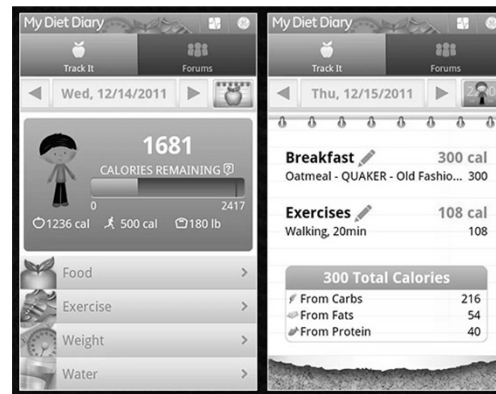
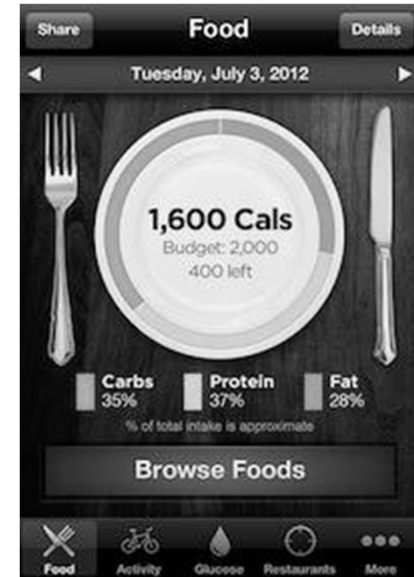


USE OF ARTIFICIAL INTELLIGENCE IN OPTIMIZING NUTRITION

Shaji Krishnan, TNO, The Netherlands

ARTIFICIAL INTELLIGENCE
IN NUTRITION

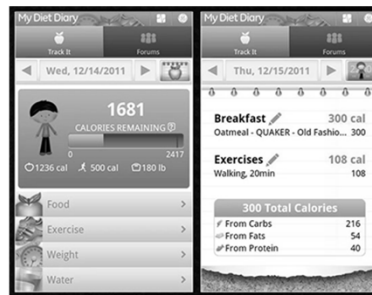
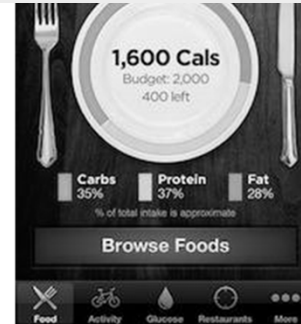
NUTRITION/DIET APPS AND MARKET



Market is flooded with nutrition/diet apps

APPS TEST-BED SAYS...

... these are not apps, but are traps



APPS TEST-BED (CONT.)

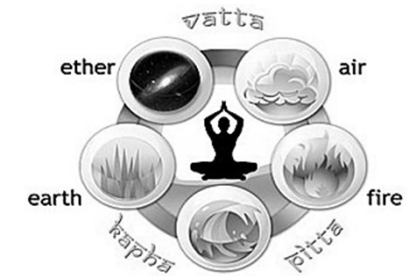
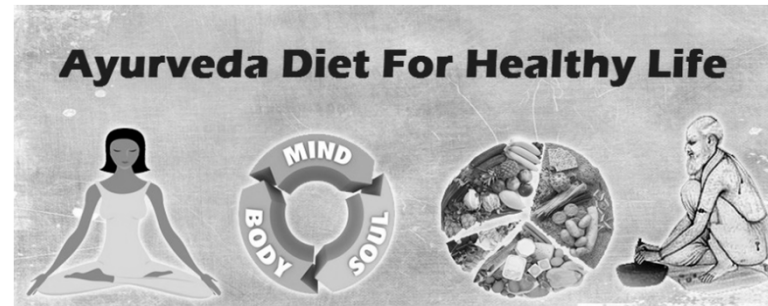
- › Does these diet apps do any good?
- › Are they modelling nutrition all right?
- › How much of the **biological (nutritional) knowledge** is taken into consideration while designing this apps?
- › **What is the role of AI in nutrition?**
- › Is it all feasible or are their any known limitations?

CONTENT

- › History of optimizing nutrition
- › Expert systems
- › Marriage of science and AI
- › Big-data analytics in nutrition
- › Conclusions

Ayurvedic diet prescriptions ~3000 years ago in India

OLDEST HISTORY



Ayurvedic diet incorporates nearly all the natural ingredients that have the positive influence throughout the body.

HISTORY ~ 1960

Menu planning with a computer

The general objectives of the menu planning are recognized as achieving:

1. palatable,
2. nutritionally balanced and
3. economical diet

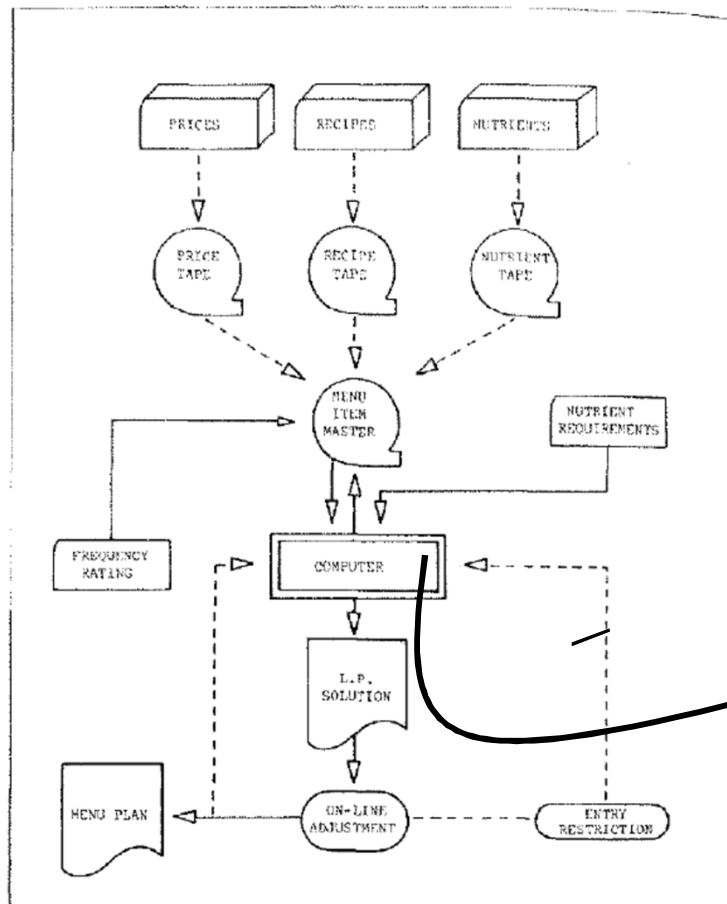


FIG. 1

Linear programming method:
has an objective function and constraints and a feasible solution need to be obtained

HISTORY ~ 1960 (CONT.)

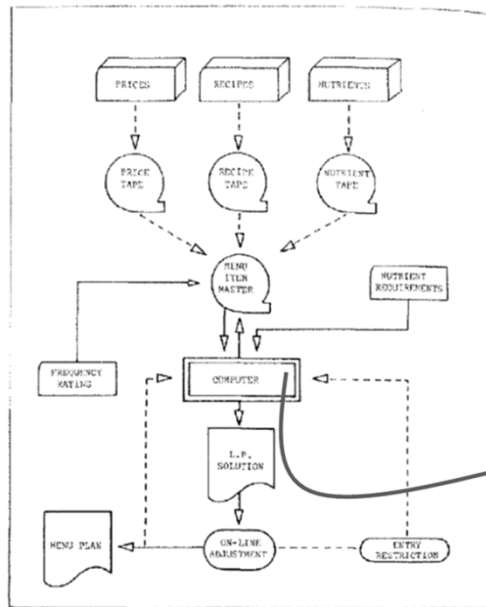


Fig. 1

The general objectives of the menu planning are recognized as achieving:

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Linear programming method:
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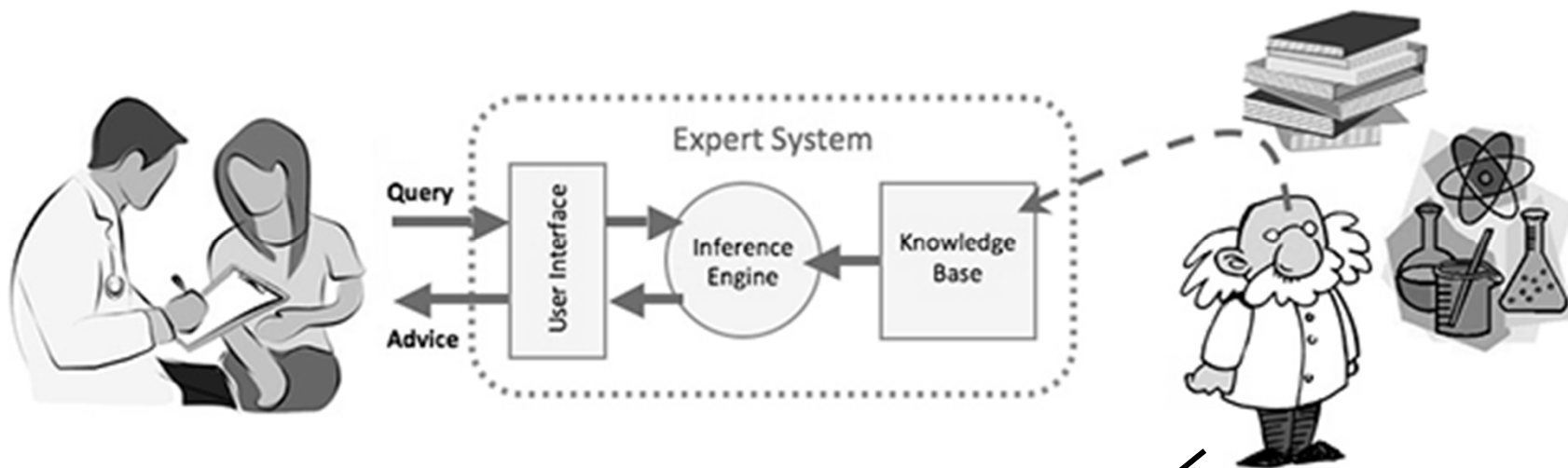
Other methods:

1. Evolutionary computation (Genetic algorithms)
2. Collective intelligence (e.g. Bacterial foraging)

Until 90's computer-assisted menu planning were not widely used. Human experts consistently outperform computers.

HISTORY ~ 1990 – 2000

Expert system: AI system that attempts to model the processes of an human expert



Methods for inference were majorly:

1. Cases based reasoning
2. Rule based reasoning

Novelty:
Incorporation
of expert
knowledge

HISTORY ~ 1990 – 2000 (CONT.)

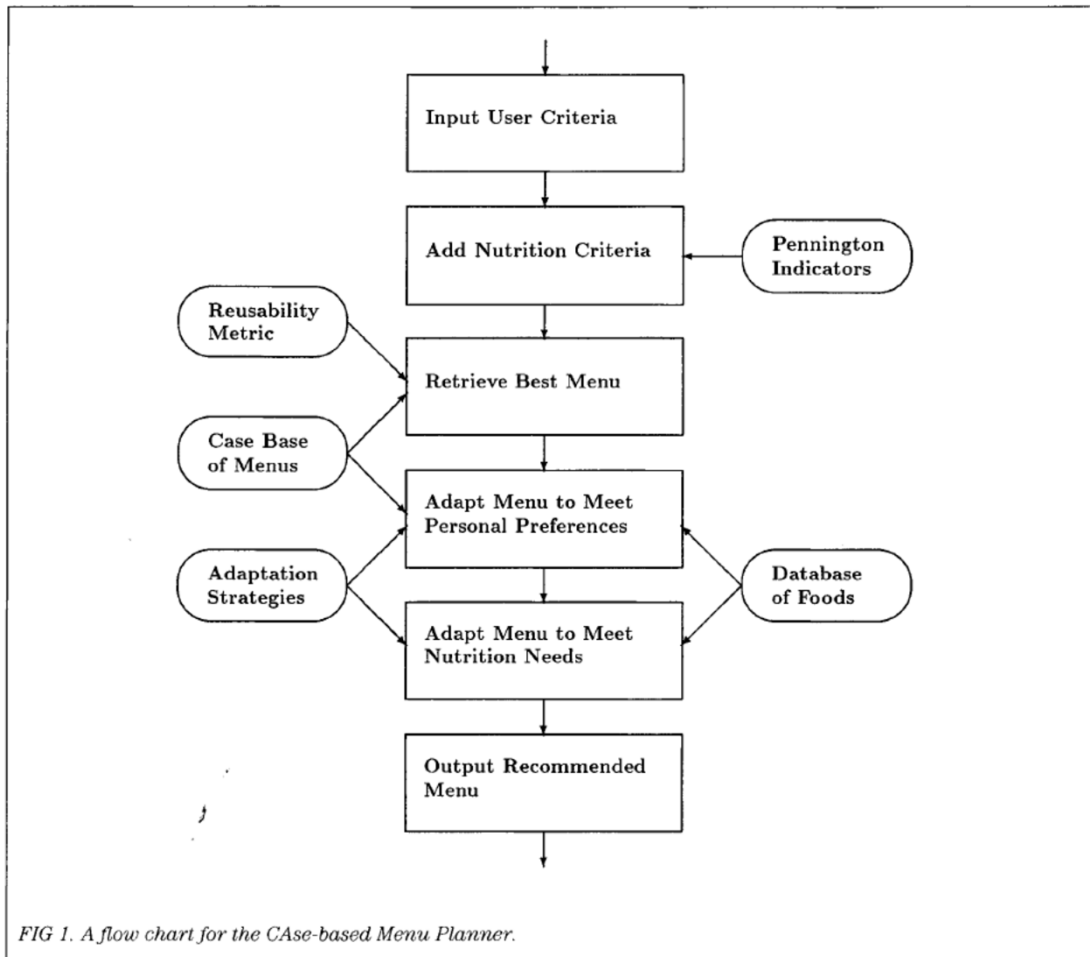
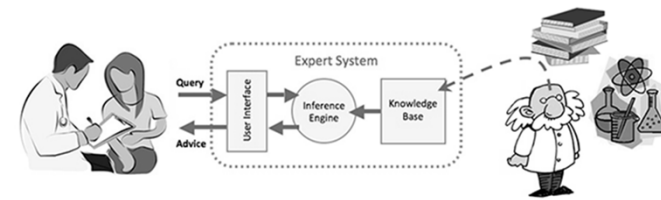


FIG 1. A flow chart for the Case-based Menu Planner.

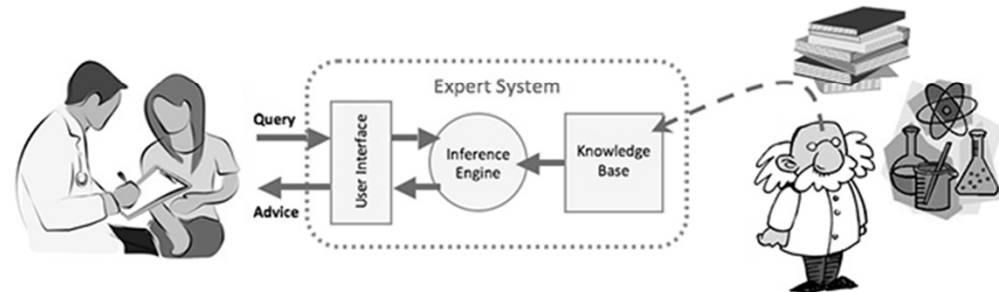


Knowledge:

1. Database of foods
2. Case base of menus (dietary guidelines)
3. Nutritional risk indicators

HISTORY ~ 1990 – 2000 (CONT.)

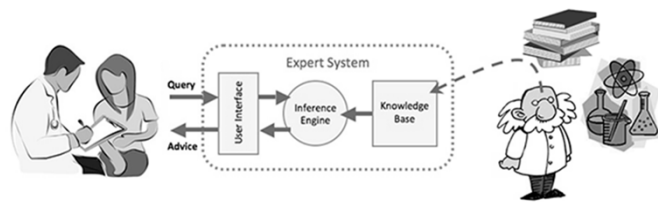
The anthropometry data	<ul style="list-style-type: none"> • Calculation of obesity • BMI • Waist/hip ratio • Kaup index
The computation of calorie expenditure	<ul style="list-style-type: none"> • Basal metabolic expenditure • Specific dynamic action • Total calorie expenditure
The state of eating habits	<ul style="list-style-type: none"> • The analysis of eating habits • Eating habits for hyperlipidemia • Convenient method for analysis of nutrients
Nutrition prescription	<ul style="list-style-type: none"> • Prescription of each test • Synthetic prescription by experts
The computation of calorie expenditure	<ul style="list-style-type: none"> • CAGE • NAST • AUDIT-K



Diet advice based on health state and health goals were added

Clinical measurement data + Physiology

HISTORY ~ 1990 – 2000 AND BIT BEYOND...



CAMP's Recommended Menu

Breakfast

- ¾ c pineapple chunks, packed in juice
- 2 English muffins with
- 2 tsp margarine
- 1 c skim milk

Lunch

- Sandwich
- 1 slice whole wheat bread
- 2 oz chicken breast
- 1 leaf lettuce
- 1 slice tomato
- 1 tsp mayonnaise-type salad dressing
- 1 c vegetable soup
- 6 saltine crackers
- 1 ½ medium oranges
- 1 c skim milk

Dinner

- Salad
- 1 c mixed salad greens
- ½ medium tomato, sliced
- 1 Tbsp Italian dressing
- 3 oz roast leg of lamb
- ¾ c spinach
- 1 medium baked potato
- 1 tsp margarine
- ½ c corn
- Coffee, tea, or water

Snack 1

- ¼ c raisins

A typical outcome from an expert system

Nutritional Profile^a

Energy: 1,830 kcal
 Percentage of energy from fat: 23
 Percentage of energy from protein: 19
 Percentage of energy from carbohydrate: 61
 Percentage of energy from alcohol: 0

Percentages of Reference Daily

Intakes (RDIs)^b

Protein: 173%
 Niacin: 137%
 Vitamin B-12: 71%
 Vitamin E: 36%
 Phosphorus: 140%
 Copper: 102%

Vitamin C: 333%
 Riboflavin: 135%
 Folic acid: 146%
 Iron: 108%
 Potassium: 132%
 Zinc: 72%

Thiamin: 134%
 Vitamin B-6: 124%
 Vitamin A: 369%
 Calcium: 123%
 Magnesium: 113%

Nutrient Data

Energy: 1,830 kcal
 Carbohydrate: 278 g
 Cholesterol: 131 mg
 Niacin: 27.42 mg
 Vitamin B-12: 4.27 µg
 Vitamin E: 7.26 mg
 Phosphorus: 1,398 mg
 Magnesium: 453 mg

Protein: 86.3 g
 Alcohol: 0.0 g
 Vitamin C: 199.60 mg
 Riboflavin: 2.29 mg
 Folic acid: 0.59 µg
 Iron: 19.44 mg
 Sodium: 2,230 mg
 Copper: 2.03 mg

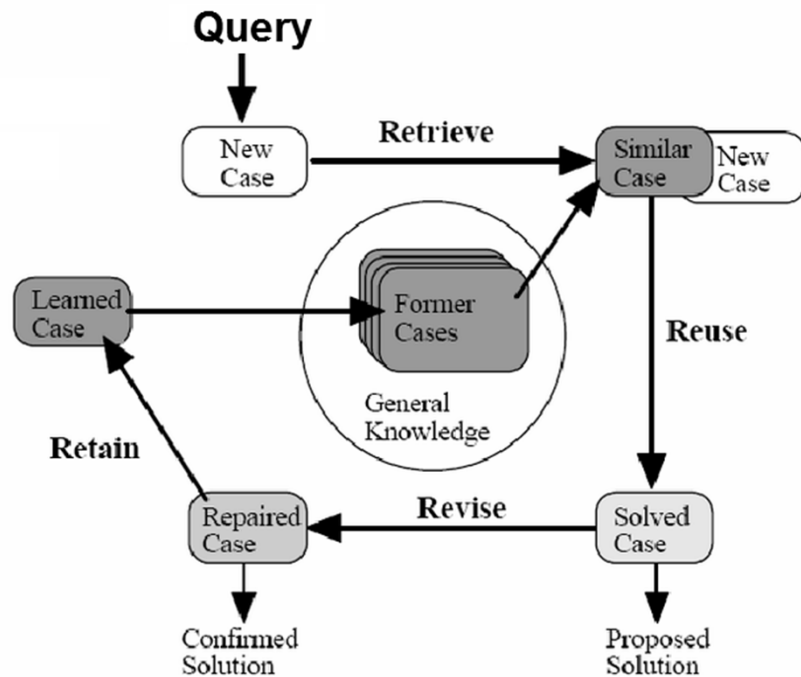
Fat: 47.6 g
 Fiber: 26.7 g
 Thiamin: 2.01 mg
 Vitamin B-6: 2,471 µg
 Vitamin A: 18,455 IU
 Calcium: 1,229 mg
 Potassium: 4,617 mg
 Zinc: 10.86 mg

FIG 4. The Case-based Menu Planner's menu and analysis for the input shown in Figure 3.

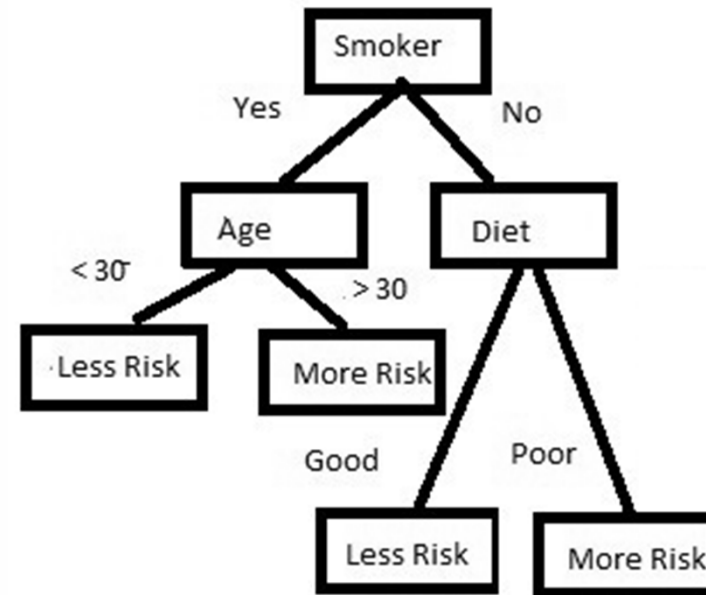
^aThe standard method of calculation does not ensure that percentages add to 100.

^bThe RDI for Vitamin B-12 is 6 µg, which is higher than other standards. See reference 13.

LIMITATIONS OF EXPERT SYSTEM



Case based reasoning



Rule based reasoning

Not suitable for personal dietary advice

MARRIAGE OF SCIENCE AND AI

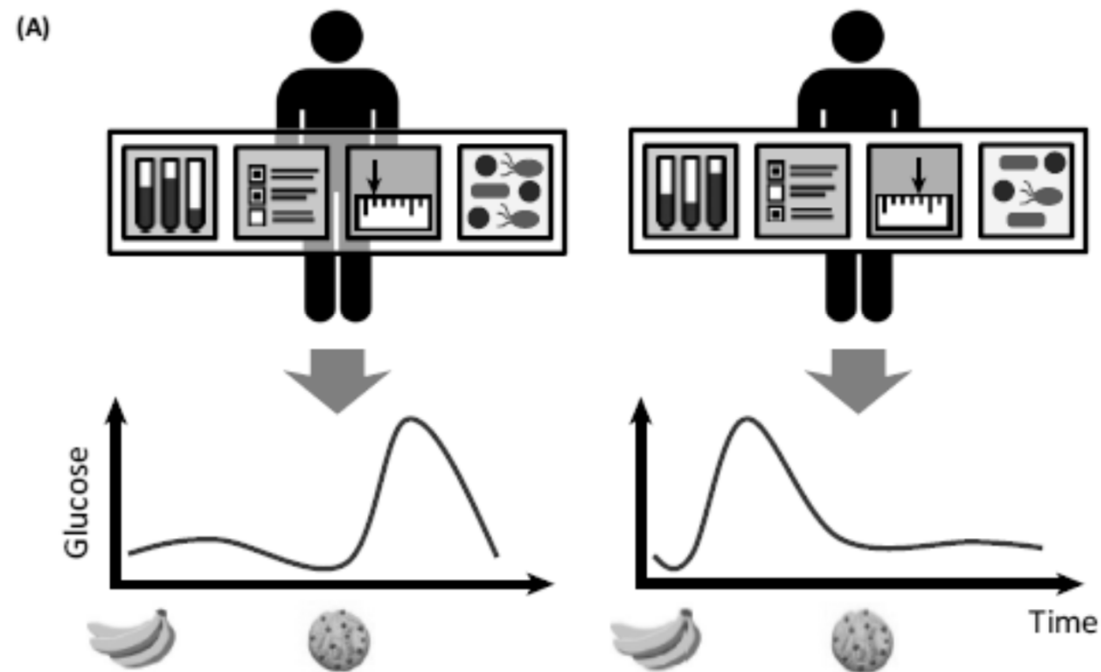
- › How much of the biological (nutritional) knowledge is taken into consideration while designing this apps?
- › What is the role of AI in nutrition?

Drivers for success; Science; AI; Marriage of science and AI



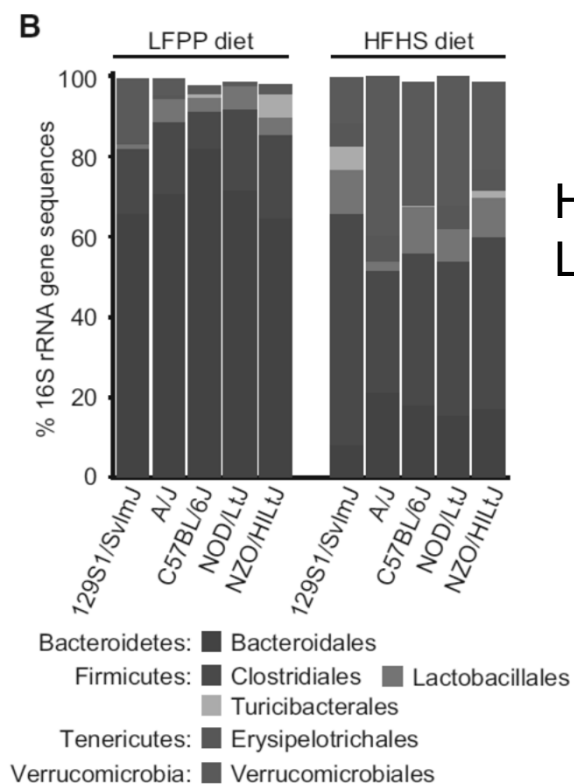
SCIENCE (1)

People eating identical meals present high variability in post-meal blood glucose response.



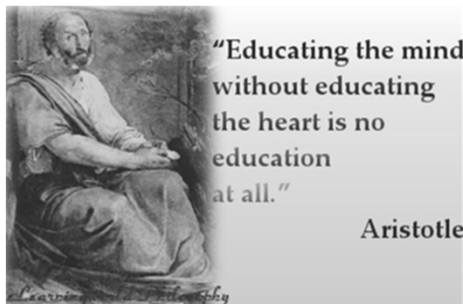
SCIENCE (2)

Diet dominates host genotype in shaping the murine gut microbiota.



HFHS: high-fat, high-sugar diet
 LFPP: low-fat, high-plant-polysaccharide diet

AI (1)



Syllogism →
deductive reasoning or
inference

e.g.
All men are mortal.
Socrates is a man.
Therefore Socrates is mortal.

→ First order logic: resulted in several AI languages. e.g. PROLOG
→ Key: mathematically expressed

Very successful: e.g. building expert systems



→ Artificial Neural network (mimic the working of the brain)
→ Driven by data

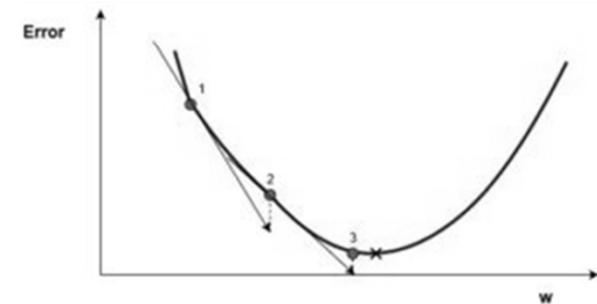
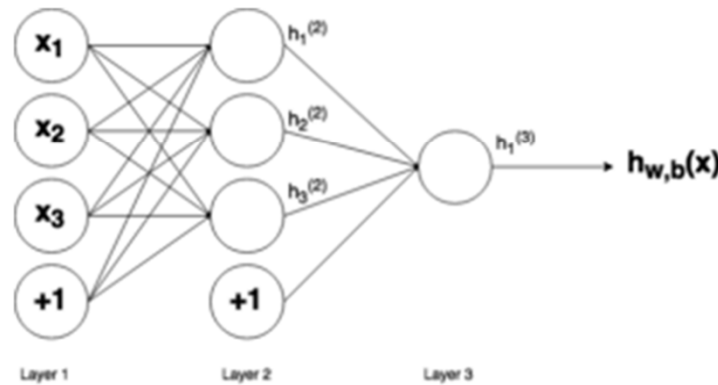
Least successful and enthusiasm over neural net came down around 1970



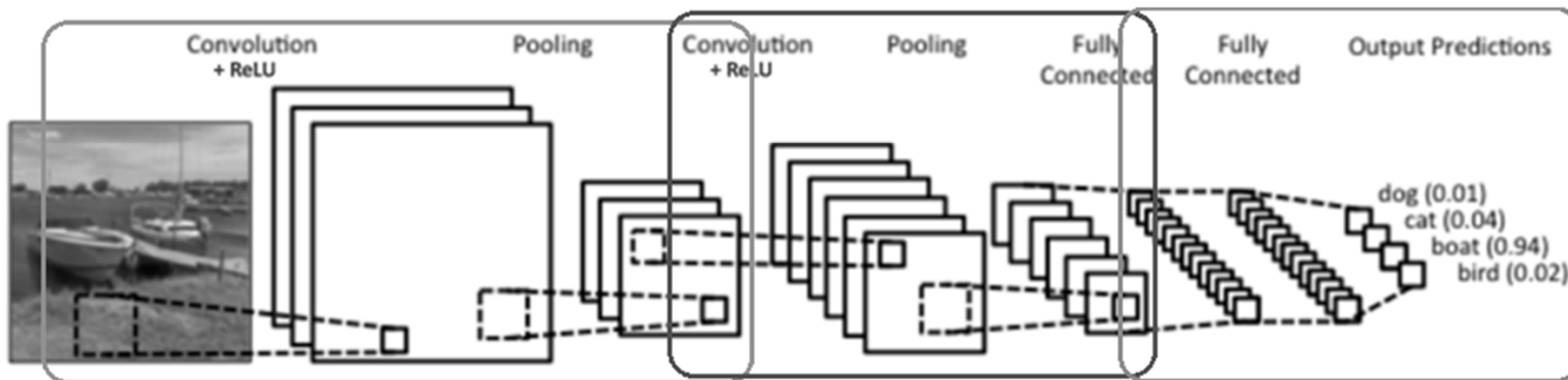
Today's algorithms crunch voluminous data and discover patterns, relationships among data variables.....teach themselves too.

AI (2)

After a silence, interest in Artificial Neural Network (ANN) sparked again

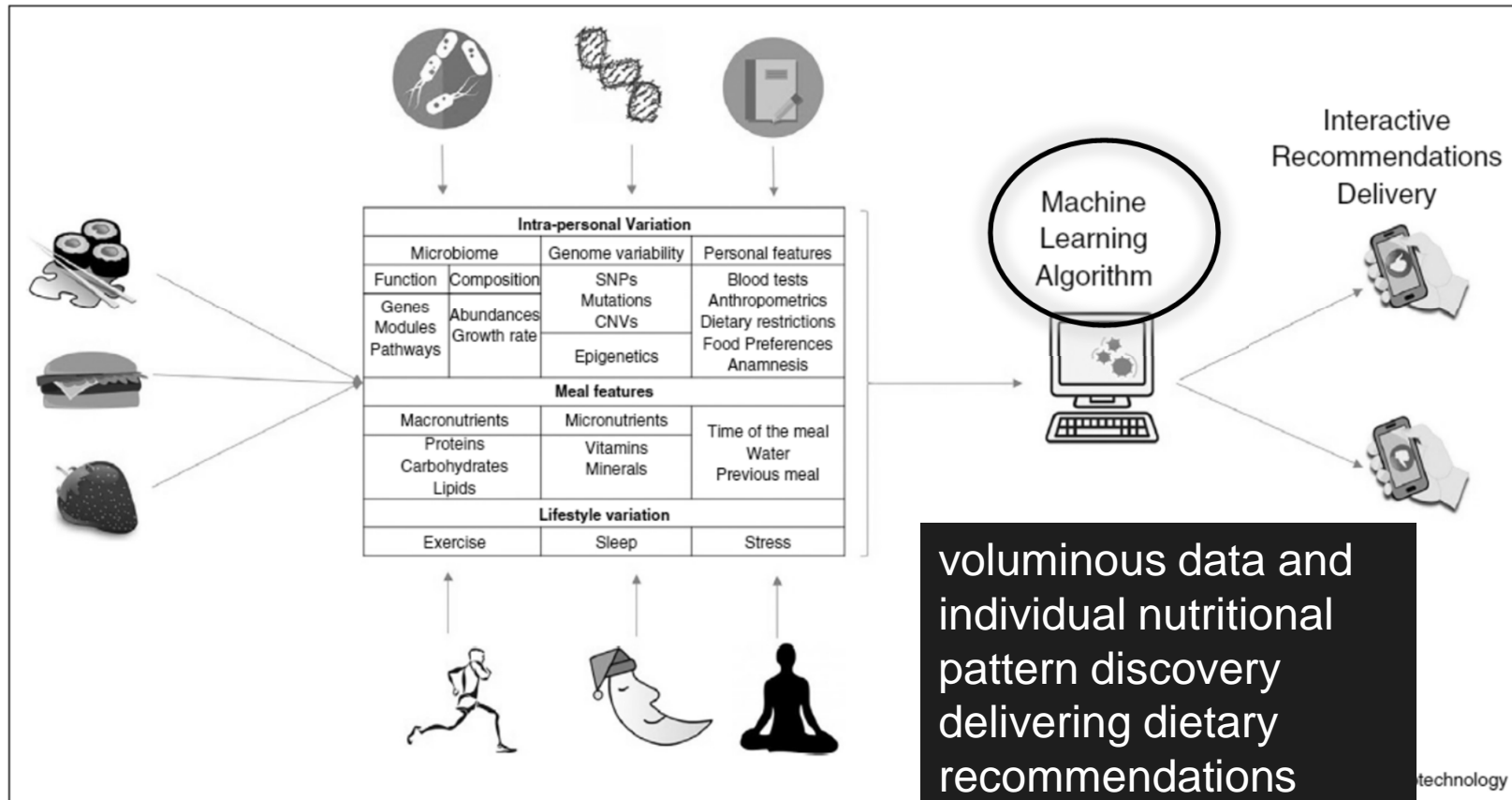


Hidden layers is greater than 2 then Deep learning architecture



Shift in paradigm...

MARRIAGE OF SCIENCE AND AI



Rationally designed personalized dietary approaches determine the effects of numerous parameters on diet response (e.g. microbiome composition, genome variability, personal lifestyle, medical metadata). Machine learning algorithms utilize these comprehensive data sets to deliver dietary recommendations.

BIG-DATA ANALYTICS

Precision nutrition aims to prevent and manage chronic diseases by tailoring dietary interventions or recommendations to one or a combination of **an individual's genetic background, metabolic profile, and environmental exposures.**

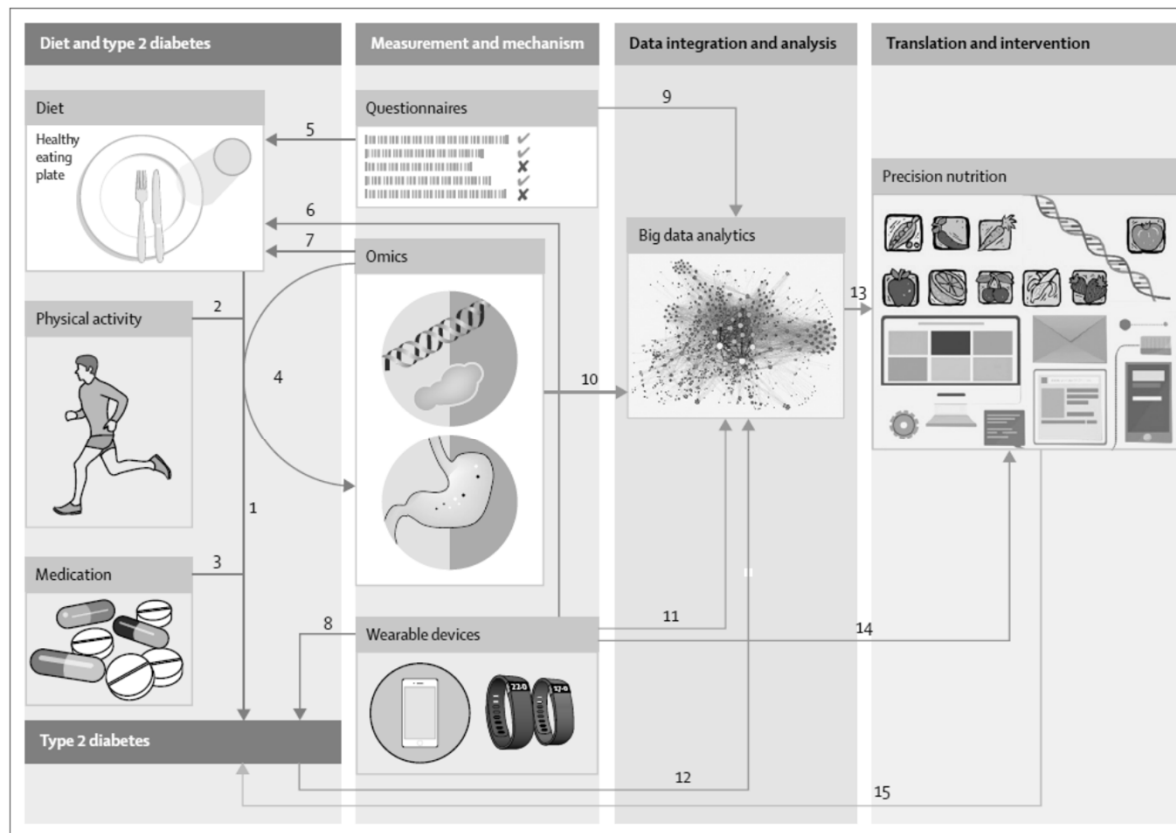


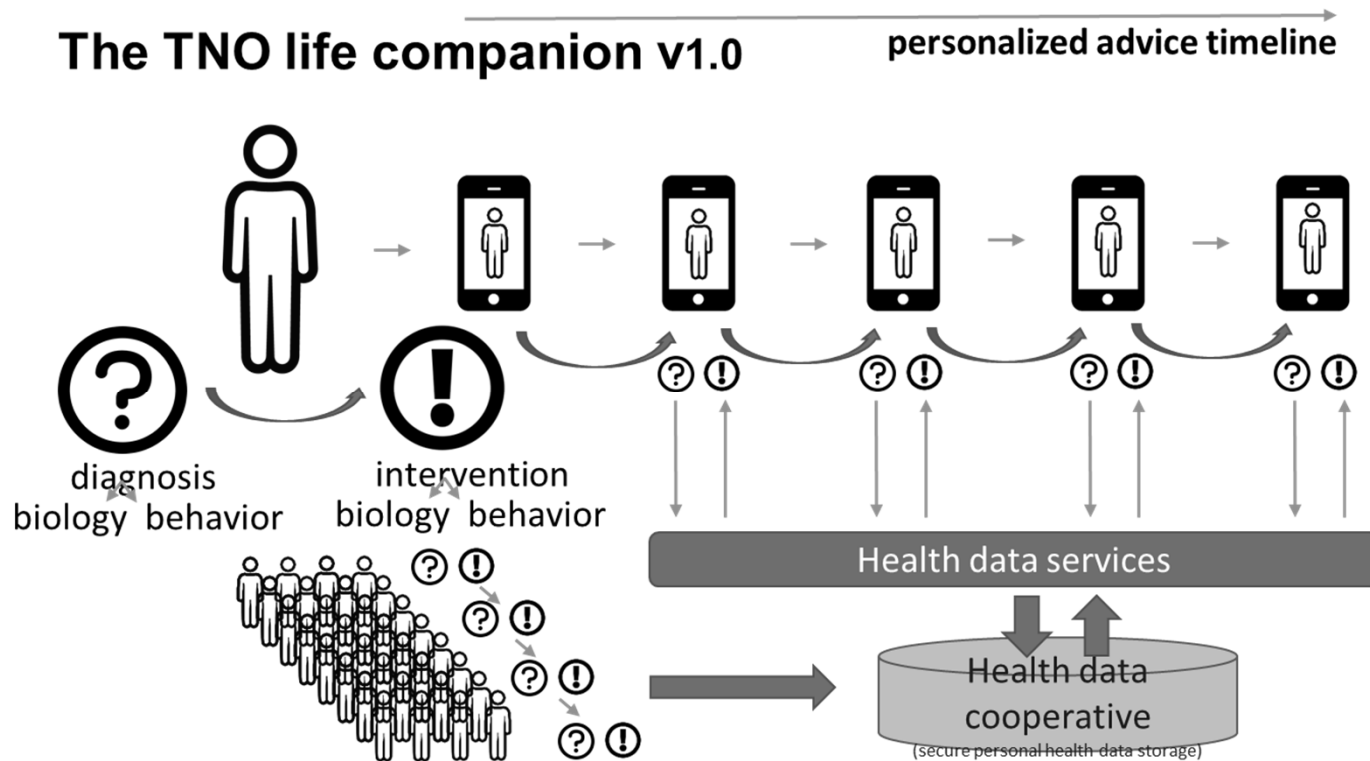
Figure 1: Conceptual framework for precision nutrition in prevention and management of type 2 diabetes

WORD OF CAUTION

Several commercial companies have started to **market personalised nutrition assessment and treatment based on genotypes**, but the benefits of such approaches on improving diet quality and health outcomes have not been demonstrated.



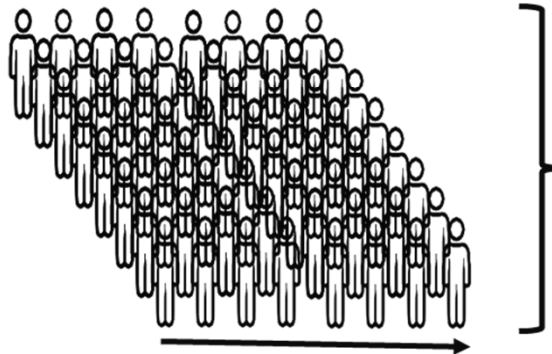
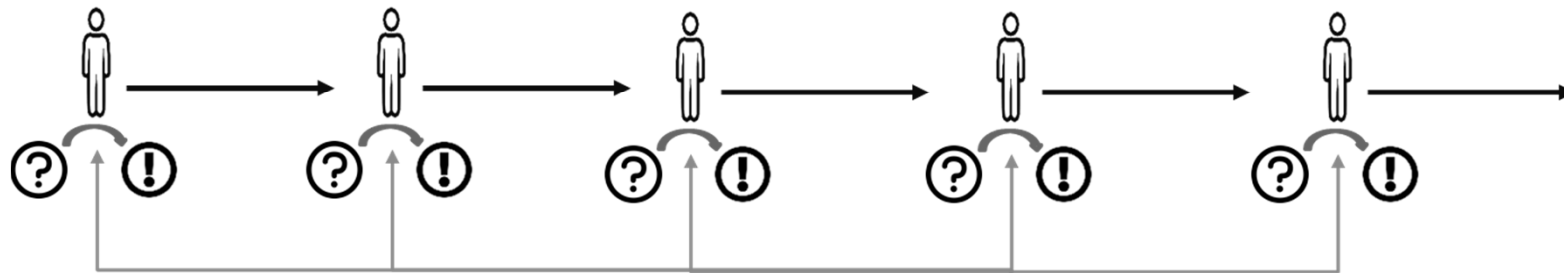
AT TNO



Personal nutrition is part of a personal health package

AT TNO (CONT.)

I make regular adjustments to my diet and behavior in order to stay on track

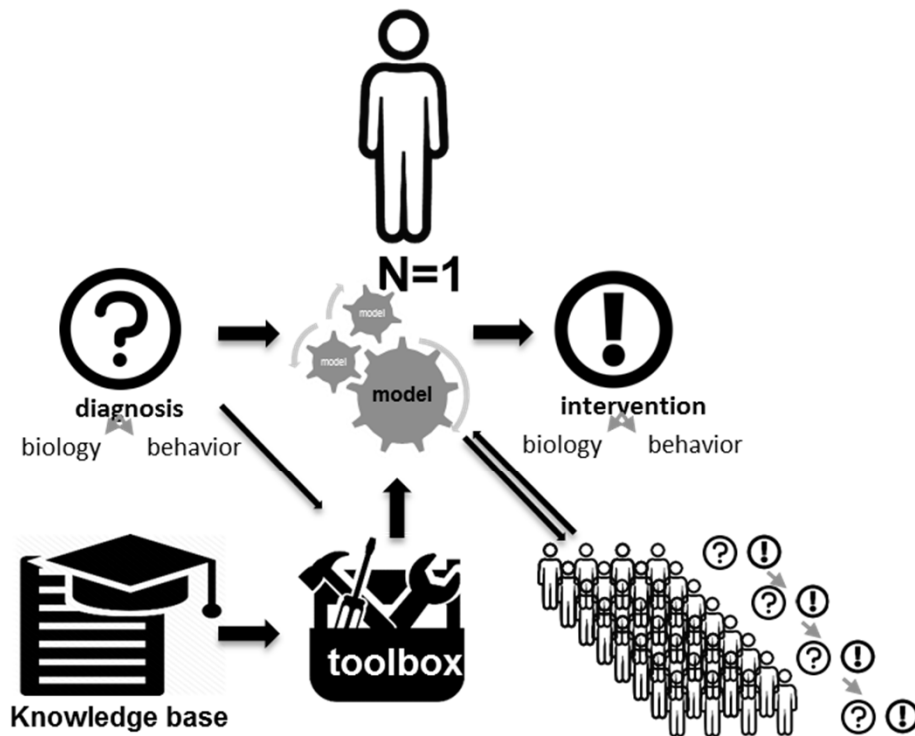


Can we make use of thousands of other personal health timelines to optimize every decision I make for my personal health ?

Bayesian networks
Artificial Intelligence

AT TNO (CONT.)

So how does personalized nutrition work?



1. It is personal
2. The intervention or advice is based on a diagnosis
3. A (science based) model is used to translate diagnosis into advice
4. The model is tailored to specific conditions and goals from a large toolbox
5. The toolbox is continuously and systematically updated with all relevant scientific knowledge
6. Exploit/use information from large numbers of personal health data

MAJOR CONCLUSIONS

- › AI assist in increasing and applying our current knowledge in science
- › Science based models augmented with the number crunching power of AI must drive nutritional research (health advice: dietary)
- › Precision medicine is to become a reality soon (AI on a chip is available today)



THANK YOU FOR YOUR ATTENTION

INNOVATION
FOR THE
FUTURE

