3.1.109	L3.1.110	L3.1.111	L3.1.112	L3.1.113	L3.1.114	L3.1.115	L3.1.116	L3.1.117	L3.1.118	L3.1.119	L3.1.120	L3.1.121	L3.1.122	L3.1.123	L3.1.124	L3.1.125	L3.1.126	L3.1.127	L3.1.128	L3.1.129	L3.1.130	L3.1.131	L3.1.132	L3.1.133	L3.1.134	L3.1.135	L3.1.136	L3.1.137	L3.1.138	L3.1.139	L3.1.140	L3.1.141	L3.1.142	L3.1.143	L3.1.144	L3.1.145	L3.1.146	L3.1.147	L3.1.148	L3.1.149	L3.1.150

BODY WEIGHT: *FTO* SNP

FTO (rs9939609)

Carriers of the **Risk** Variant (**AA** or **TA**)

Body weight

Check BMI

Overweight /Obese (BMI >25 kg.m²)

3 Check WC

High Waist Circumference (Females >88 cm; Males >102cm)

Check Physical Activity level?

4 Check PA

Sedentary **Lightly Active** **Active**

5 Check Glucose levels

Check Glucose levels?

Check Glucose levels?

6 Check Cholesterol levels

<6.1 6.1 to 7.0 >7.0 <6.1 6.1 to 7.0 >7.0

Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels? Check cholesterol levels?

Message No L3.1.136	No ^ 5	Message No L3.1.137	No 5 to 8	Message No L3.1.138	No >8	Message No L3.1.139	No ^ 5	Message No L3.1.140	No 5 to 8	Message No L3.1.141	No >8	Message No L3.1.142	No ^ 5	Message No L3.1.143	No 5 to 8	Message No L3.1.144	No >8	Message No L3.1.145	No ^ 5	Message No L3.1.146	No 5 to 8	Message No L3.1.147	No >8	Message No L3.1.148	No ^ 5	Message No L3.1.149	No 5 to 8	Message No L3.1.150	No >8	Message No L3.1.151	No ^ 5	Message No L3.1.152	No 5 to 8	Message No L3.1.153	No >8	Message No L3.1.154	No ^ 5	Message No L3.1.155	No 5 to 8	Message No L3.1.156	No >8	Message No L3.1.157	No ^ 5	Message No L3.1.158	No 5 to 8	Message No L3.1.159	No >8	Message No L3.1.160	No ^ 5	Message No L3.1.161	No 5 to 8	Message No L3.1.162	No >8
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TFAP2B Influences the Effect of Dietary Fat on Weight Loss under Energy Restriction

Tanja Stocks^{1,2*}, Lars Ängquist^{1*}, Kai Peter Arner⁶, Jean-Michel Oppert⁷, J. A. Dominique Langin¹¹, Stephan Rössner¹, Andreas F. H. Pfeiffer^{14,15}, Marie Kunes Oluf Pedersen^{3,20,21}, Arne Astrup²², Th

Pathophysiology/Complications

BRIEF REPORT

Genetic Predictors of Weight Loss and Lifestyle

RESEARCH

Open Access

C677T gene polymorphism of MTHFR and metabolic syndrome: response to dietary intervention

Laura Di Renzo^{1*}, Luigi Tonino Marsella², Francesco Carlo³, Luca Solito⁴, Santo Cratten⁵, Giovanni Abenavoli⁶ and Antonino De Lorenzo^{1,7,8}

COSTS!

17/S0007114513001116

mbined

Ghrelin, Sleep Reduction and Evening Preference: Relationships to CLOCK 3111 T/C SNP and Weight Loss

Marta Garaulet^{1*}, Carmen Sánchez-Moreno¹, Caren E. Smith², Yu-Chi Lee², Francisco Nicolás⁴, Jose M Ordovás^{2,3}

TOOLS: Microchip Scanning

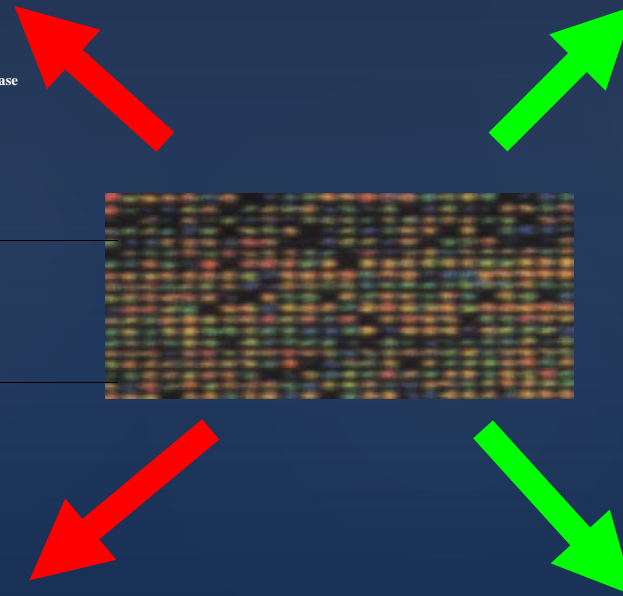


Macronutrient Metabolism		
<i>Fold</i>	<i>Code</i>	<i>Name</i>
~49.2	D45862	Leptin, ob
15.7 ⁺	J02773	Low molecular weight FABP
7.3	J00713	Carboxypeptidase-a- 5
~6.7 ⁺	U64451	Short-branched chain acyl-CoA DH precursor
~4.9 ⁺	AF063302	Carnitine palmitoyltransferase I beta
~4.6 ⁺	AF034577	Pyruvate dehydrogenase kinase isoenzyme 4
4.1	M05591	Squalene synthetase
3.3	S69874	Fatty acid-binding protein (FABP)
3.2	K03249	Enoyl-CoA-hydratase-3-hydroxyacyl-CoA DH
3	AB002558	Glycerol 3-phosphate dehydrogenase
2.9	AB005743	Fatty acid transporter
2.8	L07114	Apolipoprotein B
2.5	U20643	Aldolase A
2.5	M26594	Malic enzyme
2.4	M60322	Aldose reductase
2.2	S56481	Beta 3-adrenergic receptor
2.2	S81497	Lysosomal acid lipase
2.2	J02585	Liver stearyl-CoA desaturase
2.2	X15580	6-phosphofructo-2-kinase/fructose-2,6-bisphosphatase
2.2	L12016	Tricarboxylate transport protein
2.2	U32314	Pyruvate carboxylase
2.2	D10354	Alanine aminotransferase
2.2	L25331	Lysyl hydroxylase
2.1	D43623	Carnitine palmitoyltransferase I like protein
2	D10655	Dihydrolipamide acetyltransferase
2	AF035943	Uncoupling protein-3
Transcription factor		
3.7 ⁺	AB015724	Nuclear receptor binding factor-1
2.8 ⁺	X12752	DNA binding protein C/EBP
2.5	S77528	C/EBP-related transcription factor
2.1	AB011365	PPAR-gamma protein
2	AF022081	Small nuclear RING finger protein
2	X13167	NF-1 like DNA-binding protein
Hormone receptor and signal transduction		
~10.7 ⁺	M96159	Adenylyl cyclase type V
4	S79241	Oxytocin receptor
3.6 ⁺	U93880	Insulin receptor substrate-3 (IRS-3)
3	K03045	Retinol-binding protein (RBP)
2.9	D38036	Truncated TSH receptor
2.9	Z83757	Growth hormone receptor
2	X92069	P2X5 receptor (ATP-gated ion channels)
2.8	E12286	GM2 activator protein
2.7	X17053	Immediate-early serum-responsive JE
2.6	S74351	Protein tyrosine phosphatase
2.6 ⁺	X06107	Insulin-like growth factor I
2.5	M64300	Signal-related Kinase (ERK2)
2.4	D85183	SHP5-1 (protein tyrosine phosphatase)
2.4	L13619	Insulin-induced growth-respons protein
2.4 ⁺	L35767	Very low density lipoprotein receptor,
2.3	S49003	Short isoform growth hormone receptor
2.3	D85435	Protein kinase C delta-bindig protein
2.2	D89655	Scavenger receptor class B
2.2	U21101	Cyclic GMP stimulated phosphodiesterase
2.2 ⁺	J03819	Thyroid (T3) hormone receptor
2	AF022952	Vascular endothelial growth factor B
2	S50461	Signal-transducing G protein alpha 12 subunit
2	L25633	Neuroendocrine-specific protein
2	M12492	Type II cAMP-dependent PK regulatory subunit
Cellular cytoskeleton		
~4.9 ⁺	K00512	Myelin basic protein
~4.0 ⁺	AF004811	Moesin
3.5	X60351	Alpha B-crystallin
3.1	AF041373	Clathrin assembly protein short form
2.7	U50717	Synaptic density protein PSD-93
2.5	M83196	Microtubule-associated protein 1A

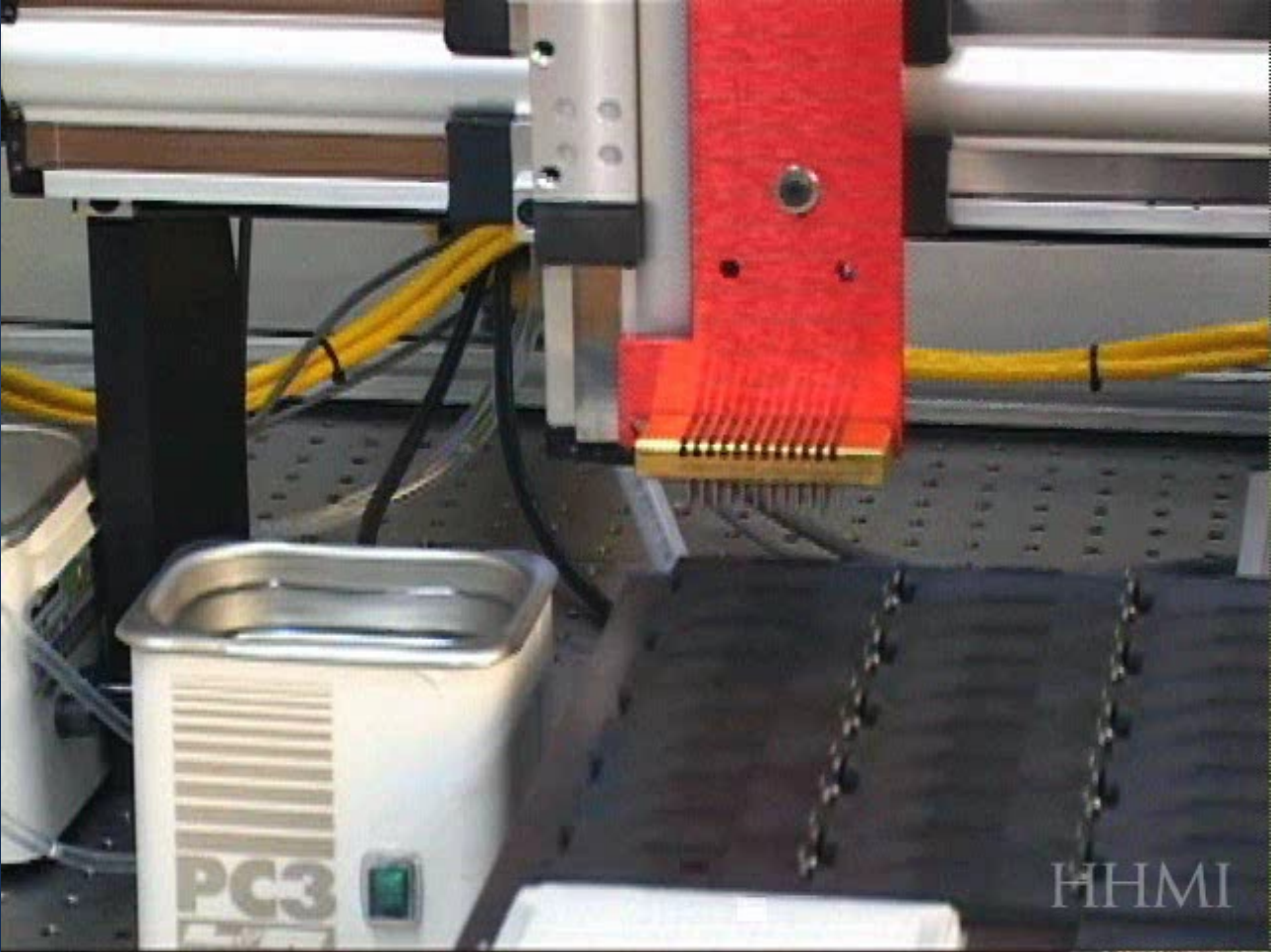
= corresponds to a transcript absent in the control group (basal line).

Macronutrient Metabolism		
<i>Fold</i>	<i>Code</i>	<i>Name</i>
-22.5	AF001898	Aldehyde dehydrogenase (ALDH)
-22.1 ⁺	AB000999	CDP-diaclyglycerol synthase
~20.0 ⁺	AB017260	High-affinity carnitine transporter
-19.0 ⁺	D37920	Squalene epoxidase
-9.1	L25387	Phosphofructokinase C
~-6.4 ⁺	AB010428	Acyl-CoA hydrolase
-6.0	S68135	GLUT1
-3.8	M18467	Aspartate aminotransferase
-2.9	AF080468	Glycogen storage disease type 1b protein
-2.8	S49760	Diaclyglycerol kinase
-2.6	X04979	Apolipoprotein E
-2.4	M93297	Ornithine aminotransferase
-2.2	L07736	Carnitine palmitoyl-transferase I
Redox and stress proteins		
-7.8-34.1 ⁺	S82820	Glutathione S-transferase Yc2 subunit
-4.8-6.2	X62660	Glutathione S-transferase subunit 8
-4.2	M11794	Metallothionein-2 and metallothionein-1
-2.6-3.2	X02904	Glutathione S-transferase P subunit
Transcription factor		
-25.2	U78102	Krox20 ó EGR-2(early growth response protein 2)
-5.2	X94246	Pax-8 protein
-2.7	M91802	Homeobox protein (Hox 1.11)
Hormone and signal transduction		
-117.5	S49491	Proenkephalin
~92.3 ⁺	J04488	Prostaglandin D synthetase
~47.3	D63772	Neuronal high affinity glutamate transporter
~8.6 ⁺	M12450	Vitamin D binding protein
-4.1	U57715	FGF receptor activating protein FRAG1
-2.8	U48596	MAP kinase kinase kinase 1 (MEKK1)
-2.3	L06096	Inositol trisphosphate receptor subtype 3 (IP3R-3)
-2.3	U53184	Estrogen-responsive uterine
-2.3	X59132	Secretin receptor
-2.2	D64045	Phosphatidylinositol 3-kinase p85 alpha subunit
-2.1	AF014009	Acidic calcium-independent phospholipase A2
-2	M91599	Fibroblast growth factor receptor subtype 4
Cellular cytoskeleton		
~21.4 ⁺	X81448	Keratin 18
~12.2 ⁺	M93638	Keratin 5
~6.6 ⁺	AF013247	Beta-A4 crystallin
~3.8 ⁺	M59936	Connexin-31
-3.2	X67788	Ezrin p81
-2.3	X81449	Keratin 19

= corresponds to a transcript absent in the obese group (basal line).



MICROARRAY/SEQUENCING



INTERPRETATION!



The Hunger Genes: Pathways to Obesity

Agatha A. van der Klaauw¹ and I. Sadaf Farooqi^{1,*}

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*Correspondence: isf20@cam.ac.uk

<http://dx.doi.org/10.1016/j.cell.2015.03.008>

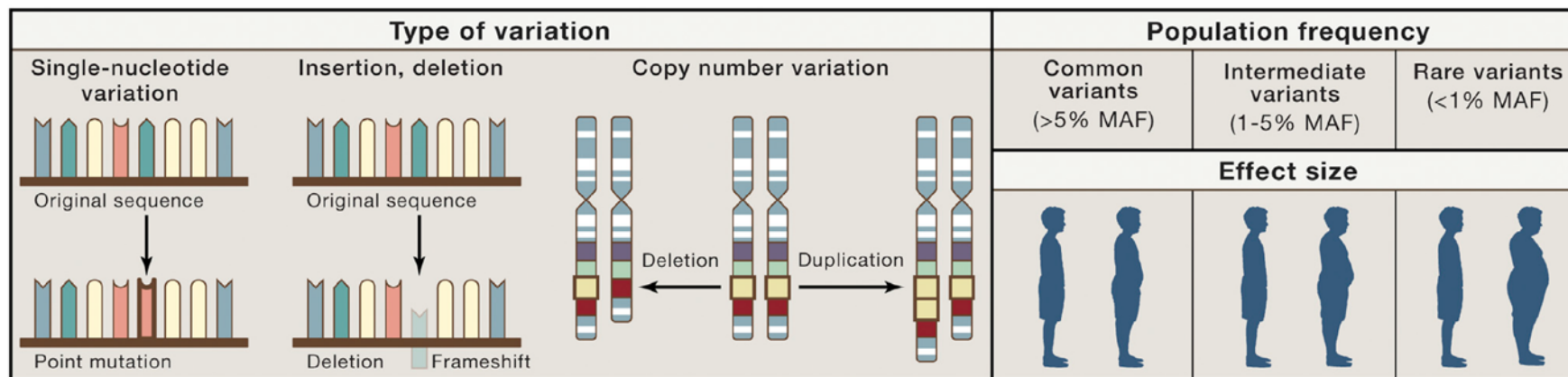
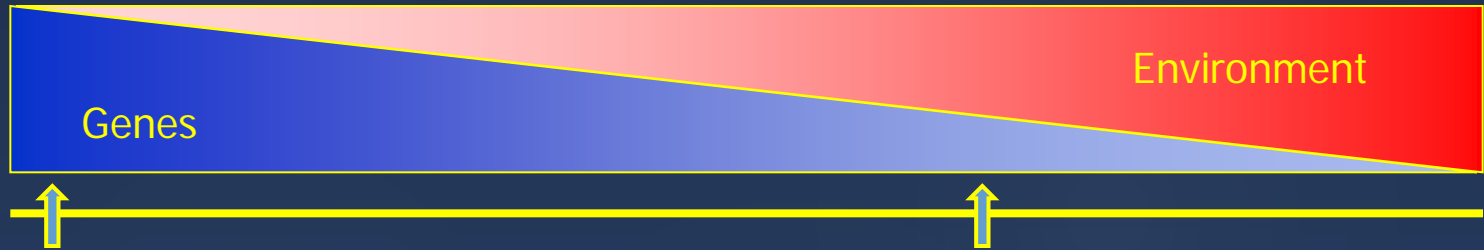


Figure 4. Types of Genetic Variation Contributing to Body Weight Regulation

Genetic effects on body weight are mediated by different types of variants, their frequency in the population, and the effect of the variant on the phenotype. Variants include single-nucleotide variations in which only one nucleotide is changed, copy number variations in which a stretch of DNA is repeated or deleted (often containing many genes), or small insertions and deletions of a few base pairs. Common variants are found at a minor allele frequency (MAF) of more than 5% in a population, whereas intermediate (1%–5%) and rare variants (< 1%) are found at lower frequencies. Generally, the effect size of common obesity-associated variants on body weight is modest. Several rare variants have been associated with severe obesity.

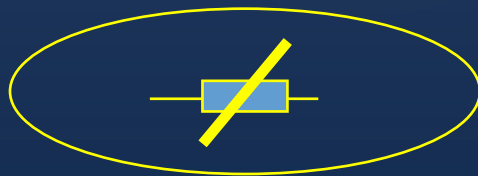
Genetics of Human Metabolism



Monogenic

- Rare cases
- Syndromes

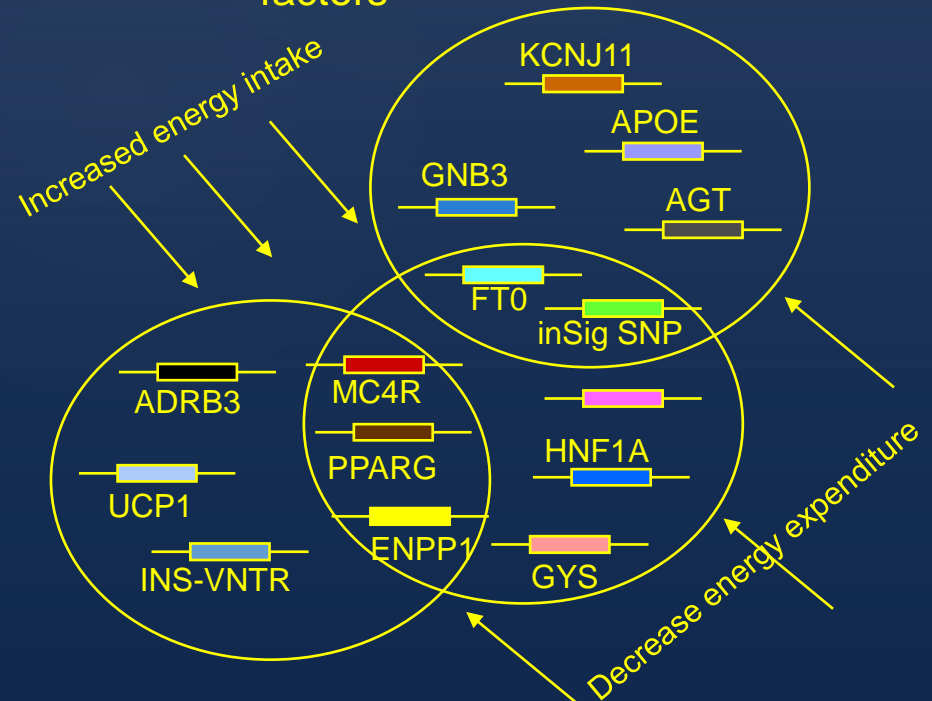
1 gene 1 disease



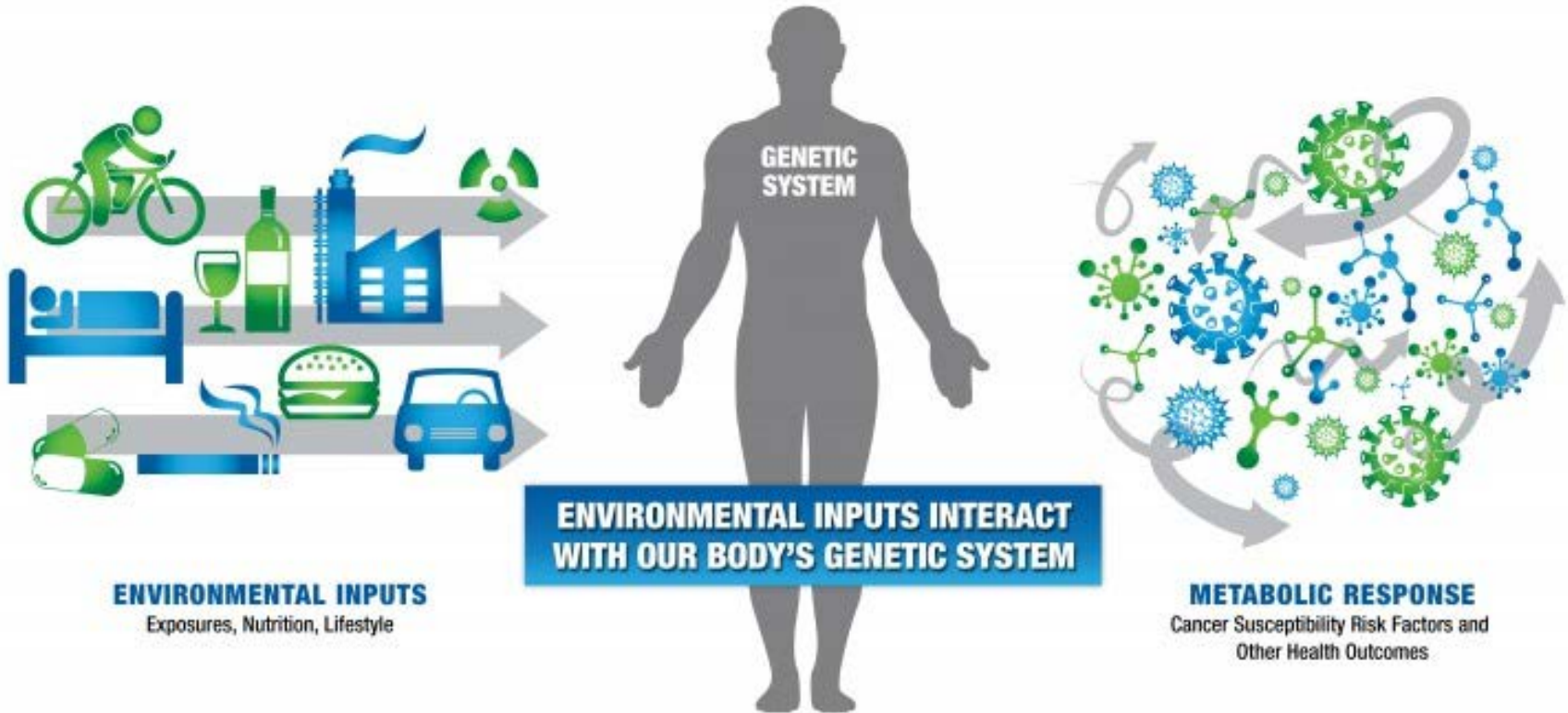
LEP, LEPR, POMC, PCSK1
SIM,,

Polygenic

Individual combination in interaction with environmental factors



GENE-ENVIRONMENTAL INPUTS INTERACTION



GENETIC TESTS

SNP	polimorfismo
01	APOA5 (rs662799) g.4430 T>C
02	APOB (rs5742904) c.10580 G>A
03	APOA1 (rs670) g.4926 G>A
04	ESR1 (rs2234693) c.453-387 T>C
05	FTO (rs9939609) c.46-23525 T>A
06	GC (rs2282679) c.*26-796 A>C
07	GCKR (rs1260326) c.1337 C>T
08	GNB3 (rs5443) c. 825 C>T
09	MTNR1B (rs10830963) c.223+5596 C>G
10	MC4R (rs17782313) g.5785109 T>C
11	LPL (rs328) c.1421 C>G
12	LIPG (rs4939883) g.47167214 C>T
13	CETP (rs1800777) c.1403 G>A
14	LIPC (rs1800588) g.4501 C>T
15	NOS3 (rs1799983) c.894 G>T
16	PLIN4 (rs894160) c.772-799 G>A
17	PPARA (rs1800206) c.484 C>G
18	PPARG (rs1801282) c.34 C>G
19	CELSR2 (rs12740374) c.*919 G>T
20	MTHFR (rs1801133) c.665 C>T
21*	LCT/MCM6 (rs4988235) c.1917+326 T>C
23	APOE (rs429358) c.388 T>C
24	APOE (rs7412) c.526 C>T

Gen

SNP

SNP
(Alternative
nomenclature)

GPS based on computing risk alleles

GENETIC TESTS

Gen	SNP	Genotipo	Score/SNP	Score/patolog (minor-minor)	(major-minor)	(major-major)	Major allele	Minor allele	
OBESIDAD									
FTO	rs9939609	AA	0,6	4,1	0,6	0,3	0	T	A
		Prevalencia	15		15	60	25		
MC4R	rs17782313	CC	2,5		2,5	2	0	T	C
		Prevalencia	3		3	47	50		
MTHFR	rs1801133	CC	0		0,2	0	0	C	T
		Prevalencia	50		10	40	50		
DIABETES									
FTO	rs9939609	AA	2	3,7	2	0,6	0	T	A
		Prevalencia	15		15	60	25		
PPARA	rs1800206	CC	0		0,3	0,2	0	C	G
		Prevalencia	95		1	4	95		
PPARG	rs1801282	CG	0,3		0,3	0,2	0	C	G
		Prevalencia	15		5	15	80		
MTNR1B	rs10830963	CC	0		0,3	0,1	0	C	G
		Prevalencia	52		4	44	52		
GNB3	rs5443	TT	0,4		0,4	0,2	0	C	T
		Prevalencia	10		10	55	35		
HIPERTENSIÓN									
MTHFR	rs1801133	CC	0	1,4	0,2	0,1	0	C	T
		Prevalencia	50		10	40	50		
NOS3	rs1799983	CT	0		0,2	0	0	C	T
		Prevalencia	34		7	34	59		
GNB3	rs5443	TT	0,4		0,4	0,1	0	C	T
		Prevalencia	10		10	55	35		
INTOLERANCIA A LA LACTOSA									
LCT	rs4988235	TT	-4	-5	4	0	-4	T	C
		Prevalencia	55		10	35	55		

(C;C) 4x lactose intolerance

(C;T) 0x lactose intolerance

(T;T) -4x lactose tolerance

GENETIC TESTS

GENE-DIET INTERACTIONS

Gen	SNP	Mayor allele	Minor allele	INTERACCIONES	
APOA1	rs670	G	A	Si GG (3)	Si su dieta es
APOA1	rs670	G	A	Si AA (1)	Una dieta rica
LIPC	rs1800588	C	T	Si TT (1)	Una dieta rica
MTHFR	rs1801133	C	T	Si TT (1)	Si la ingesta de
NOS3	rs1799983	C	T	Si TT (1)	Los ácidos grasos
PLIN	rs894160	G	A	Si AA (1)	Una dieta rica
PPARA	rs1800206	C	G	Si GG (1)	Si su dieta es
PPARG	rs1801282	C	G	Si GG (1)	Si su dieta es

Si su dieta es rica en grasas o si su ingesta de grasas monoinsaturadas, como el aceite de oliva, es muy elevada, usted tiene mayor predisposición que la mayoría de la población para desarrollar diabetes tipo 2, obesidad e hipertensión.

Le recomendamos una dieta algo más baja en grasas para prevenir estas posibles consecuencias.

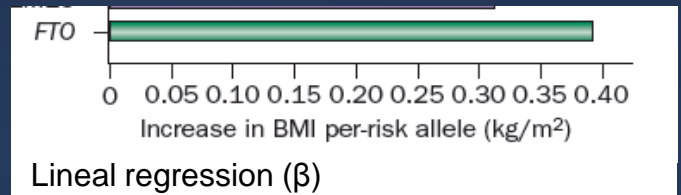
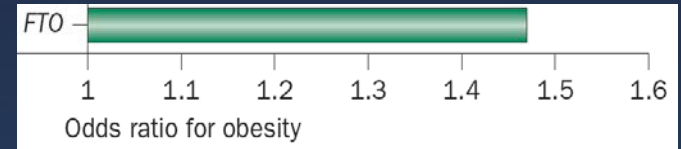
GENE CONTRIBUTION TO BODY WEIGHT MANAGEMENT

1 Risk alleles rs9939609 (FTO): TT TA AA

2 Obesity risk

3 Allele contribution to body weight

4 Genetic predisposition score (GPS)



$$\text{GPS} = (\text{SNP}_1 + \text{SNP}_2 + \dots + \text{SNP}_n)$$

Goni L. et al., 2015

$$\text{GPS} = (\text{SNP}_1 + \text{SNP}_2 + \dots + \text{SNP}_n) / \sum \text{SNP}$$

Peterson RE. et al., 2011

$$\text{Weighted GPS} = (\beta_1 \times \text{SNP}_1 + \beta_2 \times \text{SNP}_2 + \dots + \beta_n \times \text{SNP}_n)$$

Renström F. et al., 2011

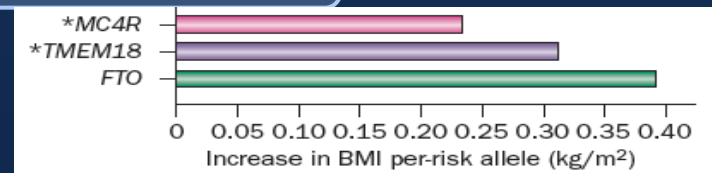
$$\text{Weighted GPS} = (\beta_1 \times \text{OR}_1 + \beta_2 \times \text{OR}_2 + \dots + \beta_n \times \text{OR}_n)$$

Cheung CY et al., 2010

$$\text{Weighted GPS} = (\beta_1 \times \text{SNP}_1 + \beta_2 \times \text{SNP}_2 + \dots + \beta_n \times \text{SNP}_n) \times (\sum \text{SNP} / \sum \beta_s)$$

Qi Q. et al., 2014

5 Propensity score matching ?



MOLECULAR NUTRITION

Nutrigenetic

Polimorphism

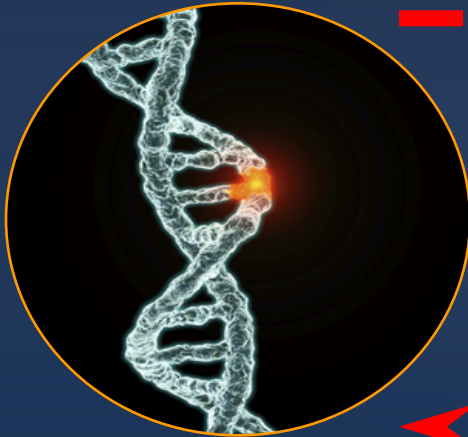
Genes

Nutrients

Nutrigenomic

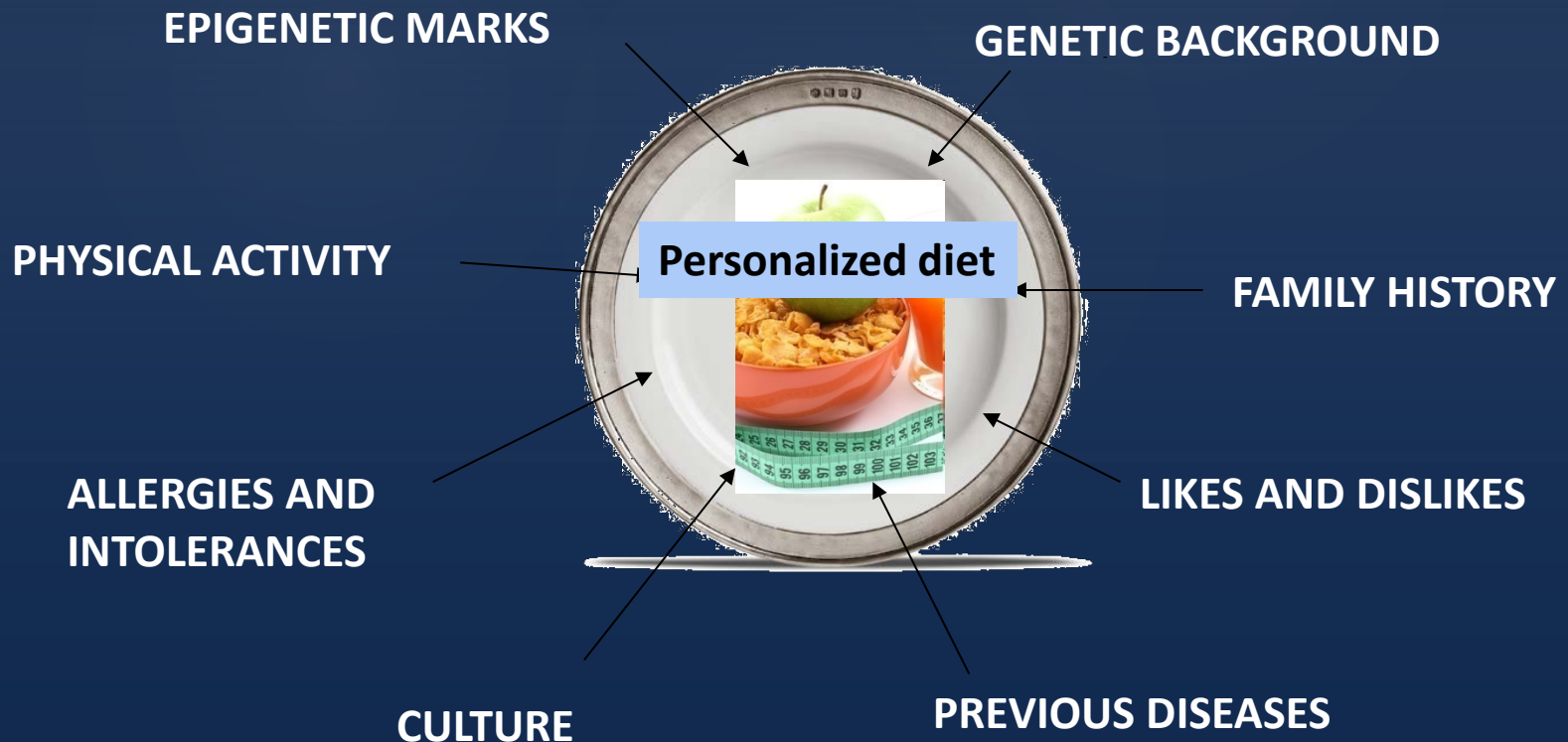
Gene expression

PERSONALISED NUTRITION



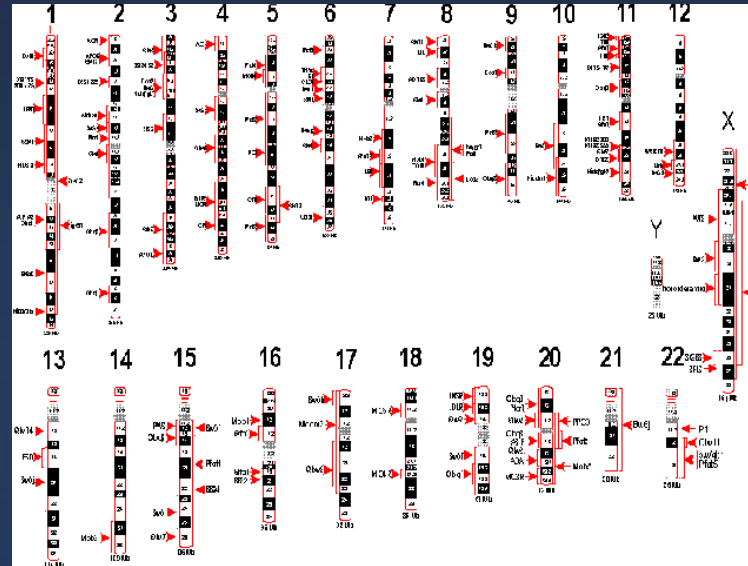
Personalized Nutrition

Rather than existing an 'optimal' diet, there is a range of adequate diets depending on genetic, biological and cultural variation.



Conclusions

GENOMA



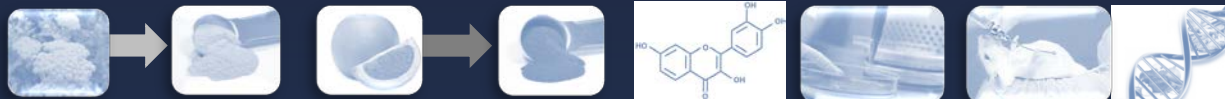
Genome: 30.000 genes (more than 30% have polimorphisms)

Gene expression = f (DNA X nutrition, physical activity environment,.....)

Diagnosis:

- Nutrient requirements
- Predisposition to nutrition related diseases
- Prescription of diets (Prophylaxis/therapy)

V



Acknowledgments



Universidad
de Navarra

ciberobn

ASOCIACIÓN DE AMIGOS

CENTRO DE INVESTIGACIÓN EN NUTRICIÓN

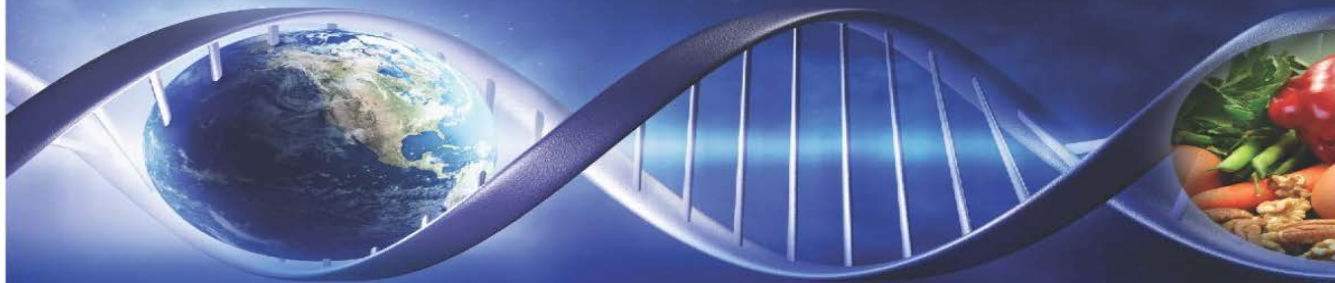


PERSONALIZED WEIGHT MANAGEMENT

SAVE THE DATE

MAY 23-26, 2016, ISRAEL

THE 10TH
CONGRESS OF THE
INTERNATIONAL
SOCIETY OF
NUTRIGENETICS &
NUTRIGENOMICS



INDIVIDUALIZED NUTRITION

