Digital Twin AI for Precision Screening

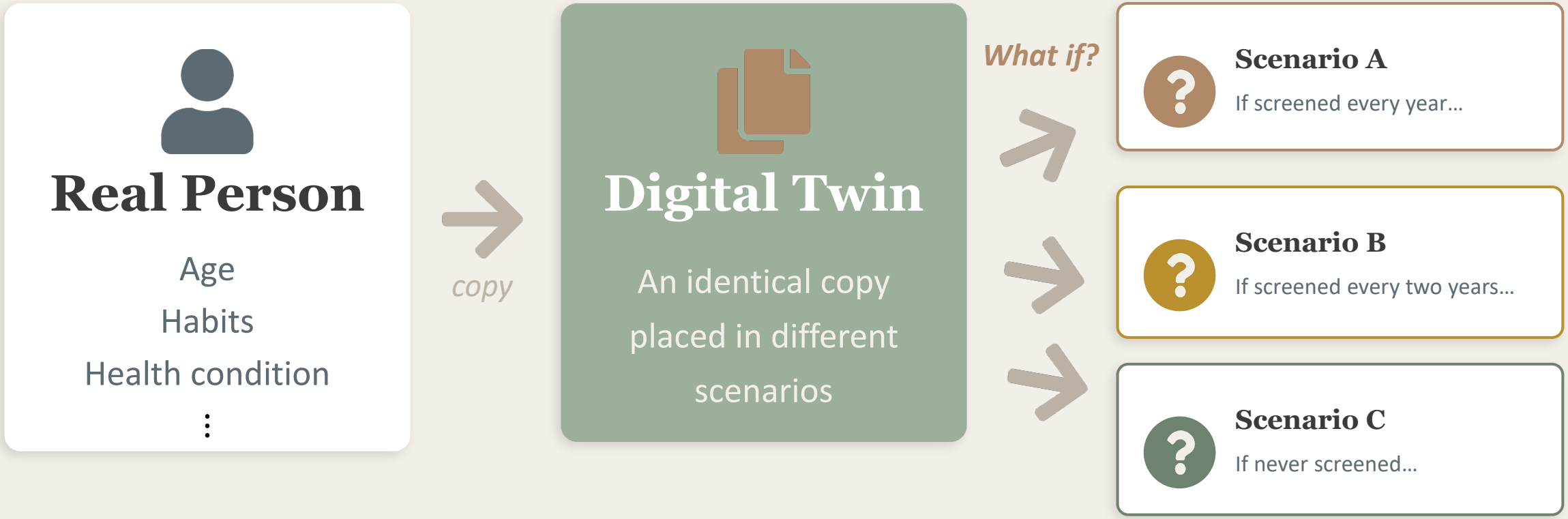
Session III. Digital Twin AI for Precision Screening

AI-Empowered Digital Twin Frameworks for Precision Screening

What is a digital twin?

Digital Twin

A copy of the same person, under different choices



The core question: what would happen to the same person under different choices?

Why we need a digital twin?

Randomized Controlled Trial:

Gold standard — built for the average

Pyramid

THE BLIND SPOT

It targets the **Average**.

An average hides who it helps and who it doesn't.

Strong Evidence But Only for Average

IACCS THEME

4P Medicine

P1

Predictive

P2

Preventive

P3

Personalized

P4

Participatory

The right intervention, for the right person, at the right time.

From what works on average → what works for *"YOU"*

Everyone → Some → 「You」

RCT

one answer for all

Everyone

Precision

a risk subgroup

Some

Metaverse

a trial of one

You

Digital Twin can help you!!!

Complementary, not competing

RCT

gives us TRUTH

+

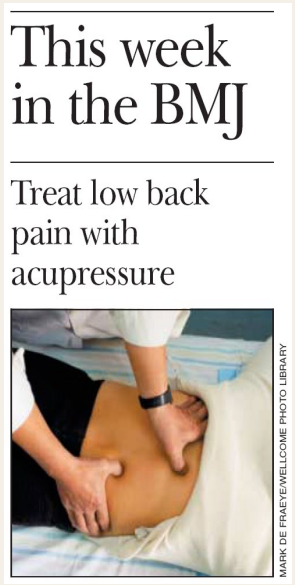
Digital Twin

gives us BREADTH

Would you trust a digital twin?

Validating the Digital Twin Through a RCT

A randomized controlled trial



129 patients

chronic low-back pain

RANDOMIZED

Randomization makes the two arms comparable at baseline

GROUP A n = **64**

Acupressure

GROUP B n = **65**

Physical therapy

ODQ=16.03

Strong Evidence

3.54

ODQ=19.57

How can we construct a digital twin?

Table 1

		Acupressure		Physical therapy		P-value
		Freq	%	Freq	%	
Gender	Female	43	67%	48	74%	0.41
	Male	21	32%	17	26%	
Marital status	Single	10	16%	11	17%	0.84
	Married	54	84%	54	83%	
Education	Low	27	42%	35	54%	0.19
	High	37	58%	30	46%	
Occupation	Heaver labour	9	14%	8	12%	0.77
	Others	55	86%	57	88%	
		Mean	Std	Mean	Std	
Age		50.5	13.8	52.9	17.2	0.30
Length of latest pain period (month)		52.2	75.3	49.1	88.7	0.84
Time since onset of pain (year)		6.1	7.3	5.2	7.4	0.55
Pain visual scale (0-100)		58.8	17.9	57.0	17.8	0.56

How can we construct a digital twin?

Table 1

		Acupressure		Physical therapy		P-value
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	High	37	58%	30	46%	
Occupation	Heaver labour	9	14%	8	12%	0.77
	Others	55	86%	57	88%	
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Age		50.5	13.8	52.9	17.2	0.30
						0.84
						0.55
Pain visual scale (0-100)		58.8	17.9	57.6	17.8	0.56

Construct the control group algorithm

Digital Twin Algorithm: Machine Leaning

GROUP A n = 64
Acupressure

GROUP B n = 65
Physical therapy

Digital Twin Algorithm

- RF
- ANN

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GROUP A n = 64
Physical Therapy

Digital Twin for Group A with Physical Therapy

Digital Twin for Control Group

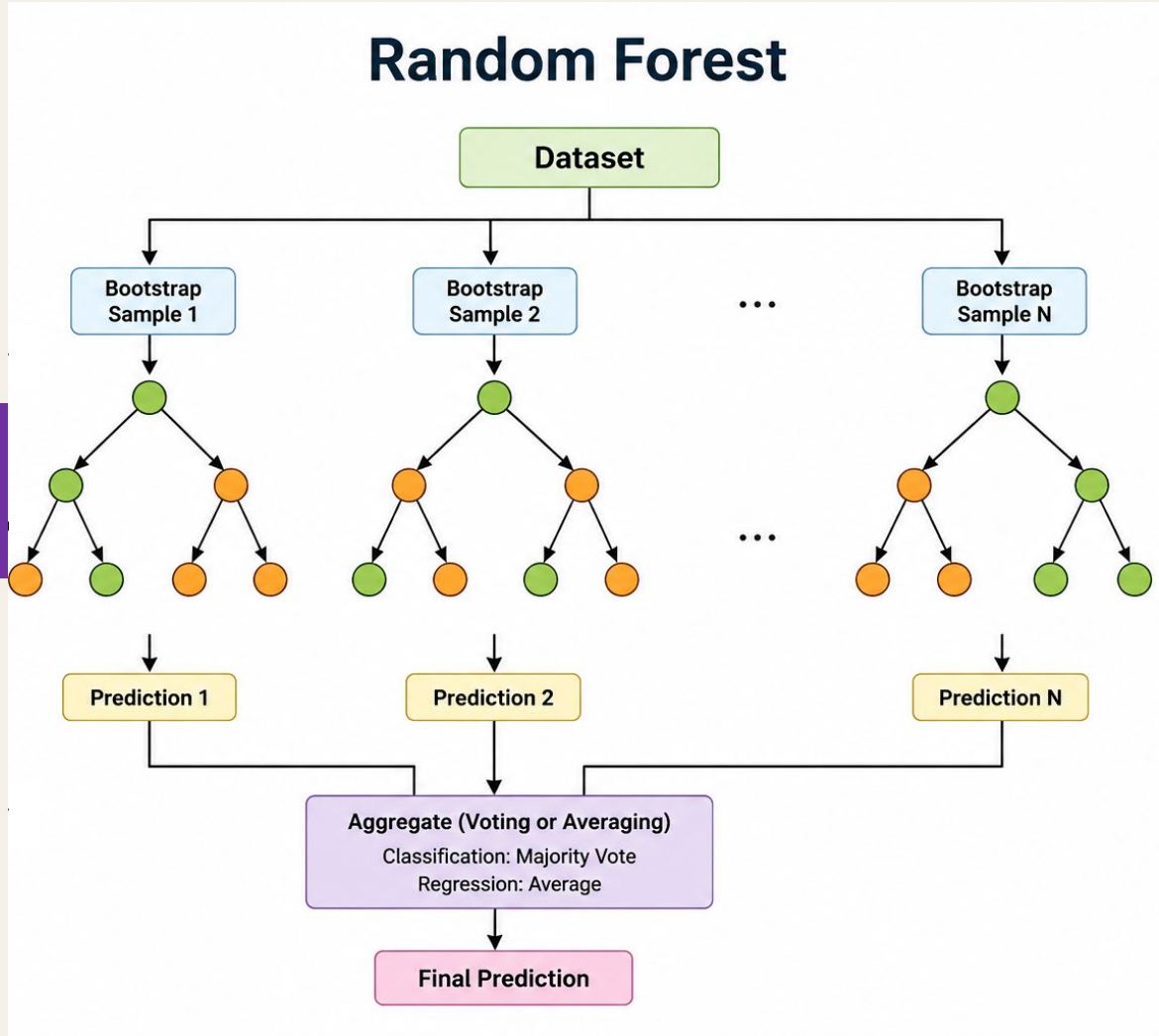
Digital Twin Algorithm: Random Forest

GROUP A n = 64
Acupressure

Digital Twin Algorithm

GROUP A n = 64
Physical Therapy

Digital Twin for Group A with Physical Therapy

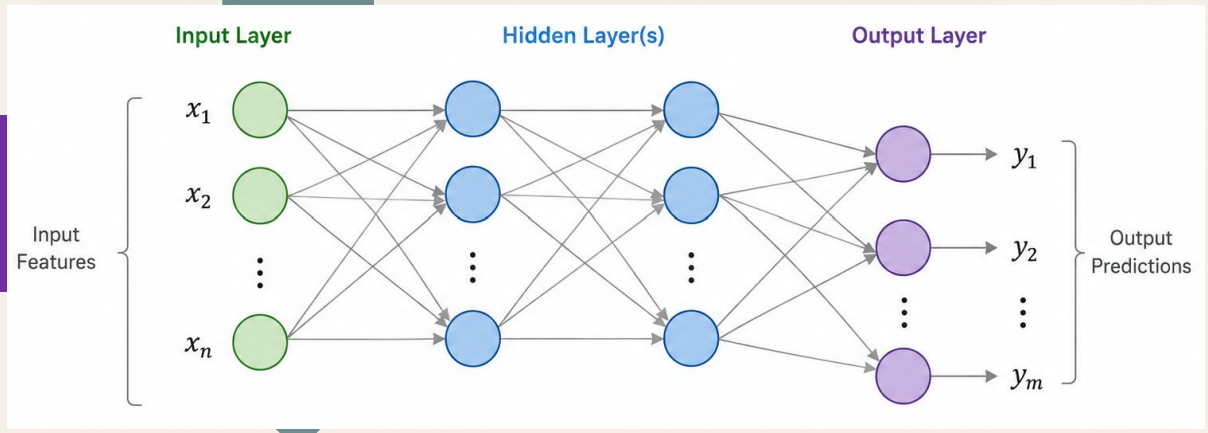


Digital Twin Algorithm: ANN

GROUP A n = 64
Acupressure

GROUP B n = 65
Physical therapy

Digital Twin Algorithm

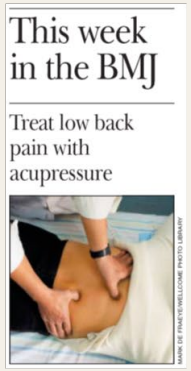


Digital Twin for Control Group

GROUP A n = 64
Physical Therapy

Digital Twin for Group A with Physical Therapy

Unlock Algorithm: ANN



129 patients
chronic low-back pain

RANDOMIZED

Randomization makes the two arms comparable at baseline

Randomized Controlled Trial

GROUP A n = 64 **Acupressure**

GROUP B n = 65 **Physical therapy**

ODQ=16.03 ↓ 3.54 ODQ=19.57

Digital Twin (ANN)

GROUP A n = 64 **Acupressure**

GROUP A n = 64 **Physical Therapy**

ODQ=16.03 ↓ 3.53 ODQ=19.56

The digital twin unlocks the RCT

WHAT THE RCT GIVES

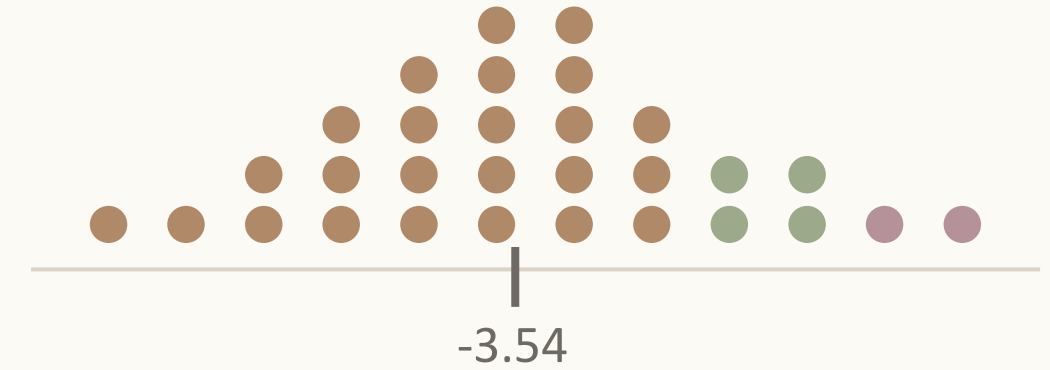
the average effect

−3·54

Digital Twin

Unlocks

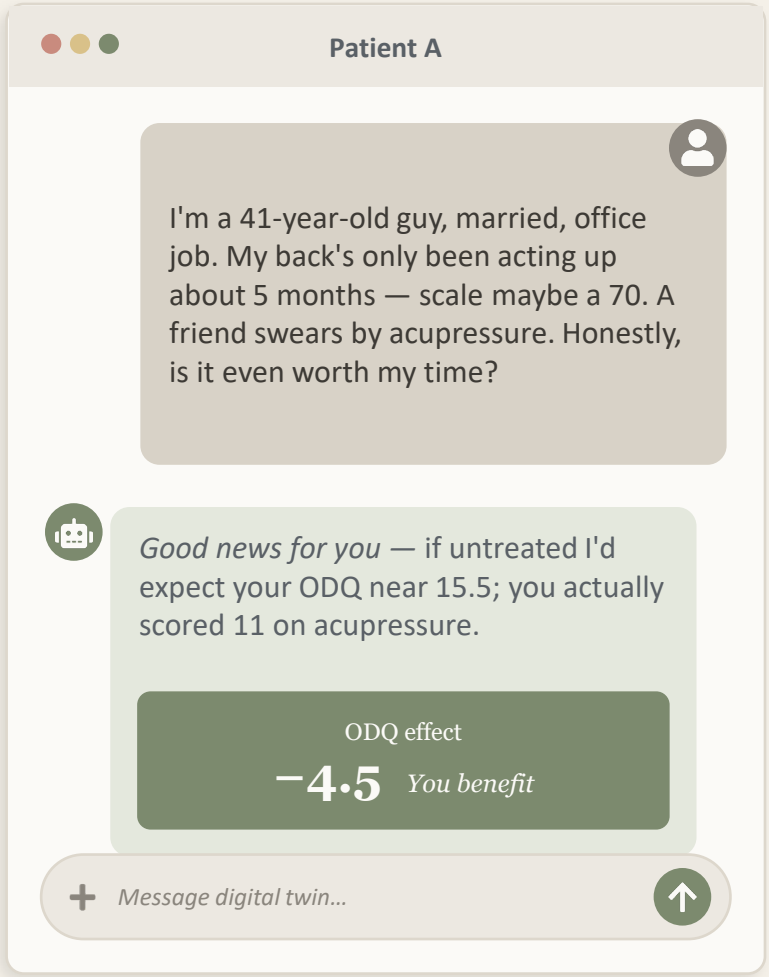
Every patient has their own effect

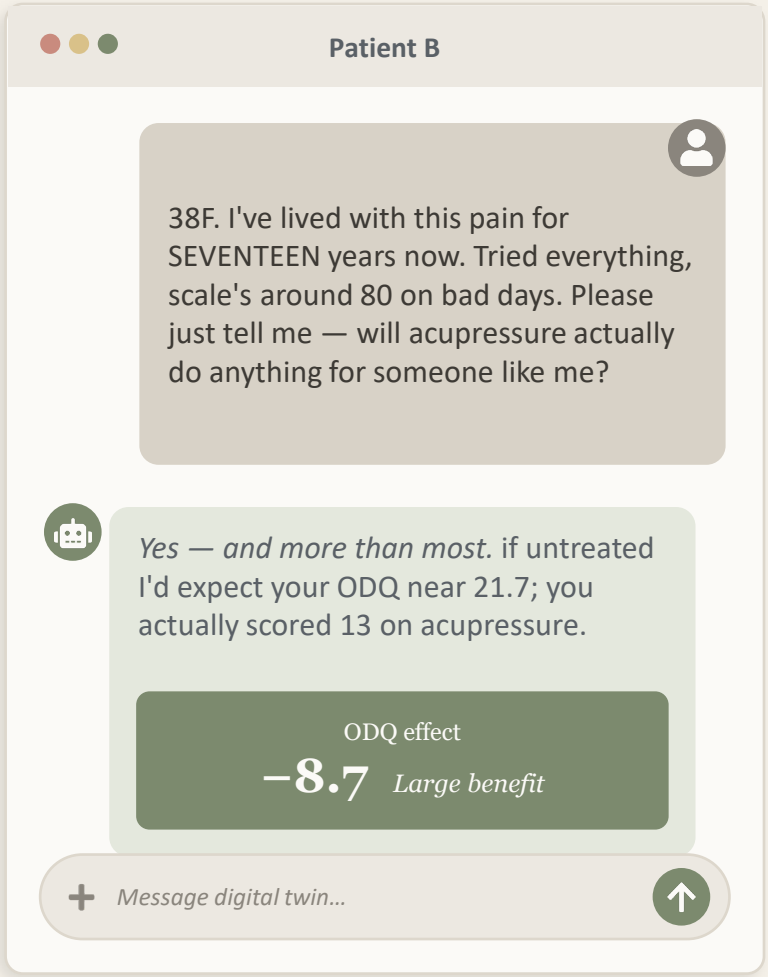


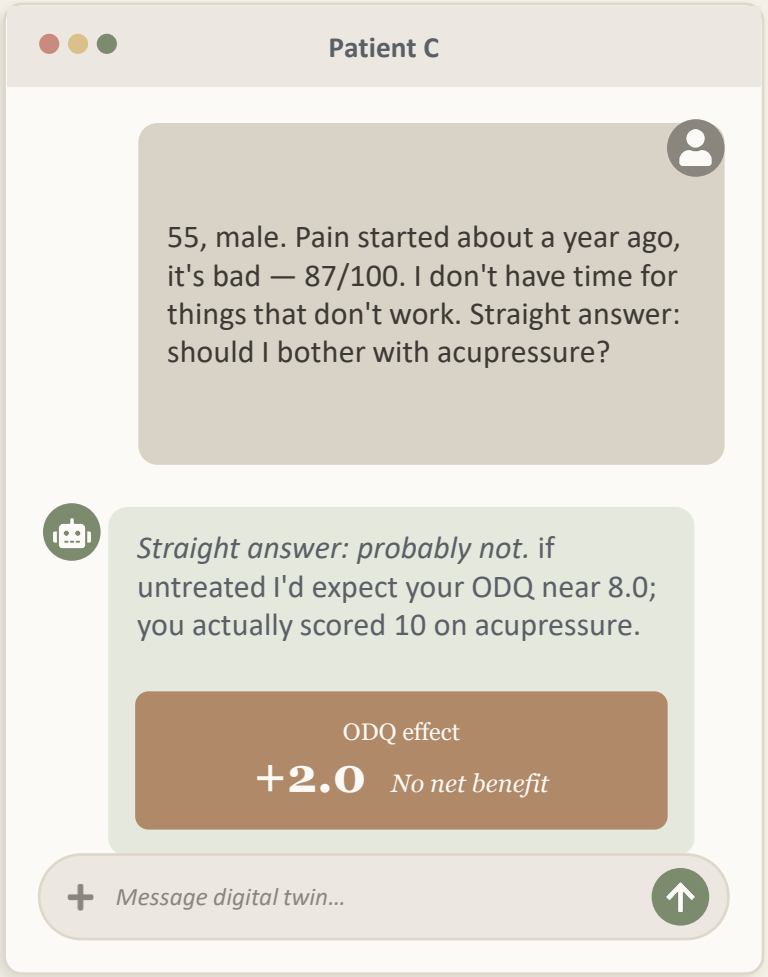
Unlock RCT: From Average to Personal

Digital twin returns each ***individual's* effect**, not the trial average.

Large Language Model



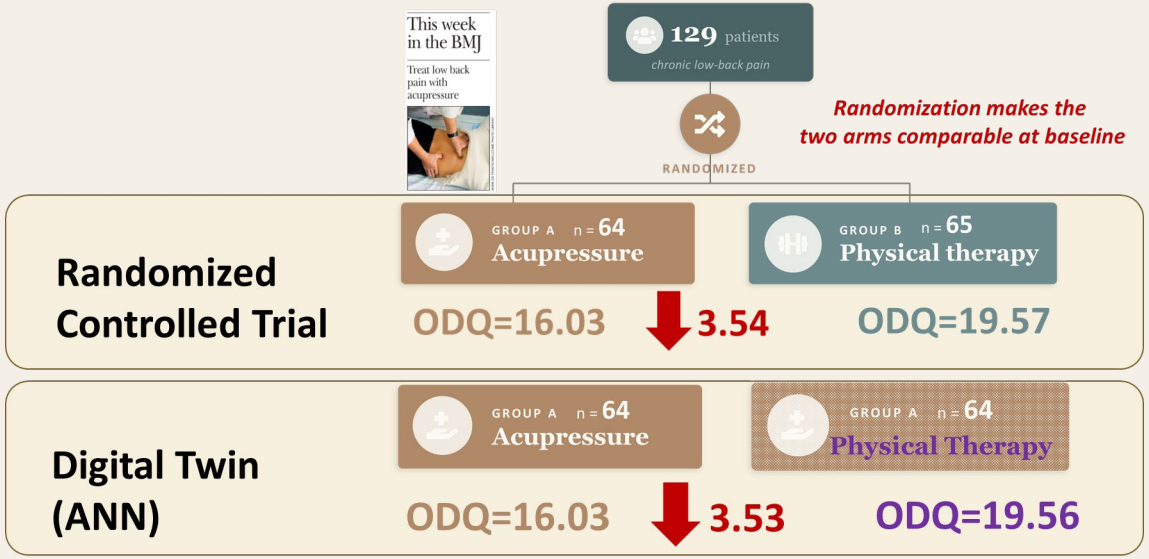




The trial average hides this — the twin recovers each patient's own effect

Global Effect

Personal Effect



In the future, when we move into another setting — a factory with no RCT

		Acupressure	
		Freq	%
Gender	Female	83	32%
	Male	169	68%
Marital status	Single	180	71%
	Married	72	29%
Education	Low	141	56%
	High	111	44%
Occupation	Heaver labour	213	85%
	Others	39	15%
		Mean	Std
Age		45.2	9.13
Length of latest pain period (month)		52.3	101
Time since onset of pain (year)		6.1	0.2
Pain visual scale (0-100)		59.4	17.4

Different populations:

- the RCT skews female (70%), early 50s, married;
- the factory skews male, ~45, single — though both are ~50% higher-educated.

Without a new RCT, we still can evaluate

Global Effect & Personal Effect

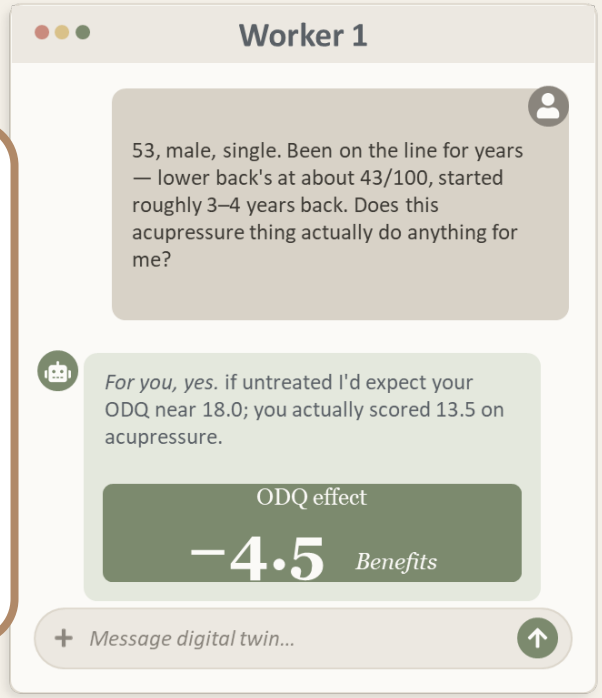
GROUP A
Acupressure

Observed : 16.7

GROUP A
Physical Therapy

4.55

Digital Twin for Physical Therapy : 21.3



QR Code

An RCT tells us acupressure lowers ODQ by 3.54 *on average*. What does the digital twin add?

(A) It proves the RCT's average is wrong

(B) It replaces the RCT — we no longer need trials

(C) It shows the effect *for each individual* — the average and the individual together

(D) It makes the average more precise

Session III. Digital Twin AI for Precision Screening

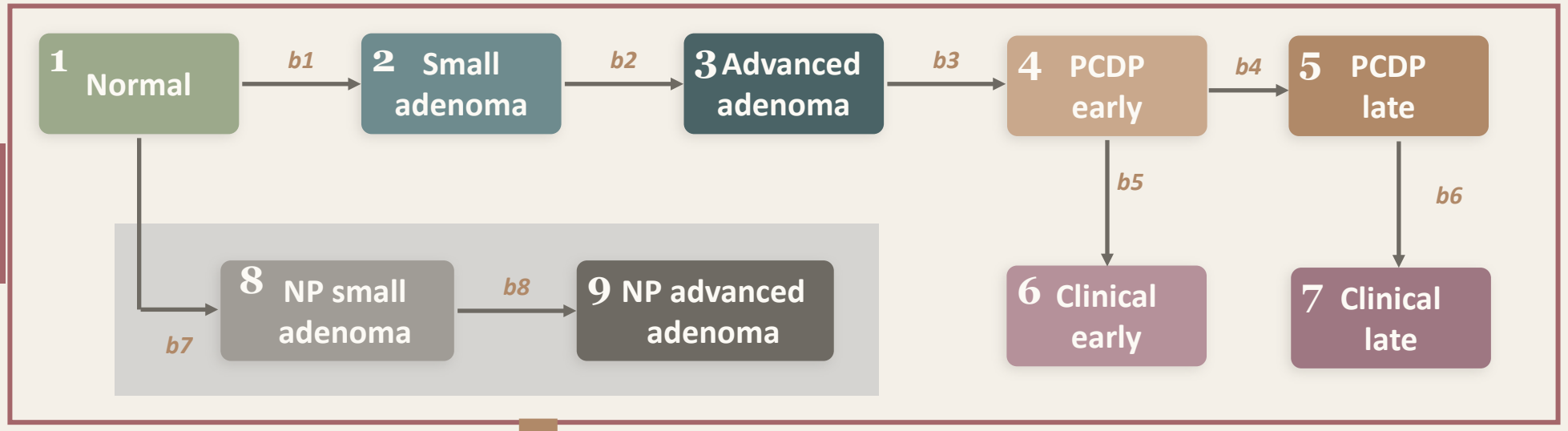
Stochastic Process for Personalized Multi-State Disease Natural History

Session III. Digital Twin AI for Precision Screening

Bayesian Network and Deep Learning Approaches for Personalized Multi-State Disease Natural History Modeling

Personalized Multi-State Disease Model

Multistate Model



Personal features

FIT (f-Hb)	Betel · Alcohol
Age · Sex	Diet
Smoking	Comorbidity

COMBINE

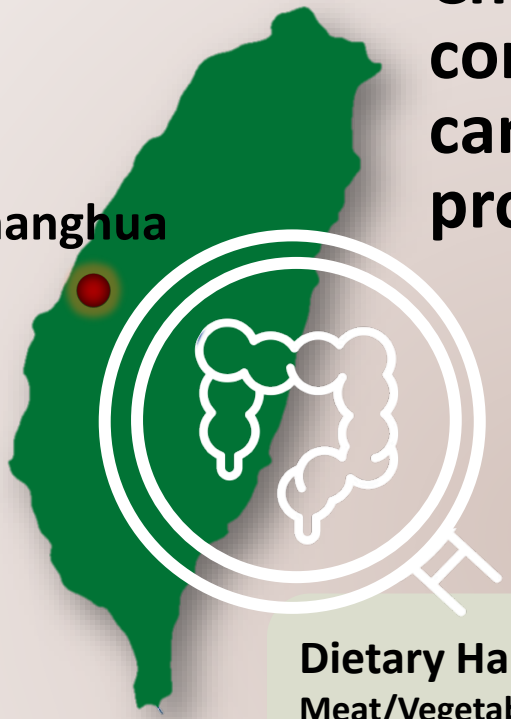
Each person's own trajectory through time

High-risk person — fast

Low-risk person — slow

same states, different speed

Data Collection for Machine Learning Classifier



Changhua community-based cancer screening program

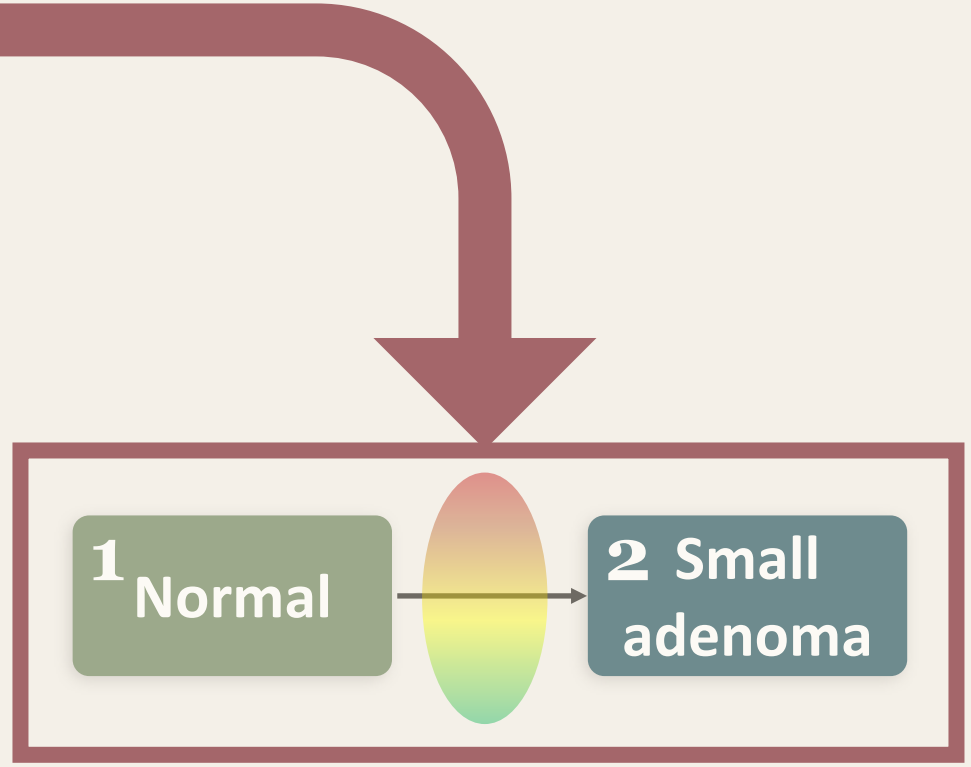
Demographic
Age, Gender, Education, Family History

Dietary Habits
Meat/Vegetable /Bean & Egg /Milk/ Coffee/ Fruit

Life Style
Smoking/ Betel quid chewing/ Alcohol Screening/ Awareness/ Health check

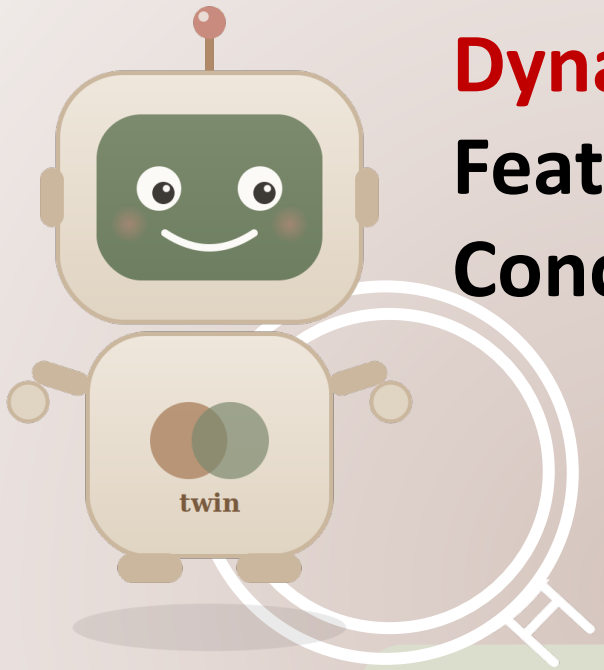
Metabolic syndrome factors
Waist/ TG/ HDL/ Blood Pressure/ Glucose

Biomarkers
Fecal hemoglobin concentration (FIT)/ Uric Acid/ Creatinine



This data is from Changhua — right where you are.

Dynamic Data using in Our Model



Dynamic Features and FIT Concentration

Demographic
Age, Gender, Education, Family History

Dietary Habits
Meat/Vegetable /Bean & Egg /Milk/ Coffee/ Fruit

Life Style
Smoking/ Betel quid chewing/ Alcohol Screening/ Awareness/ Health check

Metabolic syndrome factors
Waist/ TG/ HDL/ Blood Pressure/ Glucose

Biomarkers
Fecal hemoglobin concentration (FIT)/ Uric Acid/ Creatinine

Visit 1 — Age 58

FIT	12 μg/g
Smoking	current
BMI	26

Re-computed P(SA)

0.14 · low-mod

Visit 2 (+2 y) — Age 60

FIT	48 μg/g ↑
Smoking	current
BMI	28 ↑

Re-computed P(SA)

0.27 · moderate

Visit 3 (+4 y) — Age 62

FIT	past threshold ↑
Smoking	quit ↓
BMI	27

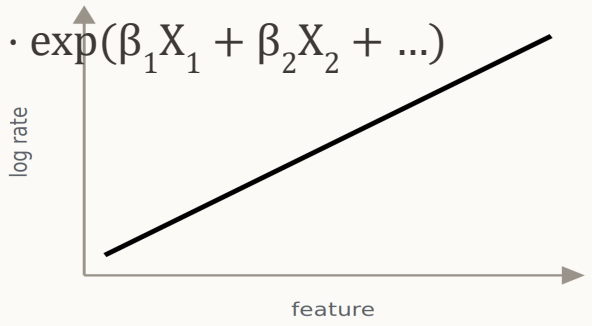
Re-computed P(SA)

0.39 · elevated

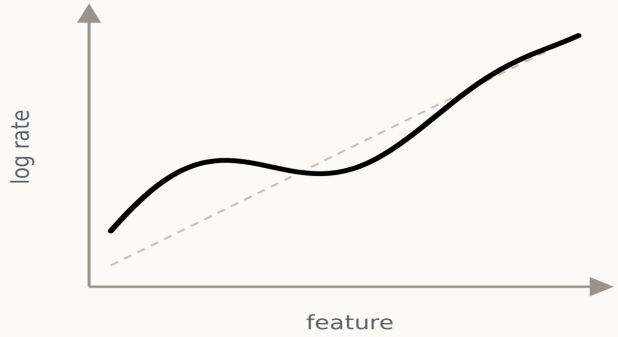
Personalized features incorporated into the multistate model

Classical: exponential / log-linear form

$$\lambda(X) = \lambda_0 \cdot \exp(\beta_1 X_1 + \beta_2 X_2 + \ldots)$$



ML relaxes the form



- Random Forest
- SVM
- Neural Network
- Bayesian Network

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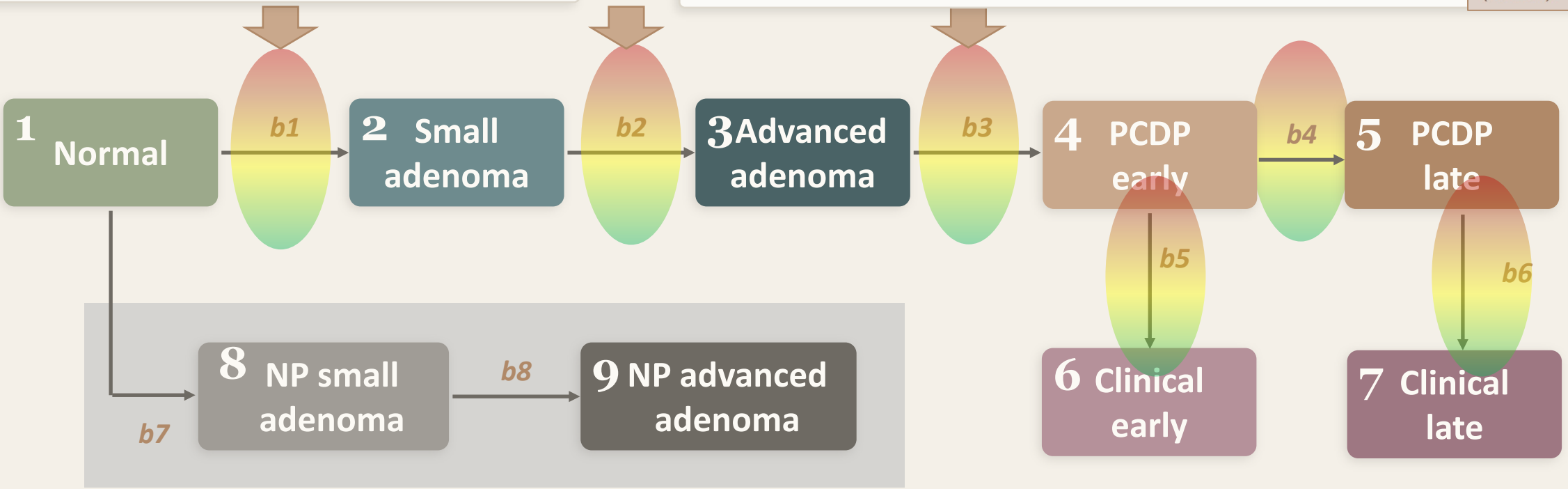
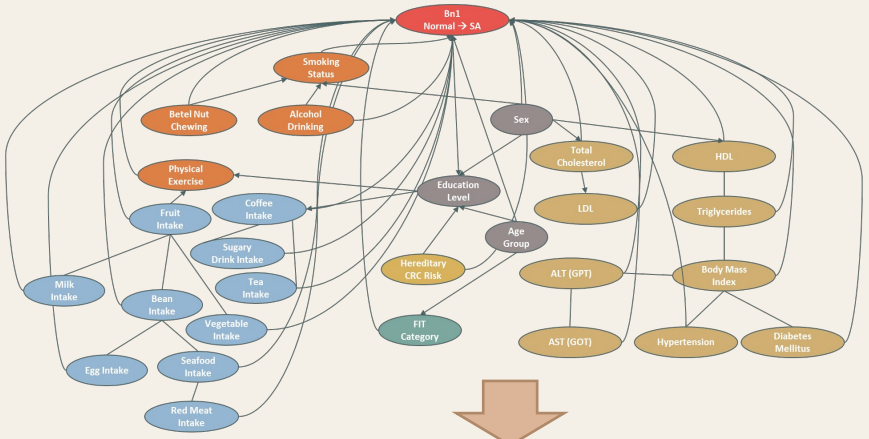
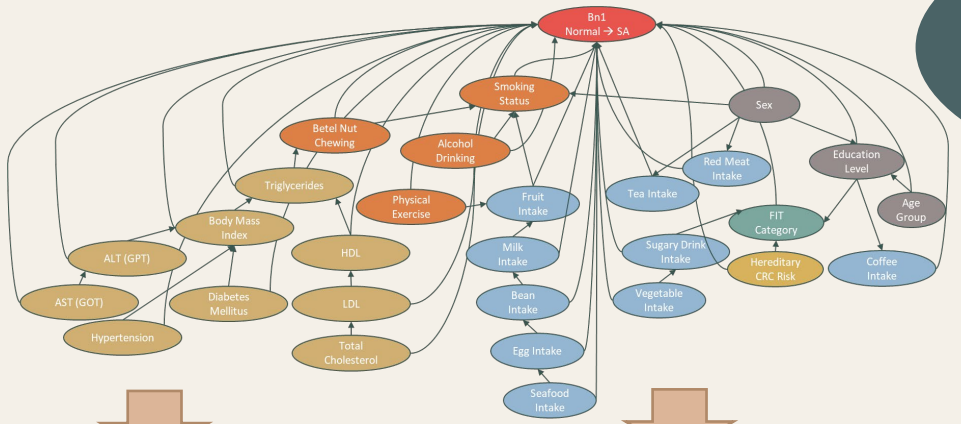


Personalized features incorporated into the multistate model through BN

Bayesian Network





1 Normal

b1

2 Small adenoma

b2

3 Advanced adenoma

b3

4 PCDP early

b4

5 PCDP late

b5

6 Clinical early

b6

7 Clinical late

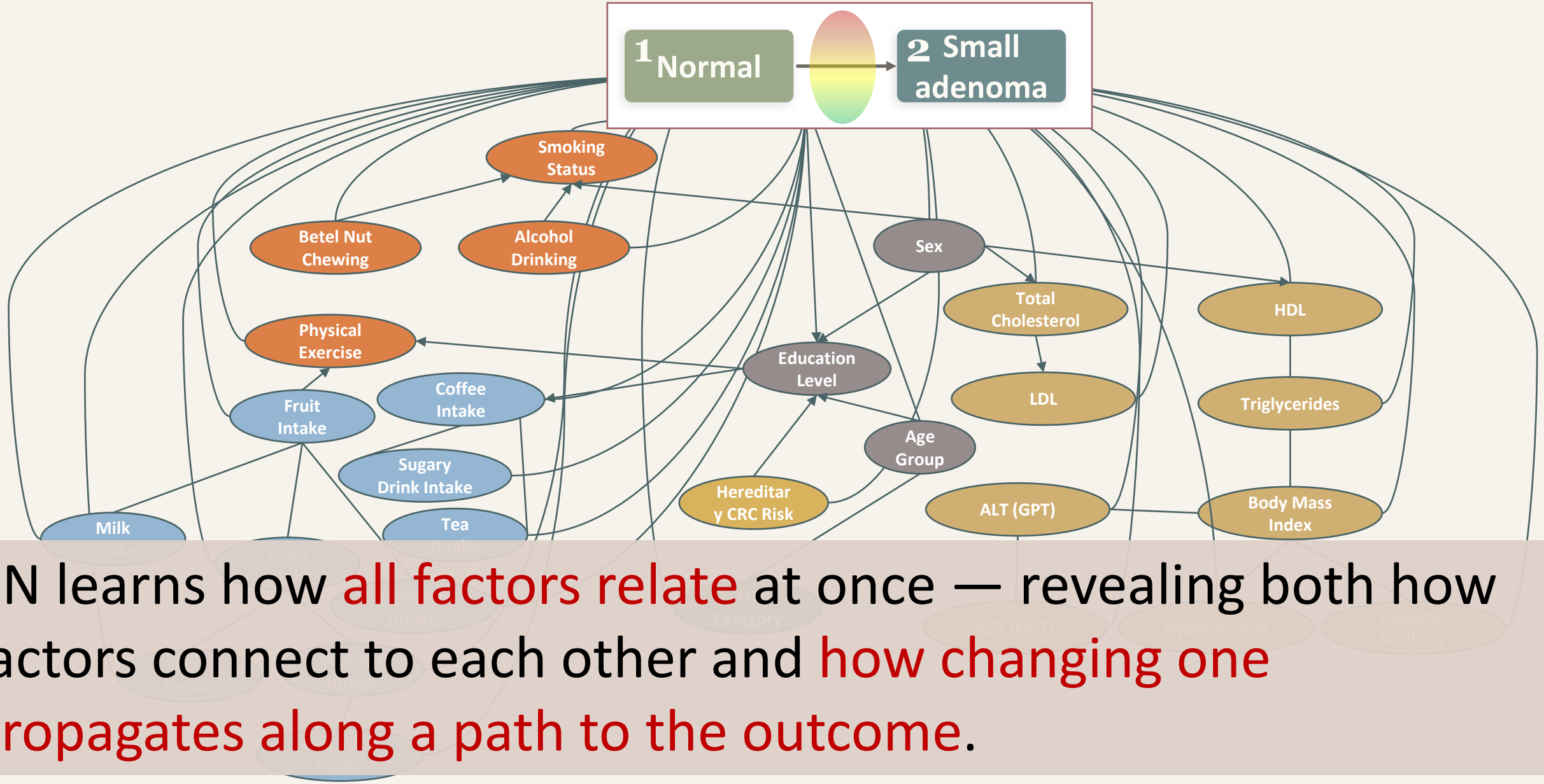
b7

8 NP small adenoma

b8

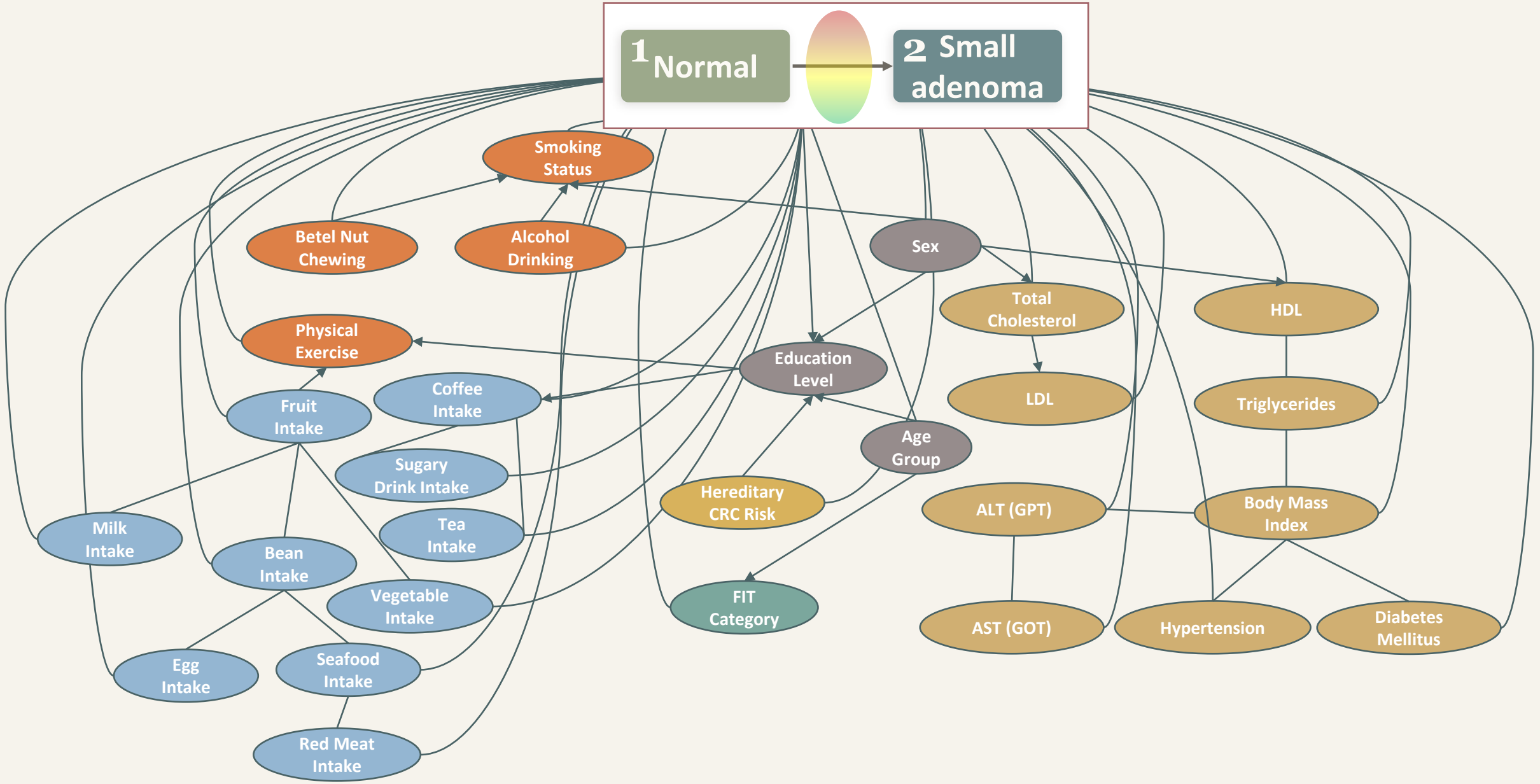
9 NP advanced adenoma

Bayesian Network Classifier

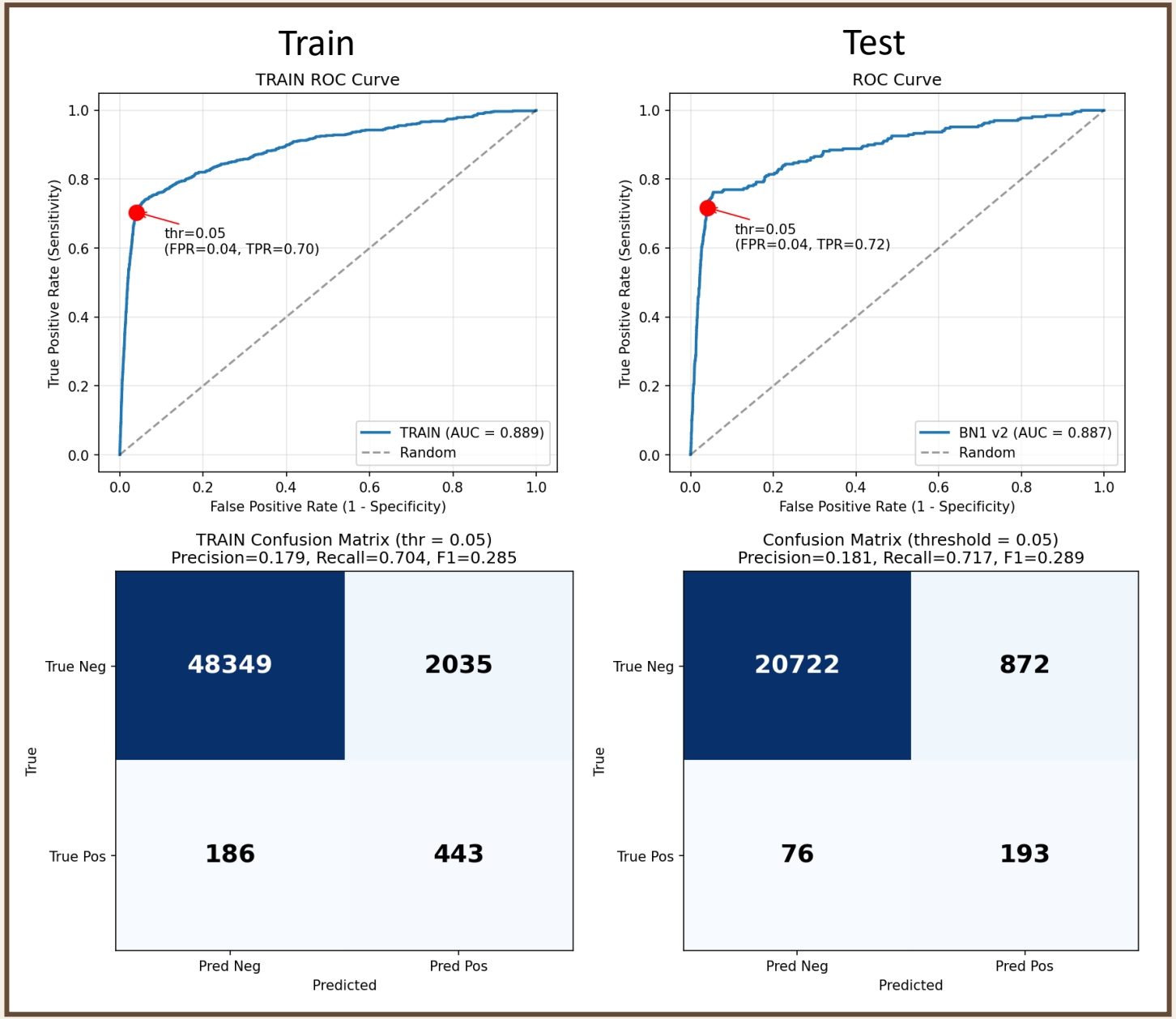


BN learns how all factors relate at once — revealing both how factors connect to each other and how changing one propagates along a path to the outcome.

Bayesian Network Classifier

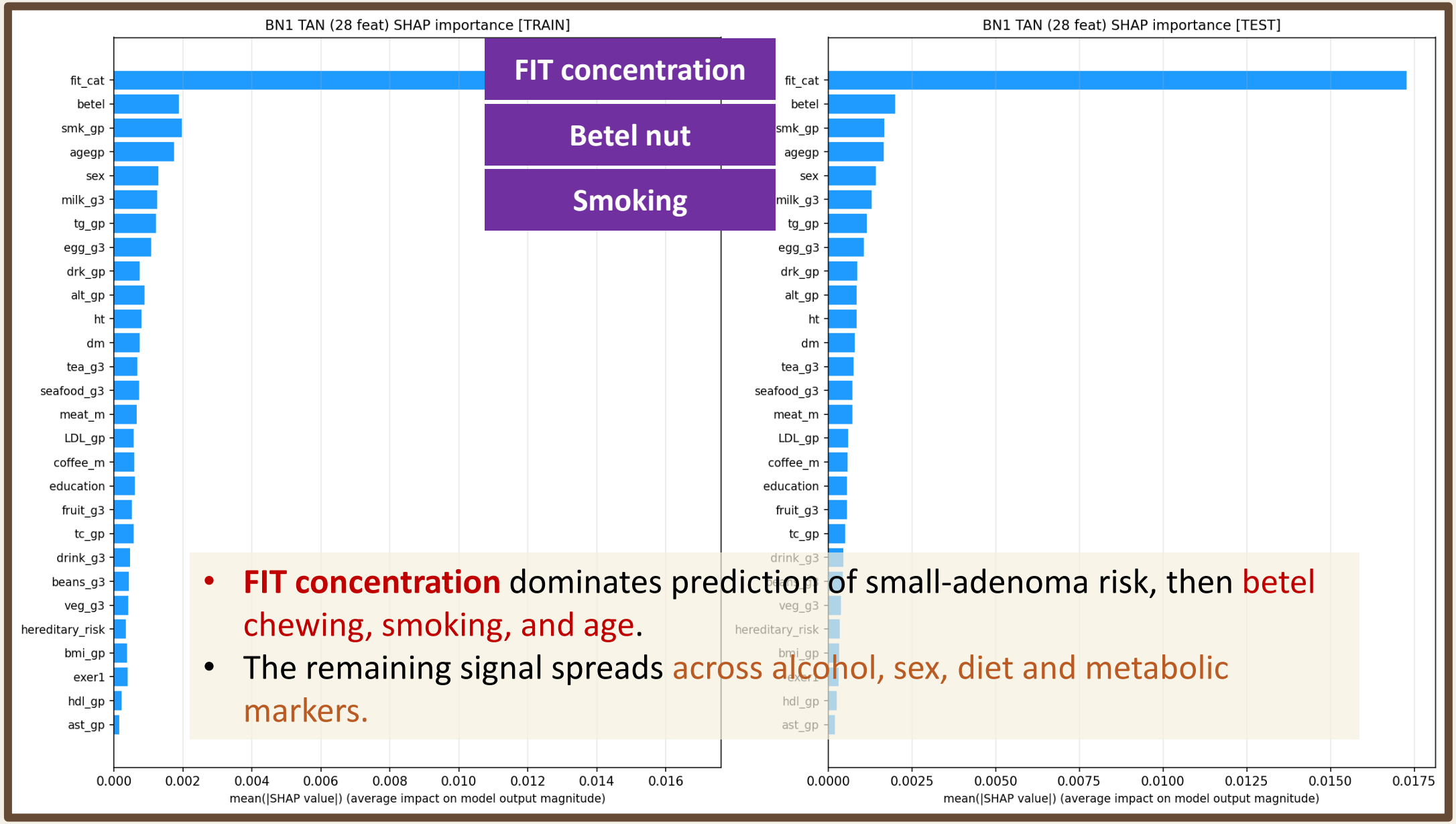


Bayesian Network Classifier – Model Performance



Metric	Train	Test
AUC	0.89	0.89
Accuracy	0.96	0.96
Precision	0.18	0.18
Recall	0.70	0.72
F1	0.29	0.29

Bayesian Network Classifier-SHAP (Global)

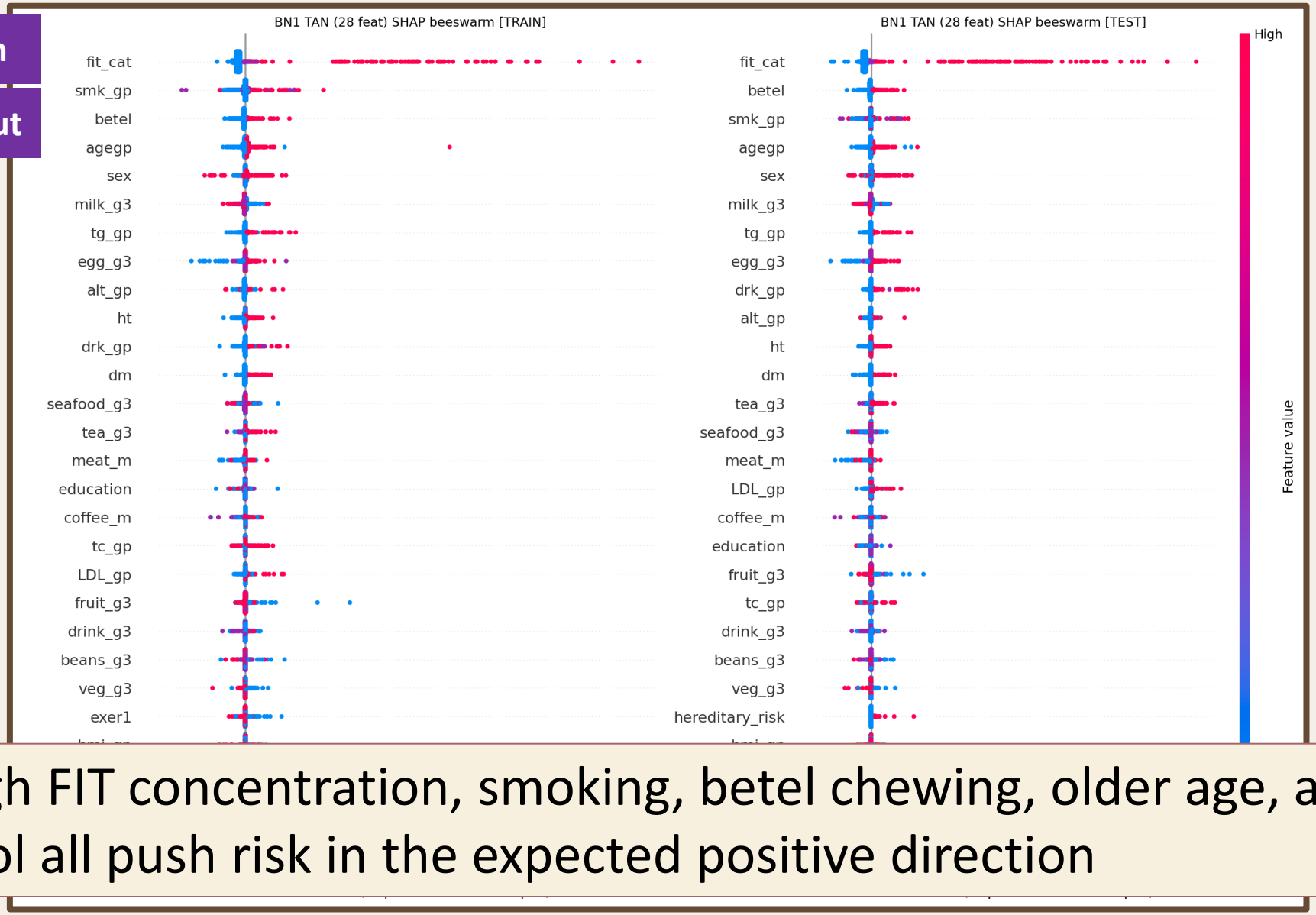


- **FIT concentration** dominates prediction of small-adenoma risk, then betel chewing, smoking, and age.
- The remaining signal spreads across alcohol, sex, diet and metabolic markers.

Bayesian Network Classifier-SHAP (Personalized)

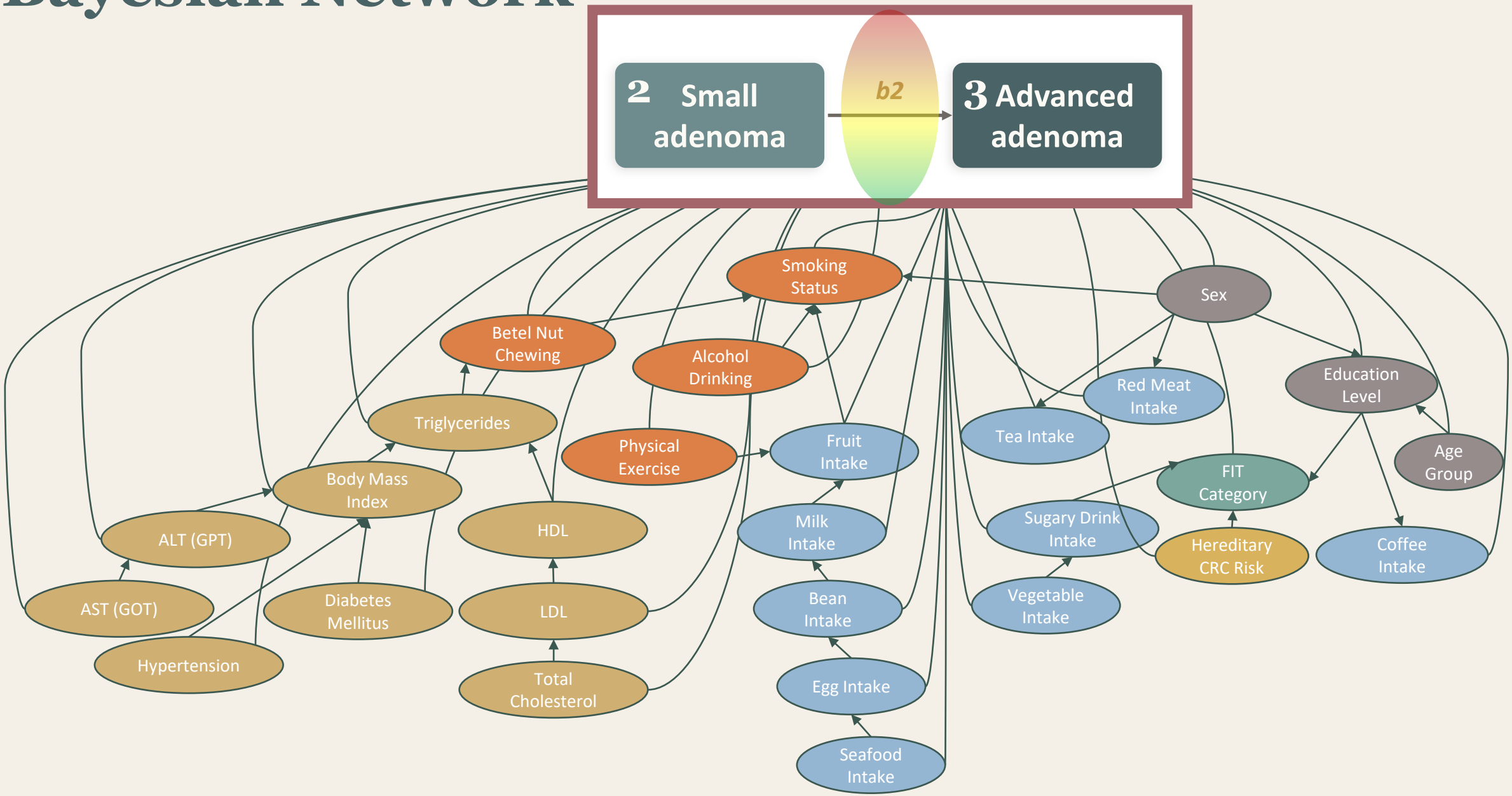
FIT concentration

Smoking/ Betel nut

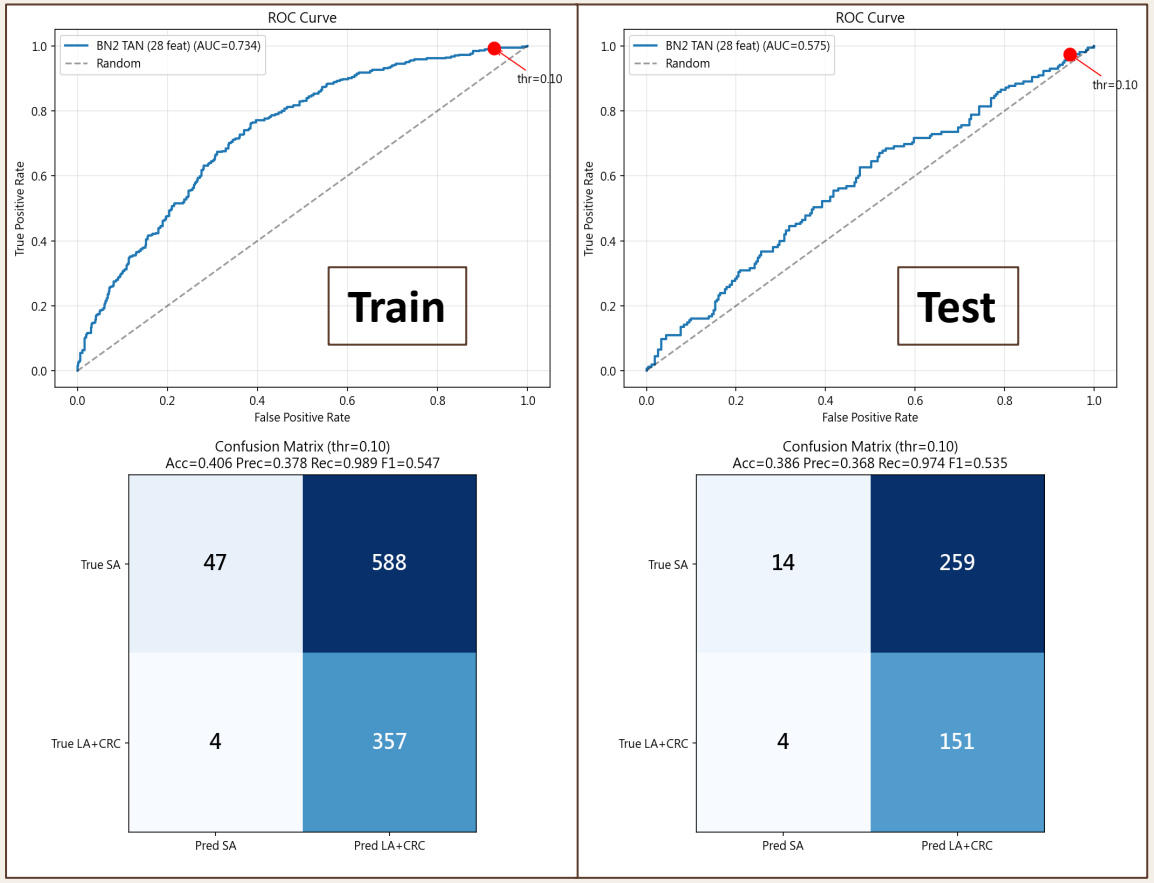


→ High FIT concentration, smoking, betel chewing, older age, and alcohol all push risk in the expected positive direction

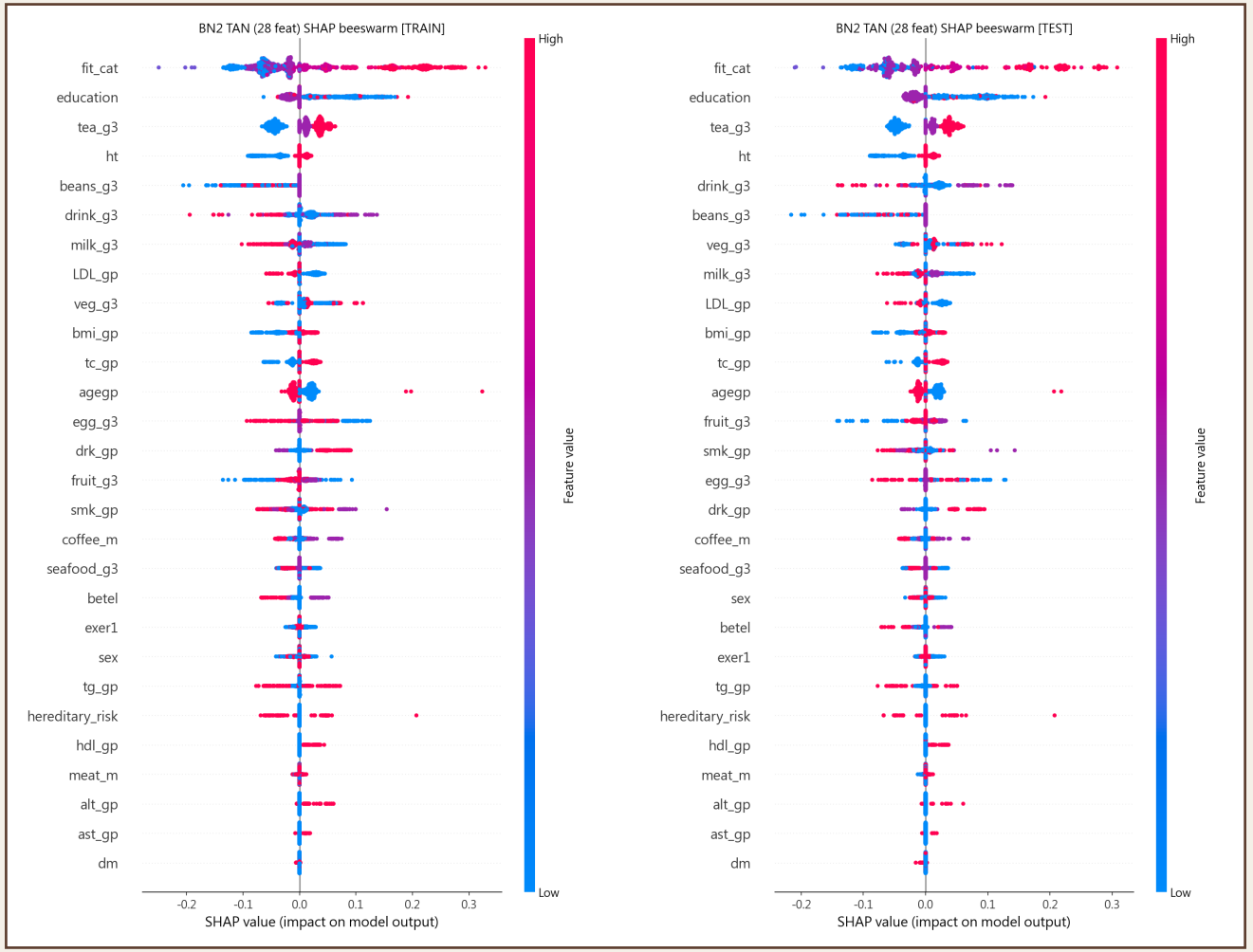
Bayesian Network



Bayesian Network Classifier-SHAP (Personalized)

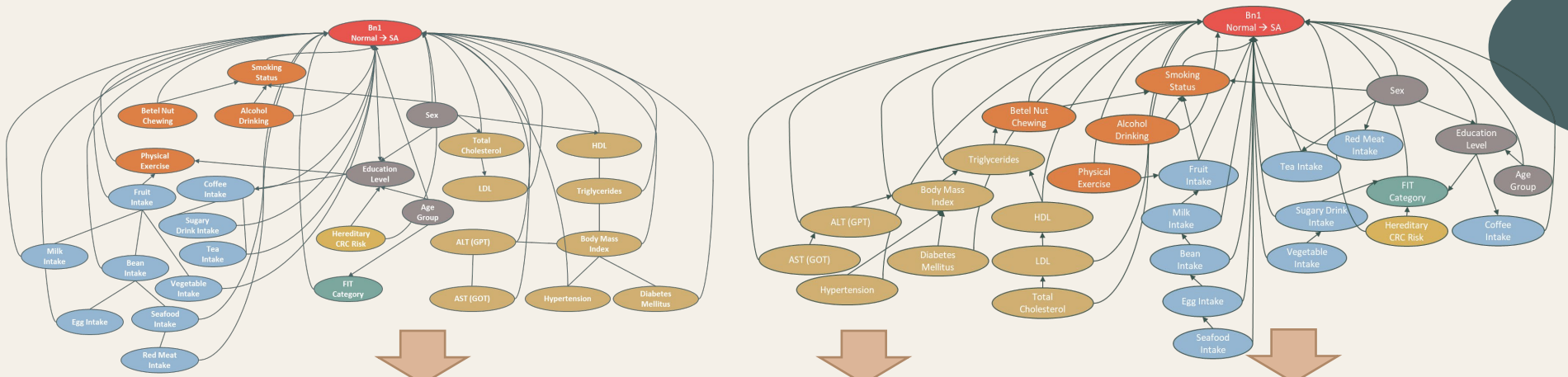


Metric	Train	Test
AUC	0.73	0.57
Accuracy	0.41	0.39
Precision	0.38	0.37
Recall	0.99	0.97
F1	0.55	0.53



Personalized features incorporated into the multistate model through BN

Bayesian Network



1 Normal

b1

2 Small adenoma

b2

3 Advanced adenoma

b3

4 PCDP early

b4

5 PCDP late

b5

6 Clinical early

b6

7 Clinical late

b7

8 NP small adenoma

b8

9 NP advanced adenoma

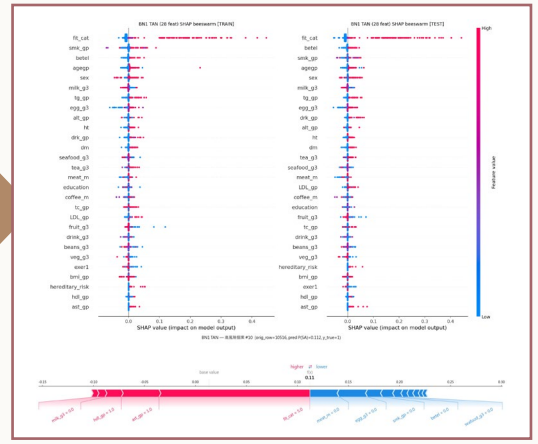
Every Patient Gets Their Own Disease Progression Risk

① Personal factors

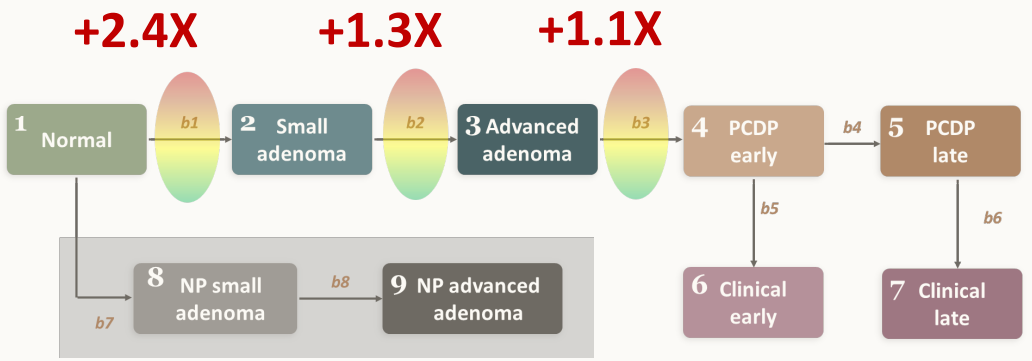
Age	68
Sex	Male
FIT (f-Hb)	18 mg/g
Smoking	current
Betel chewing	No
Alcohol	No
HDL	Elevated

② Bayesian Network

convert factors into personalized risk



③ Individualized Disease Progression Risk

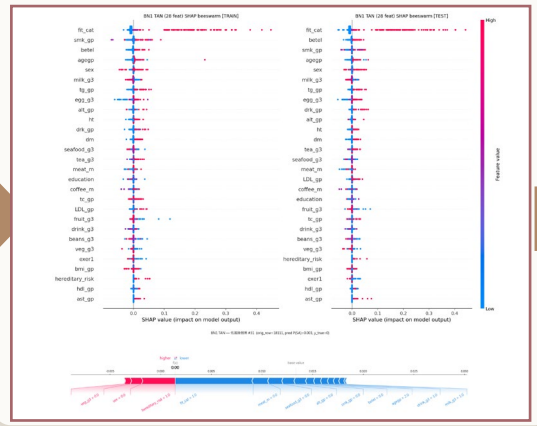


① Personal factors

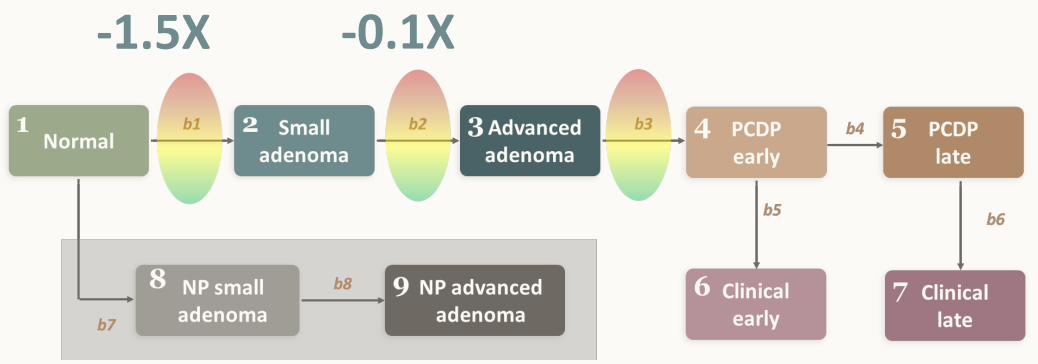
Age	55
Sex	Female
FIT (f-Hb)	0 mg/g
Smoking	No
Betel chewing	No
Alcohol	No
Tea intake	High

② Bayesian Network

convert factors into personalized risk



③ Individualized Disease Progression Risk



QR Code

What does incorporating a Bayesian Network into the multistate model allow?

(A) Models progression over time, but treats everyone the same.

(B) Personalizes risk, but loses the progression dynamics.

(C) Keeps the progression dynamics and personalizes each patient's rates.

(D) Guarantees each person has exactly one twin

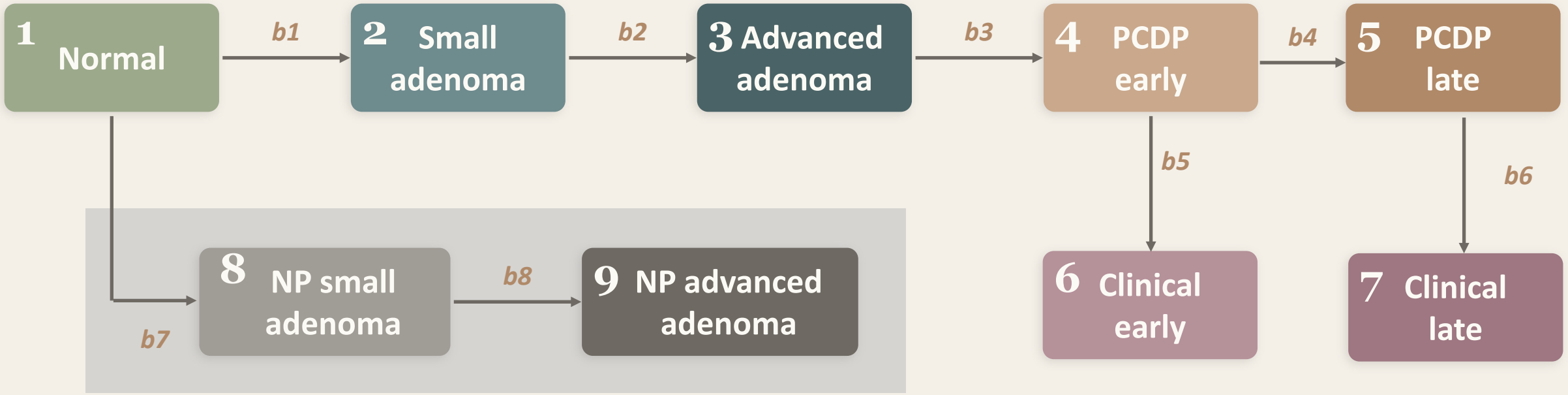
Session III. Digital Twin AI for Precision Screening

Reinforcement Learning–Enabled Digital Twins for Risk-Adaptive Screening Strategies with LLM

The role of digital twins in cancer screening.

Validating the Digital Twin Through a RCT

Stochastic Process: Multistate Model



PROGRESSIVE PATHWAY

- 1 Normal
- 2 Small adenoma
- 3 Advanced adenoma
- 4 PCDP — early
- 5 PCDP — late
- 6 Clinical cancer — early
- 7 Clinical cancer — late

NON-PROGRESSIVE PATHWAY

- 8 NP small adenoma
- 9 NP advanced adenoma

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Taipei Medical University (Taiwan)

Stochastic Process: Multistate Model

1 Normal — b1 → 2 Small adenoma — b2 → 3 Advanced adenoma — b3 → 4 PCDP early — b4 → 5 PCDP late

b6

b7 → 8 NP sma… adenon…

PROGRESSIVE PATHWA…

1 Normal

2 Small adenoma

3 Advanced aden…

4 PCDP — early

Multi-state Disease Prediction System

States

3

At least 2 States

Path

h1: s[1]→s[2] x

h2: s[2]→s[3] x

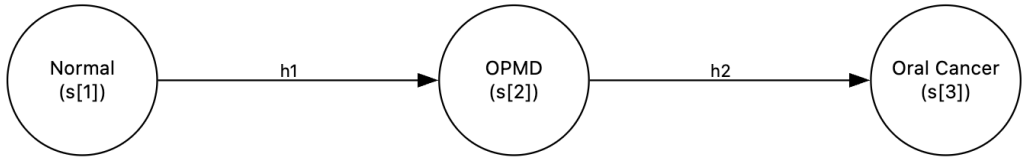
+ Add parameter | Labels ✓

Apply | Next

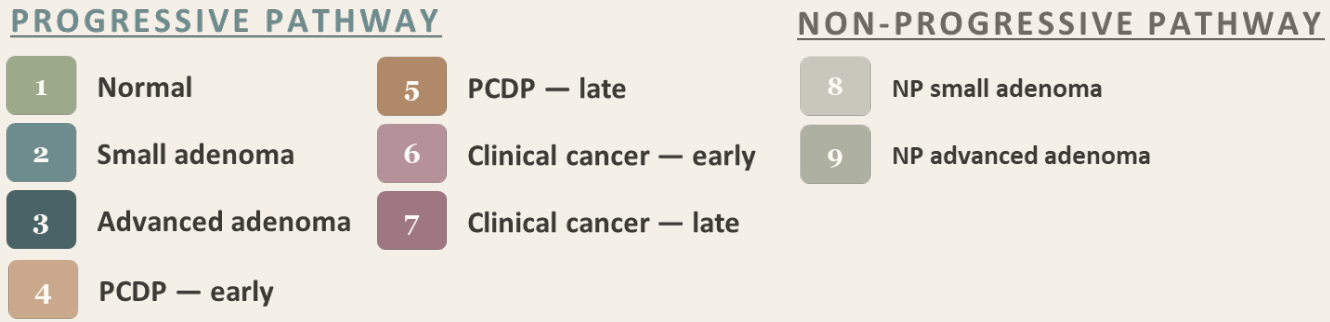
Intensity Matrix (Q)

State	Normal	OPMD	Oral Cancer
Normal	−h1	h1	0
OPMD	0	−h2	h2
Oral Cancer	0	0	0

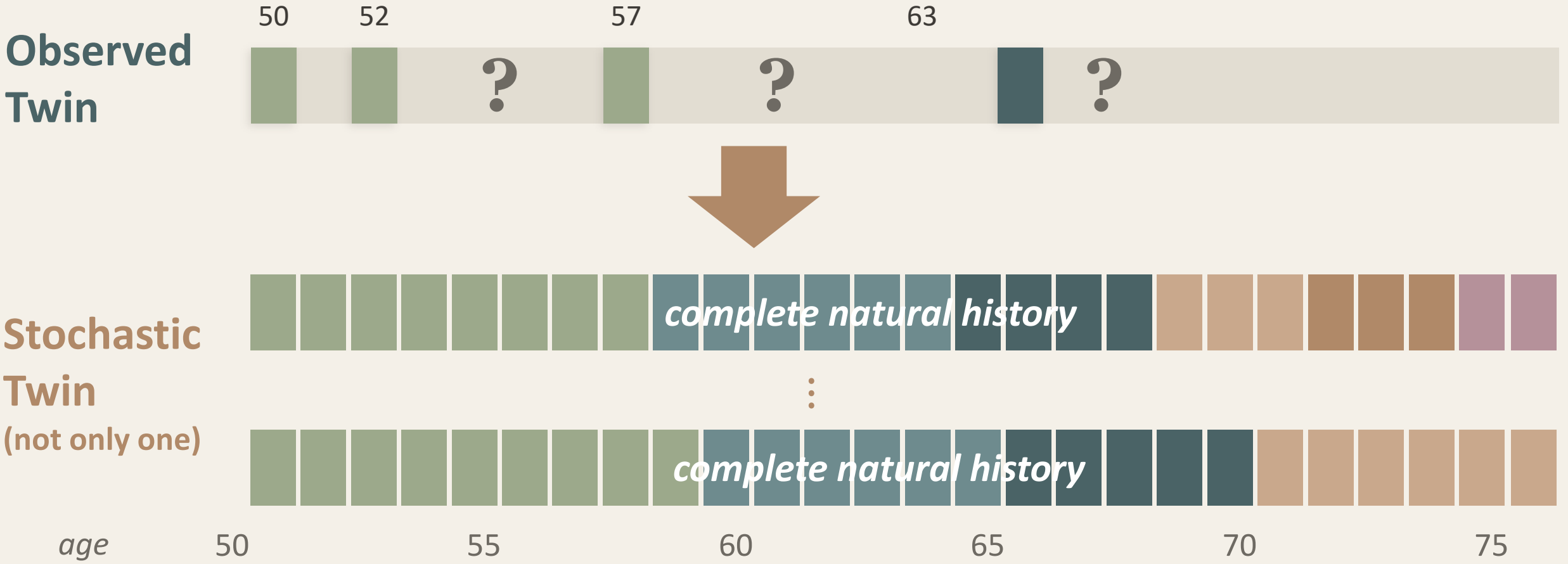
State Transition Diagram



Stochastic Twin



Real screening visits



Stochastic Twin: Unlock the natural history, address the biases in screening evaluation

Stochastic Twin

MEASURABLE

Lead-time bias

The twin knows when the cancer would have surfaced clinically — so lead time stops being a bias and becomes a number we can measure.

Individual Lead-time

COUNTABLE

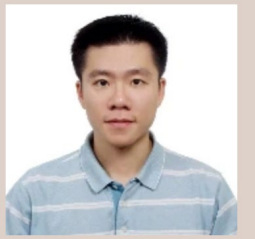
Overdiagnosis

Because the model separates progressive from non-progressive lesions, the twin can count the cancers that never would have harmed.

PARTLY CONTROLLED

Selection bias

Matching withi
controls the sel
though unmeas
remains.



HSU, Chen-Yang
National Taiwan University (Taiwan)

CHEN, Li-Sheng
Taipei Medical University (Taiwan)

From incomplete data to your digital twin

1 Screening data

real, but sparse and full of gaps

a few visits · most years unknown

2 Multistate model

simulates complete natural histories

3 Stochastic Twins

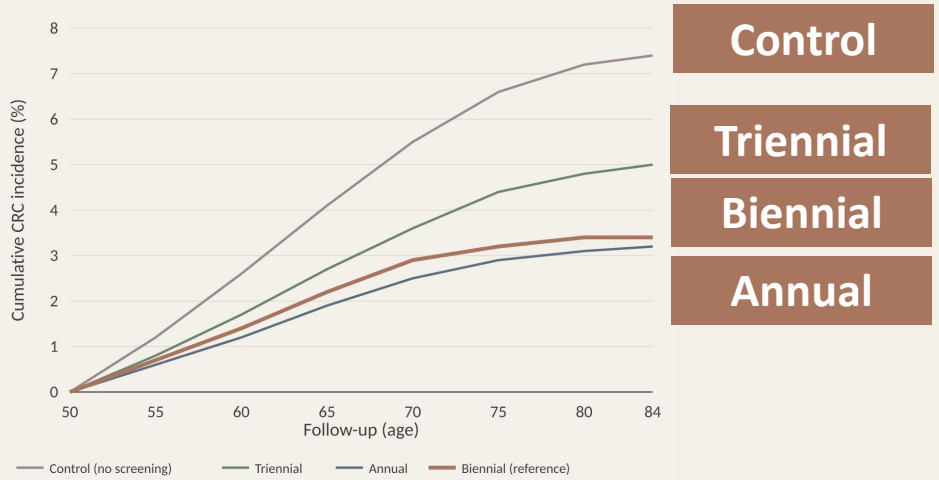
each = age x state, a random trajectory

4 Metaverse-driven Twin

your synthesis twin

Digital twin cohort

Annual | **Biennial** | Triennial | Control



Evaluating Cancer Screening with a Digital Twin Approach

Outcome	Annual	Biennial (Current)	Triennial
CRC incidence reduction	31.3%	22.5%	17.8%
Advanced-stage CRC reduction	50.2%	40.7%	34.3%
Adenoma overdiagnosis	+20%	— ref	−16%
FIT testing frequency	higher	— ref	lower
Colonoscopy demand	higher	— ref	lower

QR Code

Digital Twin in Cancer Screening — which is correct?

(A) The digital twin uncovers the hidden disease process, enabling personalized lead-time estimation.

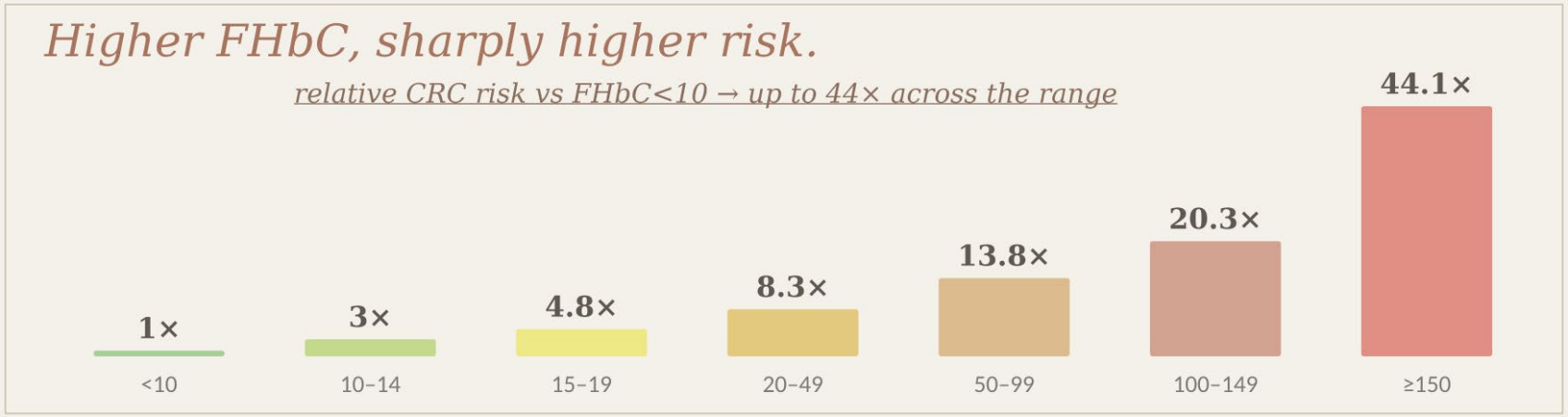
(B) The digital twin uncovers the hidden disease process, distinguishing progressive from indolent cancer per individual (Overdiagnosis).

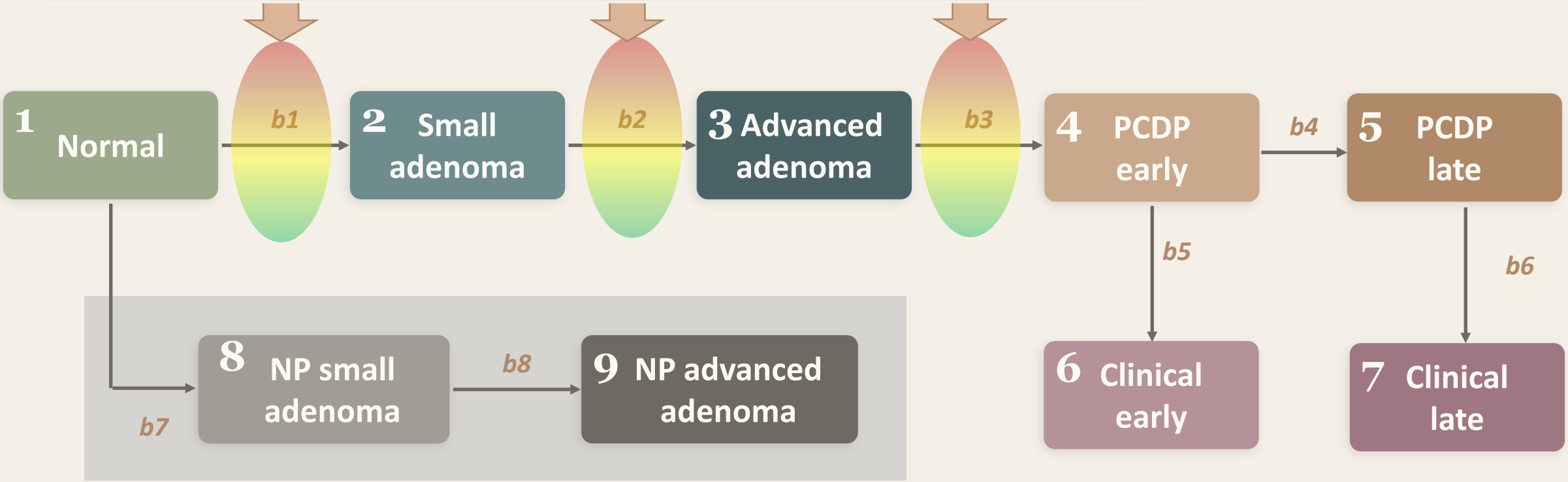
(C) More individualized data sharpens twin identification and reduces selection bias.

(D) All of the above

FIT-driven precision screening through a digital twin framework

Multistate Model with FIT Concentration





Your FIT concentration guides the twin

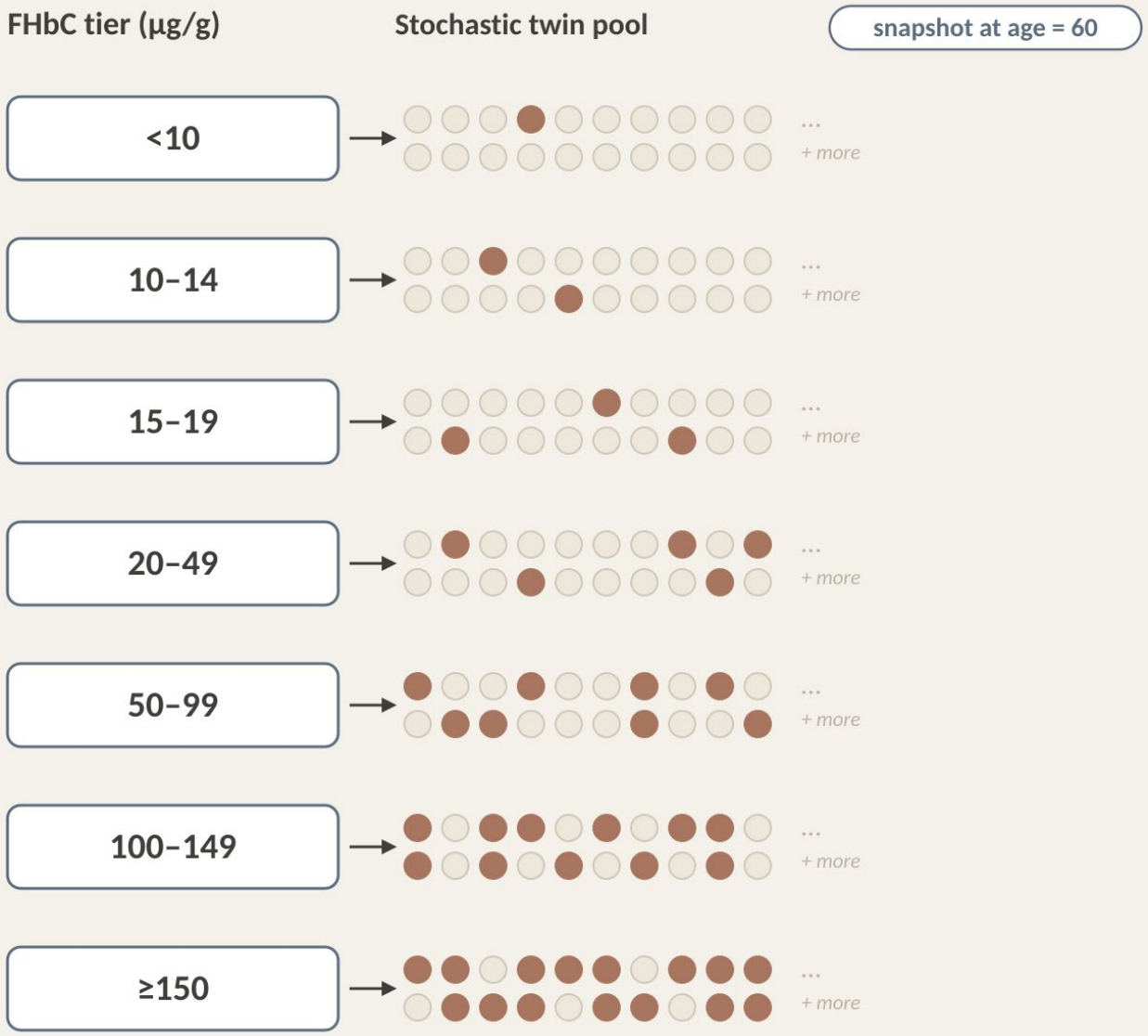
Quantitative FIT concentration

↓

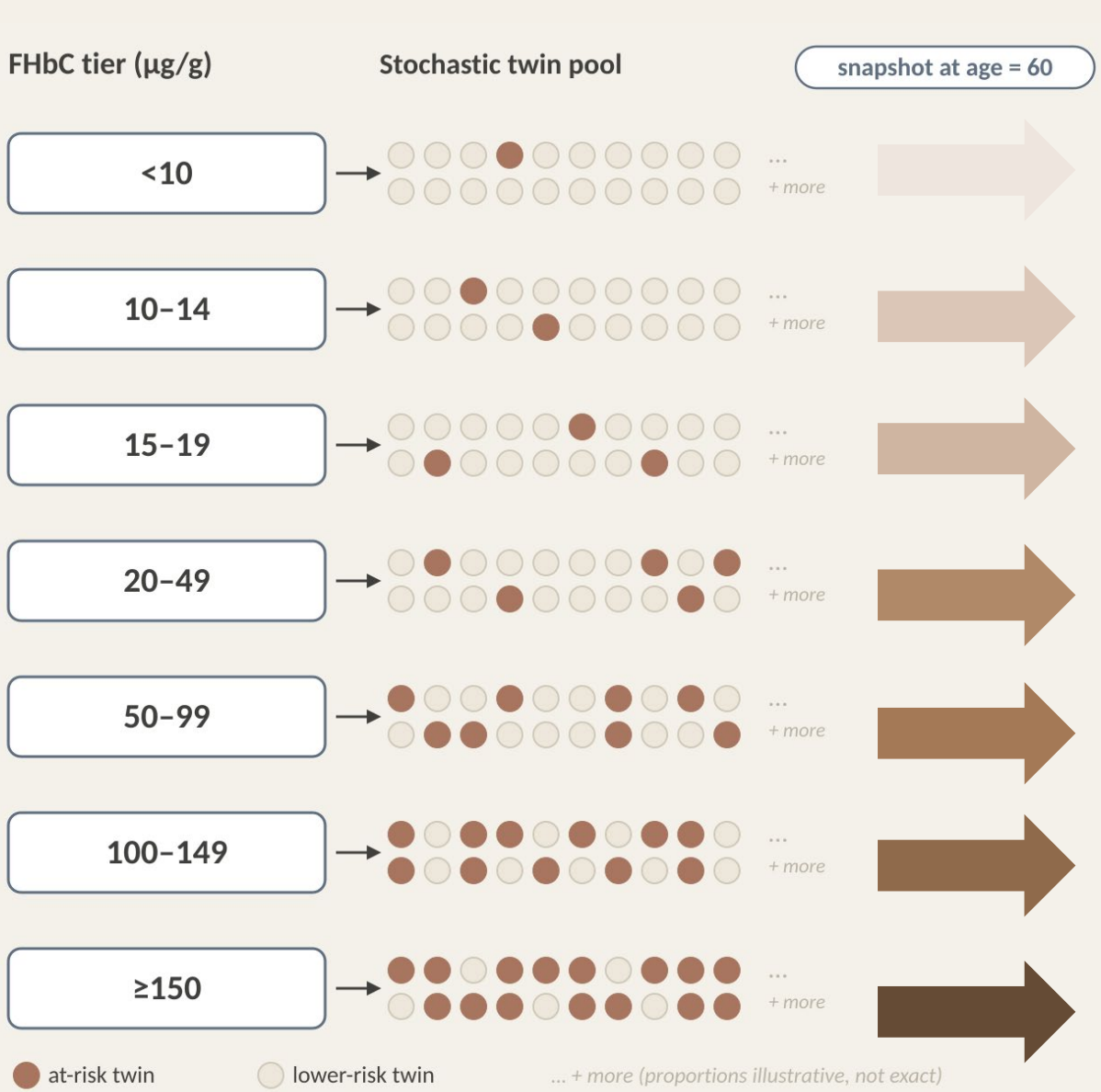
Enter multistate model

↓

FIT guided stochastic twin



Your FIT concentration guides your screening interval



What-if A *placeholder*

FHbC	interval (yr)
<10	2
10–14	2
15–19	2
20–49	2
50–99	2
100–149	2
≥150	2

What-if B ✓ *selected*

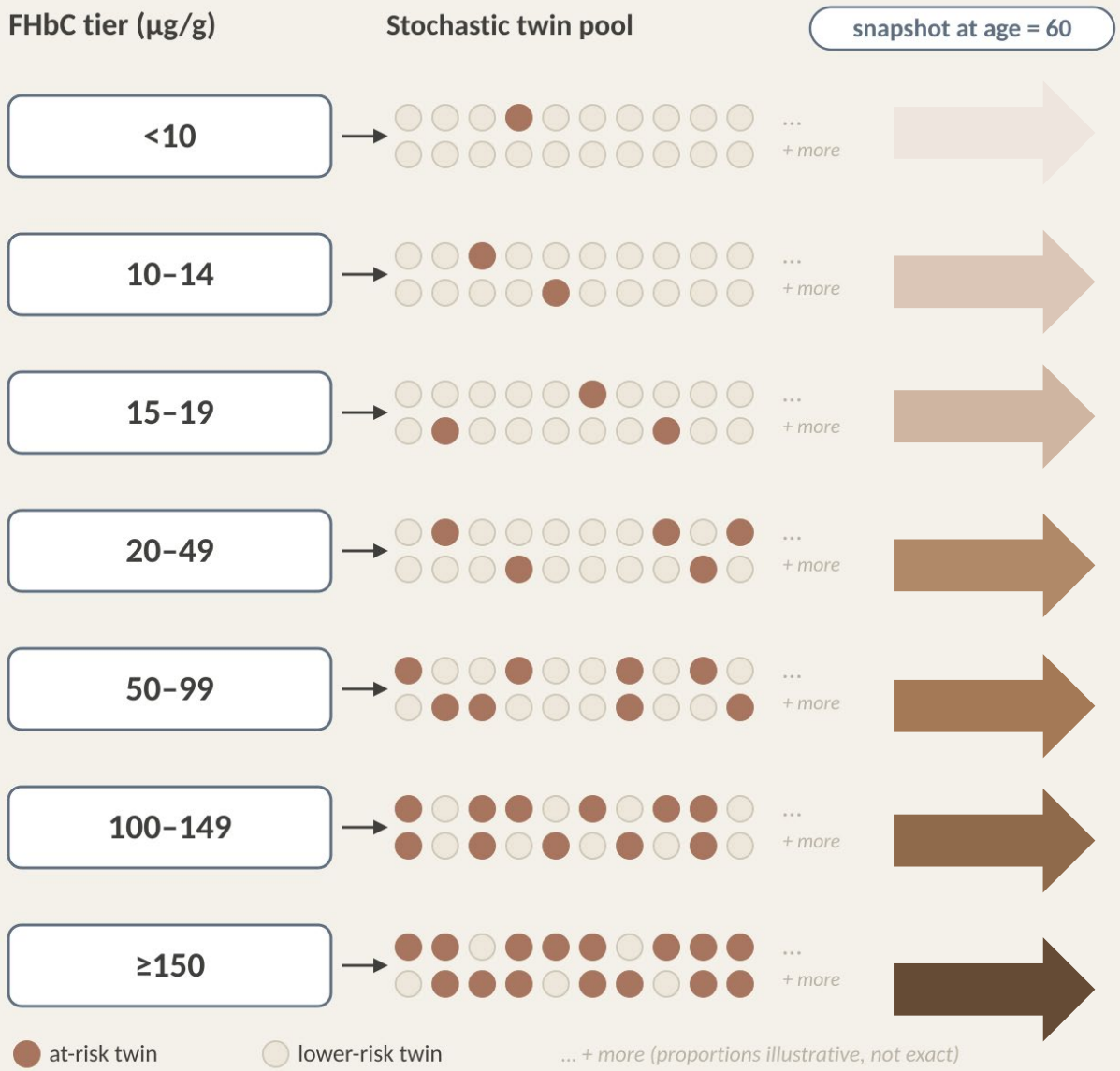
FHbC	interval (yr)
<10	6
10–14	3
15–19	2
20–49	10
50–99	5
100–149	1
≥150	0.5

What-if C *placeholder*

FHbC	interval (yr)
<10	5
10–14	3
15–19	2
20–49	8
50–99	3
100–149	1
≥150	0.5

Normal after Colonoscopy

Your FIT concentration guides your screening interval



What-if A *placeholder*

FHbC	interval (yr)
<10	2
10–14	2
15–19	2
20–49	2
50–99	2
100–149	2
≥150	2

What-if B ✓ *selected*

FHbC	interval (yr)
<10	6
10–14	3
15–19	2
20–49	10
50–99	5
100–149	1
≥150	0.5

What-if C *placeholder*

FHbC	interval (yr)
<10	5
10–14	3
15–19	2
20–49	8
50–99	3
100–149	1
≥150	0.5

Normal after Colonoscopy

Personalized Screening Matches Biennial Benefit at Lower Cost

Constraint: Bioequivalence design

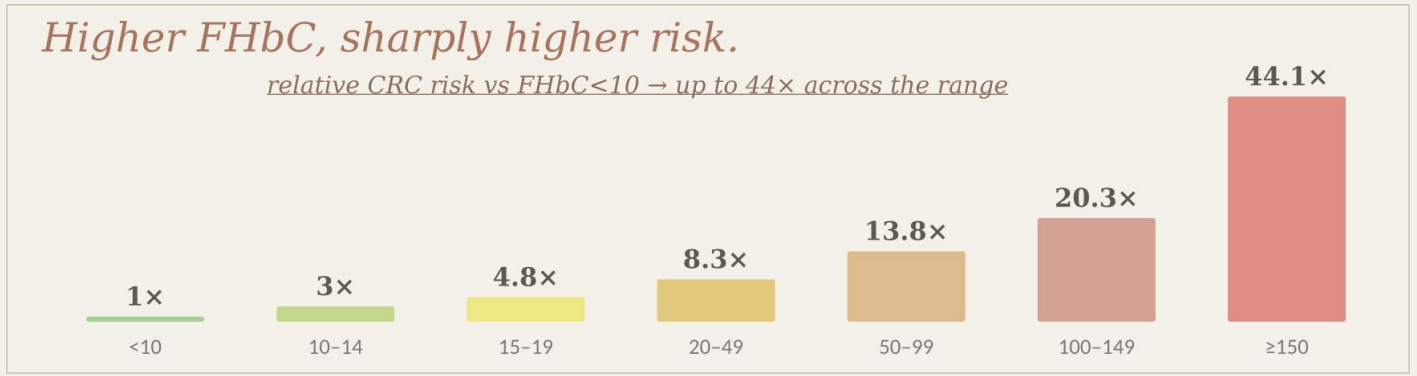
Outcome	Annual	Biennial (Current)	Triennial	Precision
CRC incidence reduction	31.3%	22.5%	17.8%	**≈ Biennial**
Advanced-stage CRC reduction	50.2%	40.7%	34.3%	**≈ Biennial**
Adenoma overdiagnosis	+20%	— ref	−16%	**−20%**
FIT testing frequency	higher	— ref	lower	**−39%**
Colonoscopy demand	higher	— ref	lower	**−35%**

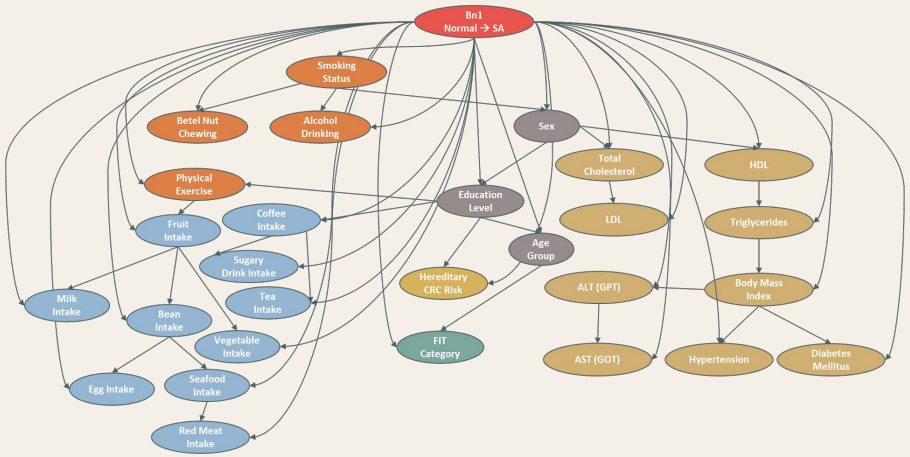
Session III. Digital Twin AI for Precision Screening

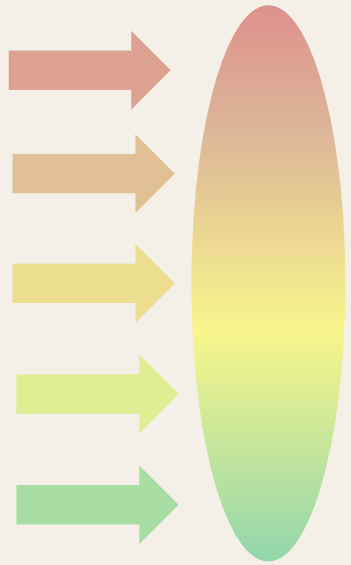
Reinforcement Learning–Enabled Digital Twins for Risk-Adaptive Screening Strategies with LLM

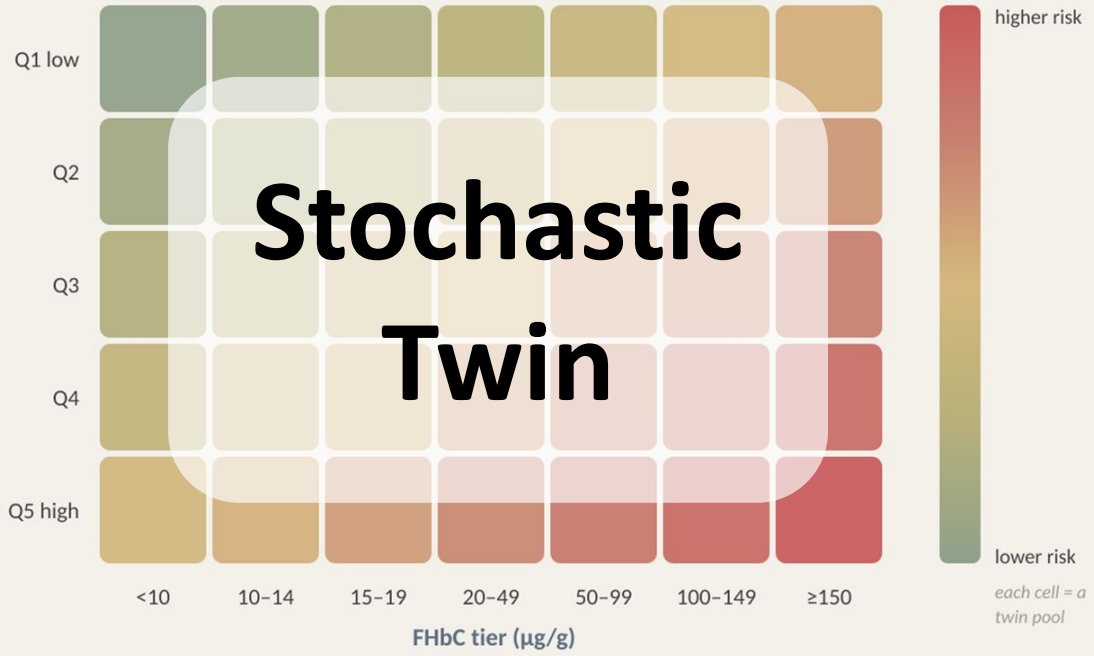
Personalized screening through a digital twin framework

Bayesian Network Classifier with FIT concentration information for generating stochastic twin



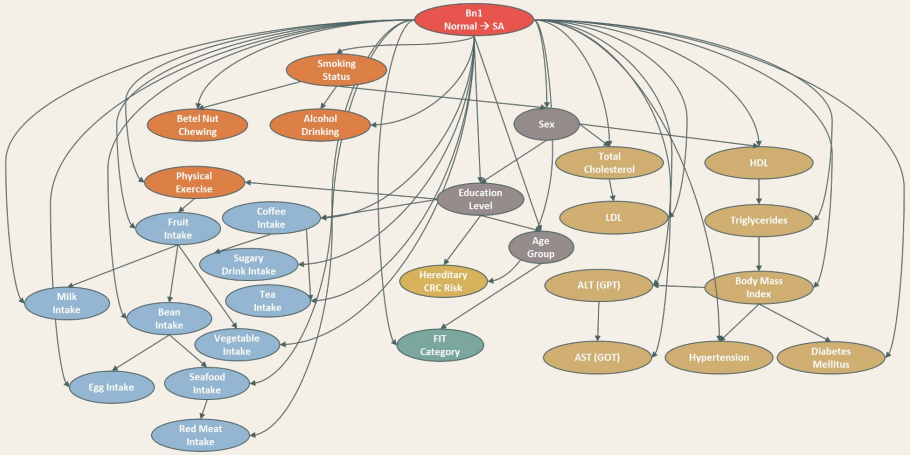


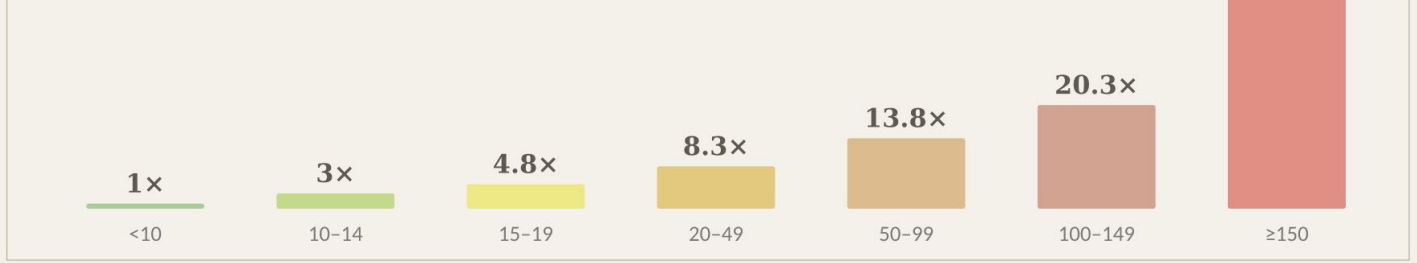




Your risk and FIT concentration guide your screening interval

Adaptive Screening Interval





	FHbC Tiers						
	<10	10–14	15–19	20–49	50–99	100–149	≥150
FIT-Negative	6	3	2	N/A	N/A	N/A	N/A
Normal Colonoscopy (High ADR)	N/A	N/A	N/A	10	10	10	6
Normal Colonoscopy (Low ADR)	N/A	N/A	N/A	10	10	6	2
Advanced Adenoma	N/A	N/A	N/A	3	3	3	2
Non-Advanced Adenoma	N/A	N/A	N/A	10	9	7	6
Advanced Adenoma	N/A	N/A	N/A	3	3	3	2

Session III. Digital Twin AI for Precision Screening

Reinforcement Learning–Enabled Digital Twins for Risk-Adaptive Screening Strategies with LLM

A person is not static — how about our digital twin?

A person is not static — how about our digital twin?

Everything we used to personalize the twin drifts over time.

FIT concentration drifts

A person's f-Hb today is not their f-Hb in five years. Baseline FIT was a lifetime label — reality keeps moving.

Personal features change

The BN factors — lifestyle, comorbidity, habits — evolve. The risk profile we fixed at entry slowly goes stale.

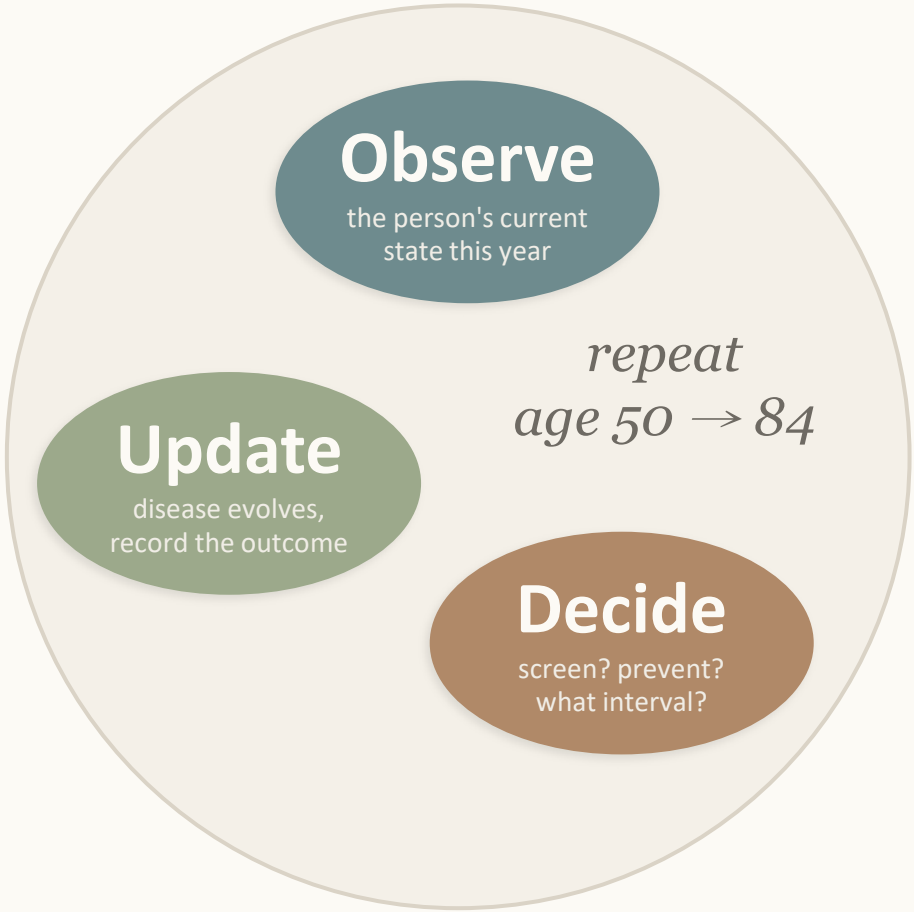
So the right interval changes too

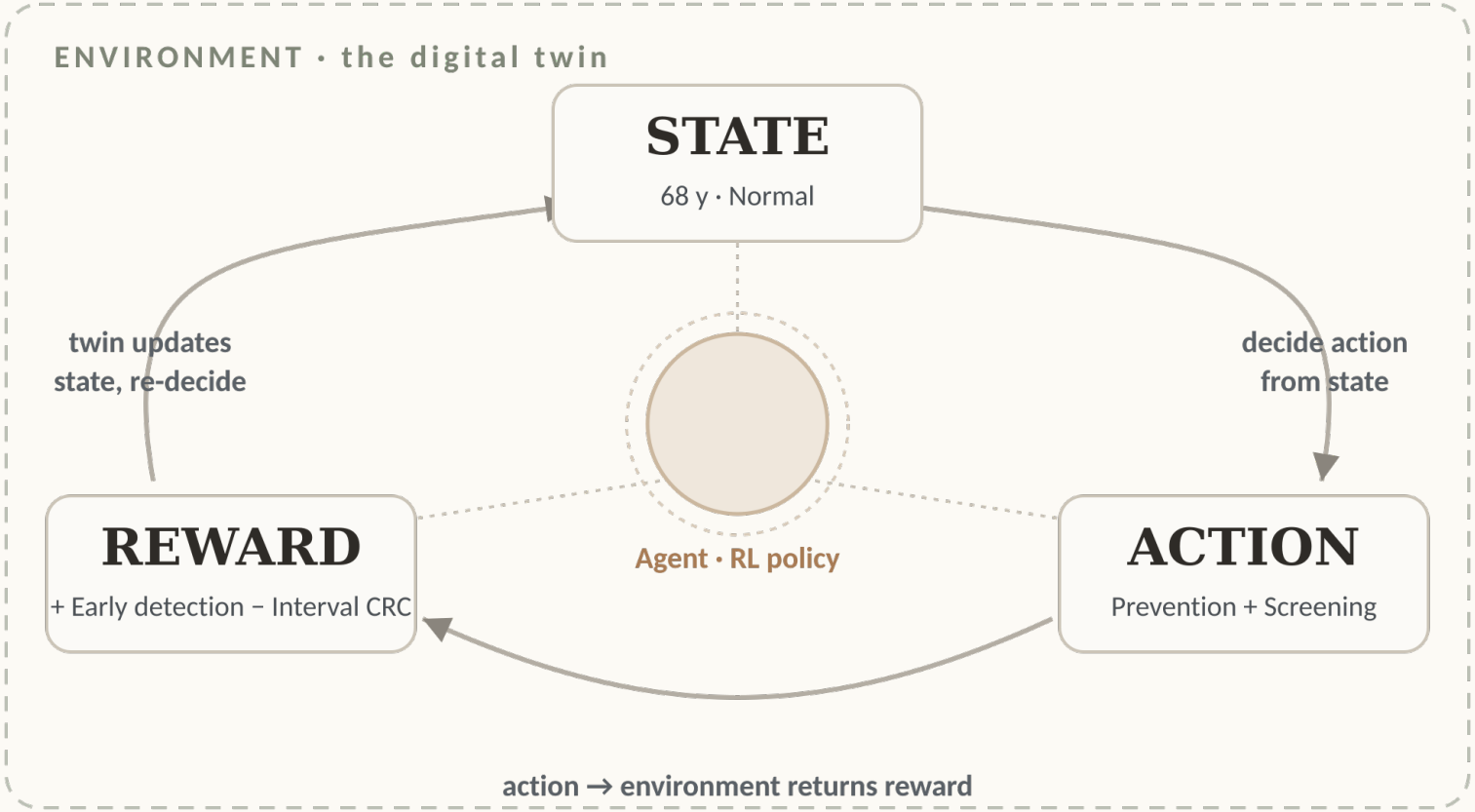
If risk rises, the schedule should tighten; if it falls, it can relax. A one-time plan cannot follow the person.

We need a twin that does not just hold one schedule — but re-decides every time new information arrives.

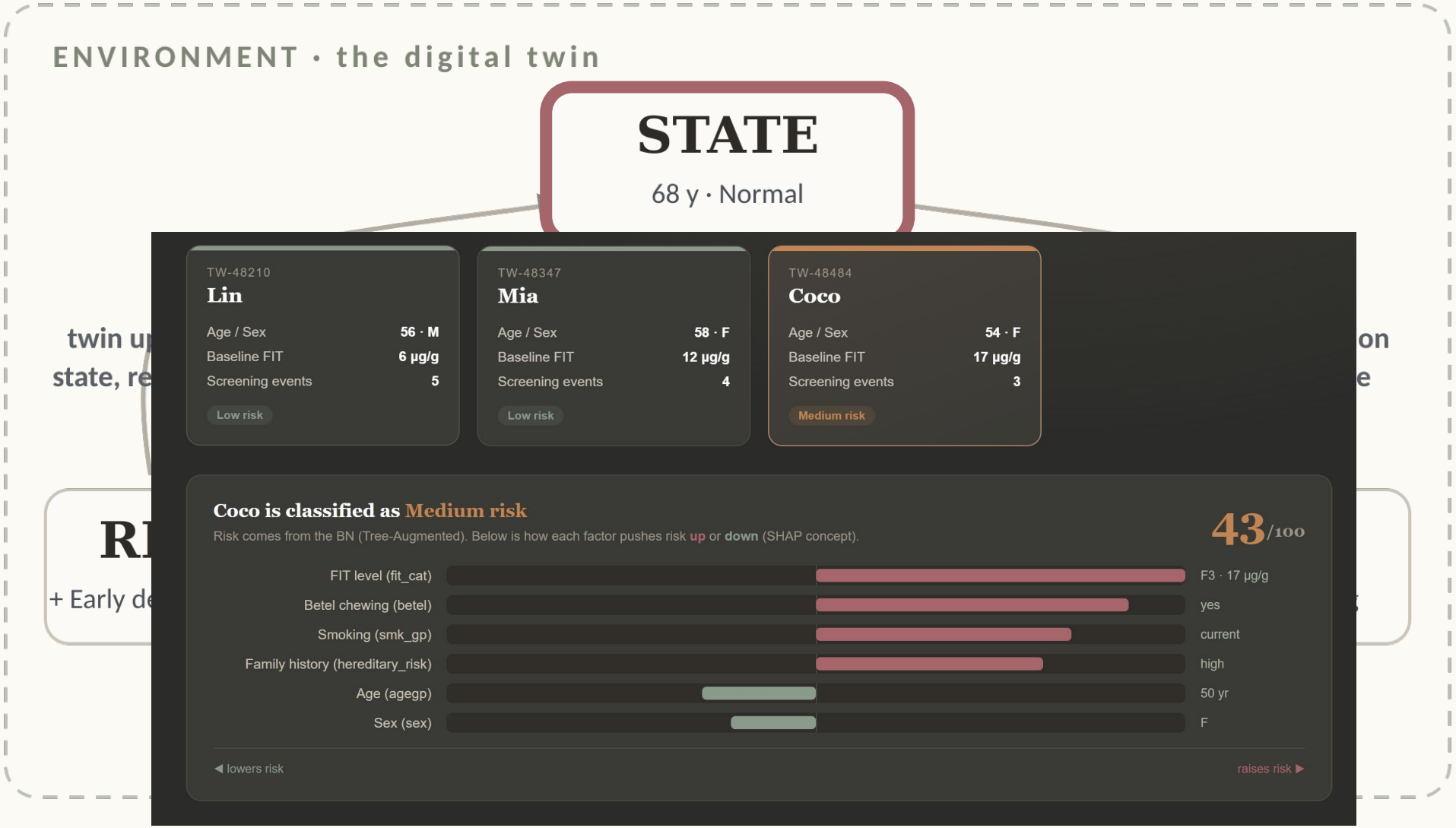
Screening is a sequence of decisions, not one plan

Each year, the twin observes, decides, and sees the consequence — then does it again.





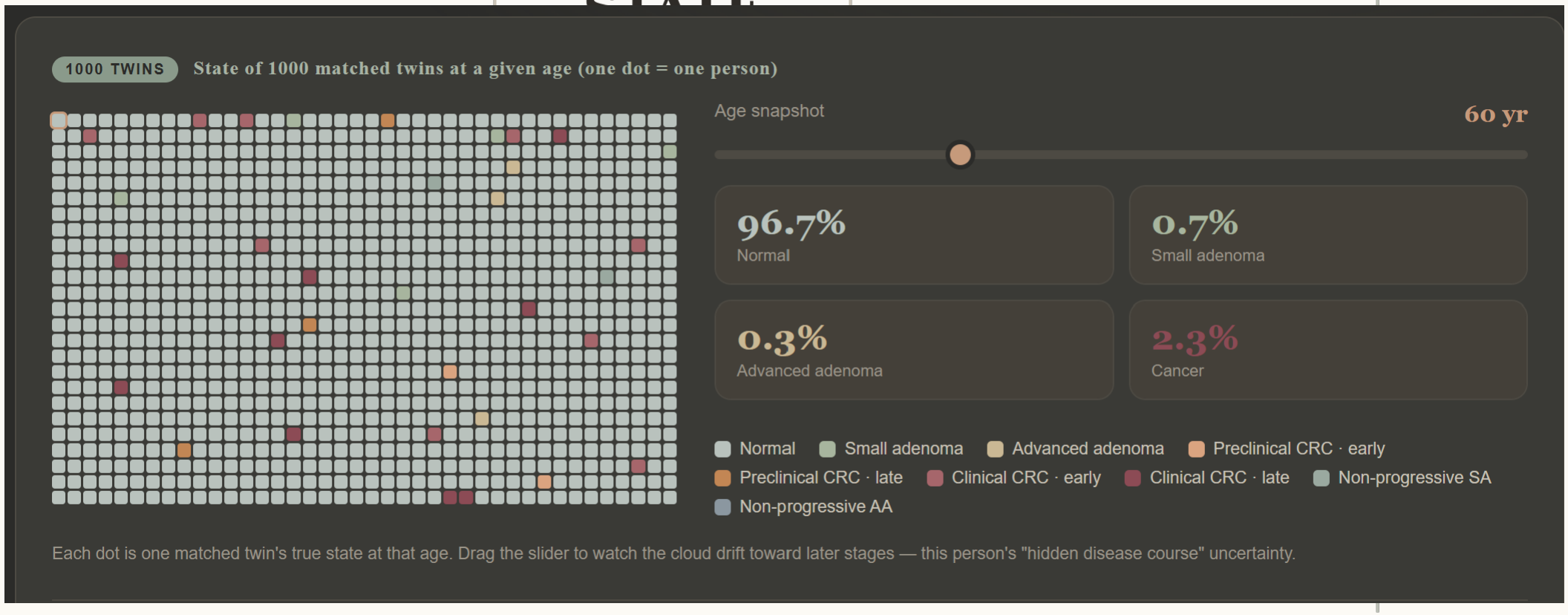
Reinforcement Learning - State



Reinforcement Learning - Enviroment

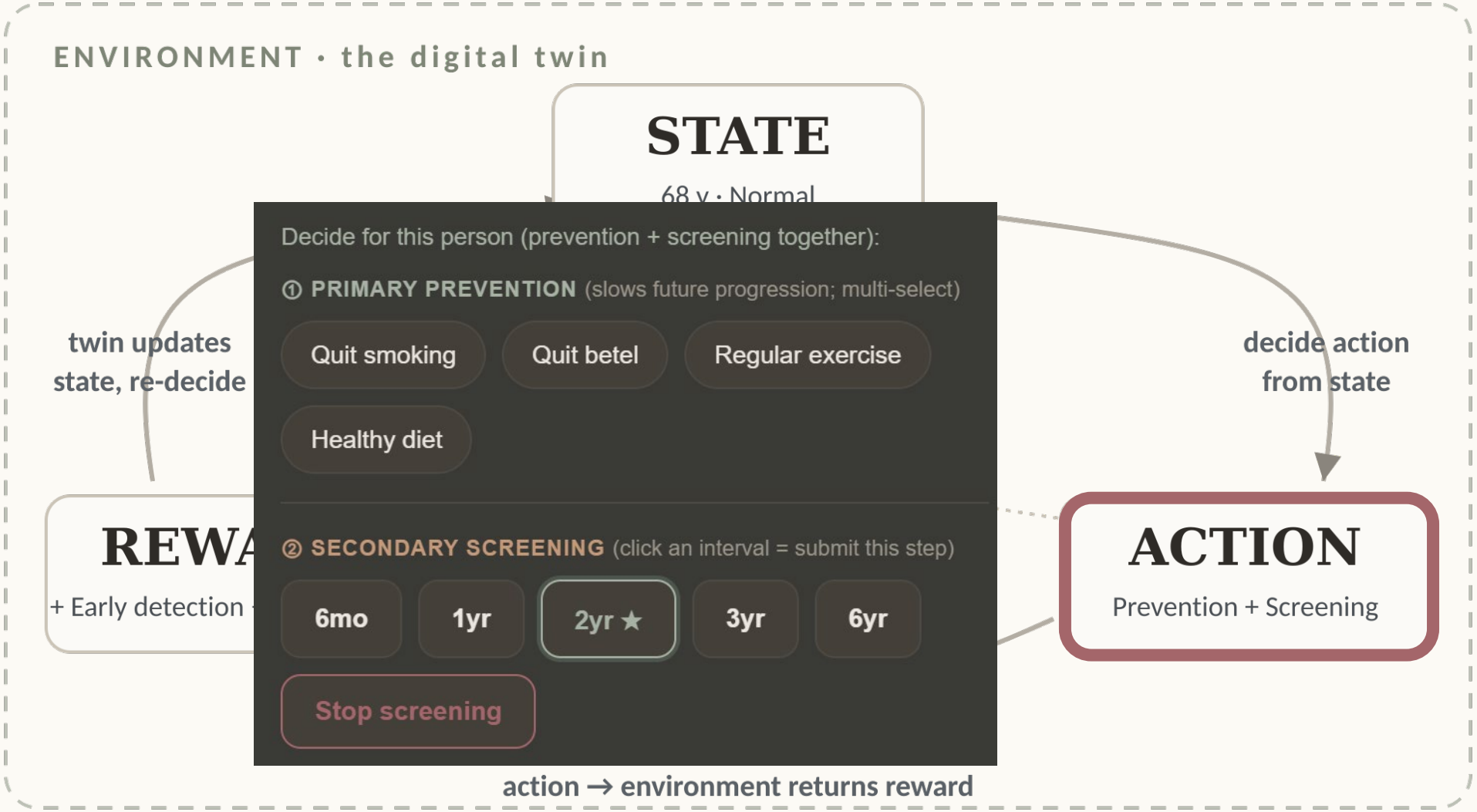
ENVIRONMENT · the digital twin

STATE



action → environment returns reward

Reinforcement Learning - Action



Two kinds of action — Primary & Secondary Prevention

Screening · secondary prevention

Screen or not — and at what interval.

Does ***not*** change whether cancer develops — only **when we see it.**

acts on → detection (FIT sensitivity)

Primary prevention · permanent

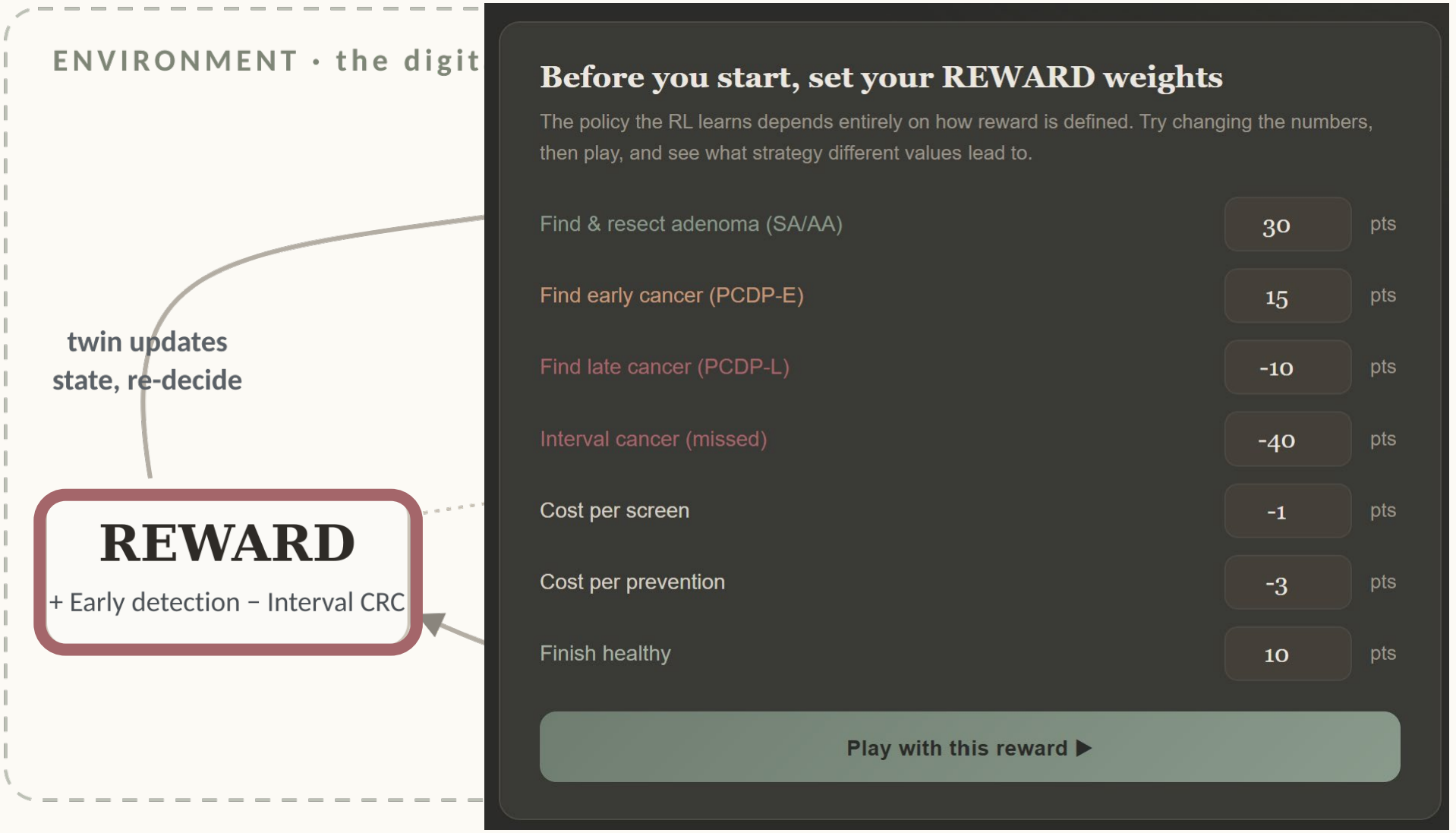
A lifestyle intervention.

Permanently rewrites the person's BN factors → they become a **lower-risk type**.

acts on → transition rates (the trajectory itself)

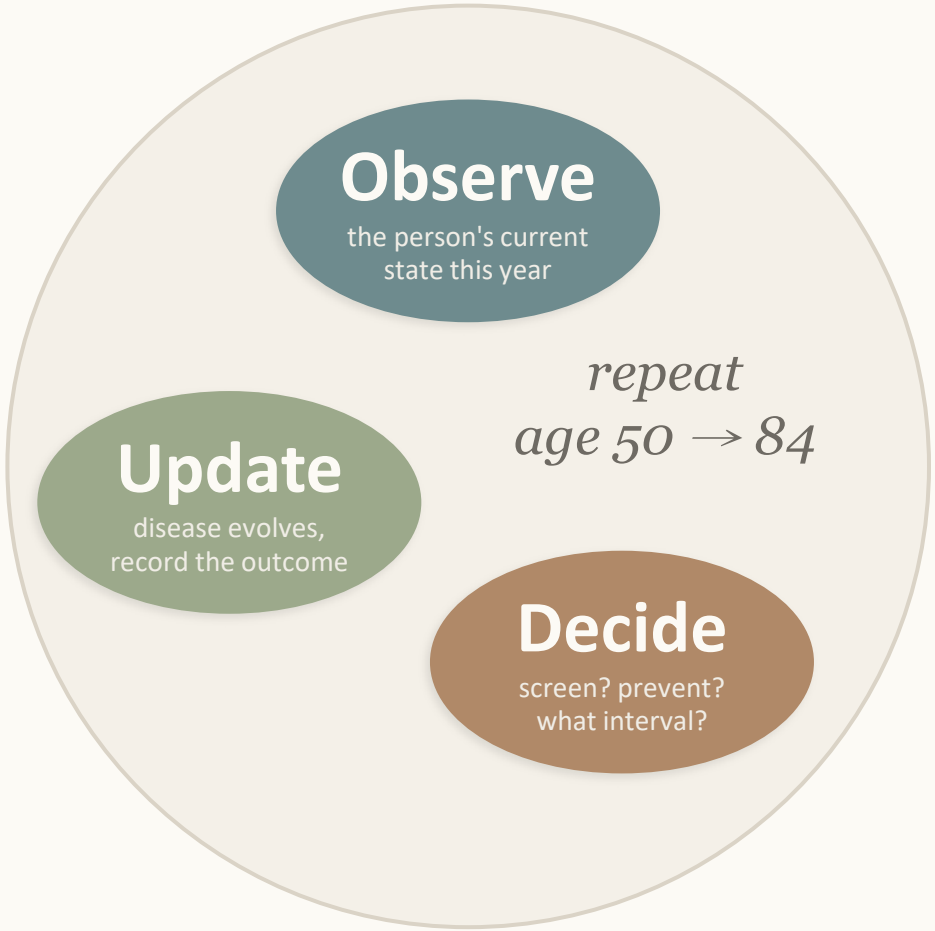
Screening changes when we know.
Prevention changes whether it happens.

Reinforcement Learning - Rewards



Screening is a sequence of decisions, not one plan

Each year, the twin observes, decides, and sees the consequence — then does it again.



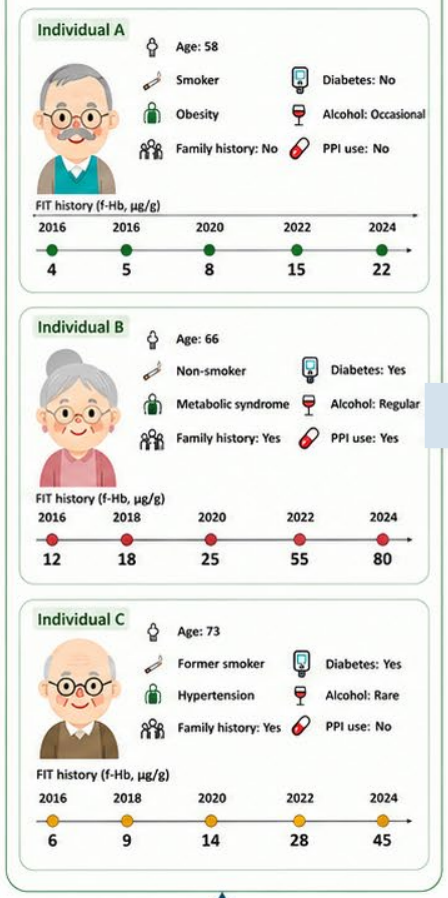
Reinforcement Learning

State	**Features; FIT level; Disease Status**
Action	**Primary Prevention; Secondary Screening**
Reward	**(+) Cancer prevented or early detection, (-) Cost/ Overdiagnosis**
Policy	**The rule it learns**

Reinforcement Learning for Adaptive Screening

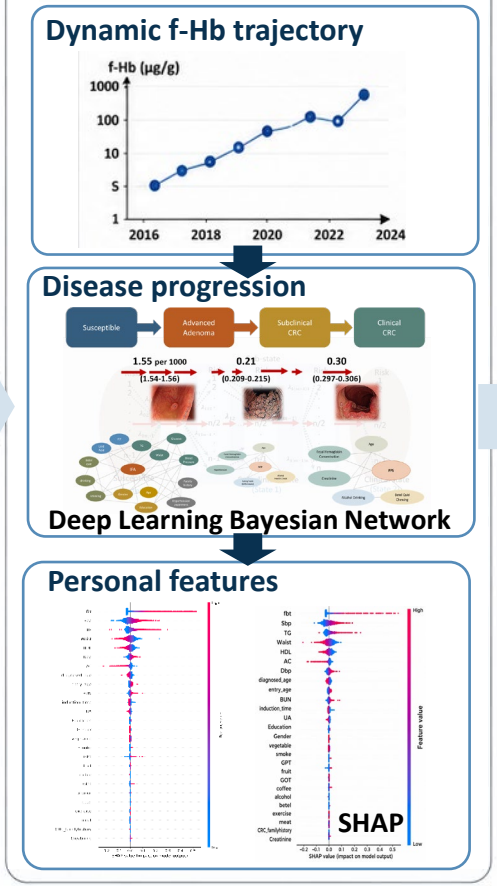
1. Physical Data Layer

Individuals with personal features & longitudinal FIT history



2. Computational Layer

Digital Twin: personalized risk modelling (Dynamic FIT + Features)



3. Decision-supported Layer

(eg. Inter-screening Interval & Emerging detection modality)

Dynamic f-Hb concentration (μg/g)

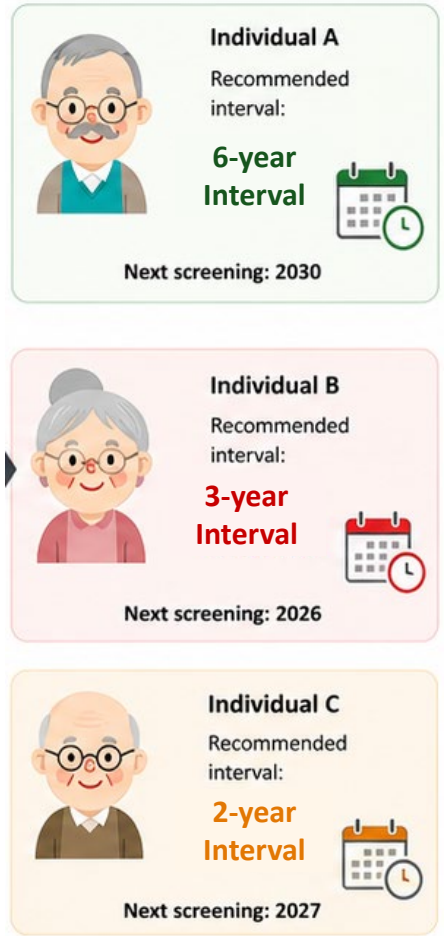
Personal risk score (mrt (fom BN)

	<10	10–14	15–19	20–49	50–99	100–149	≥150
Extremely High Risk	Surveillance (<1 year)	1 year	1 year	1 year	1 year	<1 year	<1 year
High Risk	2 years	2 years	1–2 years	1–2 years	1 year	1 year	<1 year
Moderate Risk	3 years	3 years	2–3 years	2 years	1–2 years	1–2 years	1 year
Low Risk	6 years	6 years	3–6 years	3 years	2–3 years	2 years	1–2 years
Extremely Low Risk	6 years	6 years	6 years	6 years	3–6 years	3 years	2–3 years

Longer interval (lower risk) ← → Shorter interval (higher risk)

Notes:
- Risk score is derived from the Bayesian Network (personal features).
- f-Hb trajectory is dynamically updated over time.
- Map is learned from the Digital Twin (multistate model).
- Interval recommendations balance benefit, harm, and resource use.

4. Personalized Service Layer



Reinforcement Learning

5. Intervention Layer

Primary Prevention and Surveillance & Early awareness of CRC

You are the RL agent: find Coco's best screening plan

Each plan runs one episode and scores a reward.

Round 1 — try three plans

Which plan scores highest?

(A) Screen every 2 years

(B) Screen every 6 years

(C) Quit smoking, then screen every 3 years

Round 2 — can you beat the best?

A real agent doesn't stop — it tweaks the winner to try for more.

Which of these beats?

(A) Keep every 2 years

(B) Add quit-smoking on top of A

(C) Screen even more often, every 1 year

DIGITAL TWIN PIPELINE

Follow one person through the whole pipeline

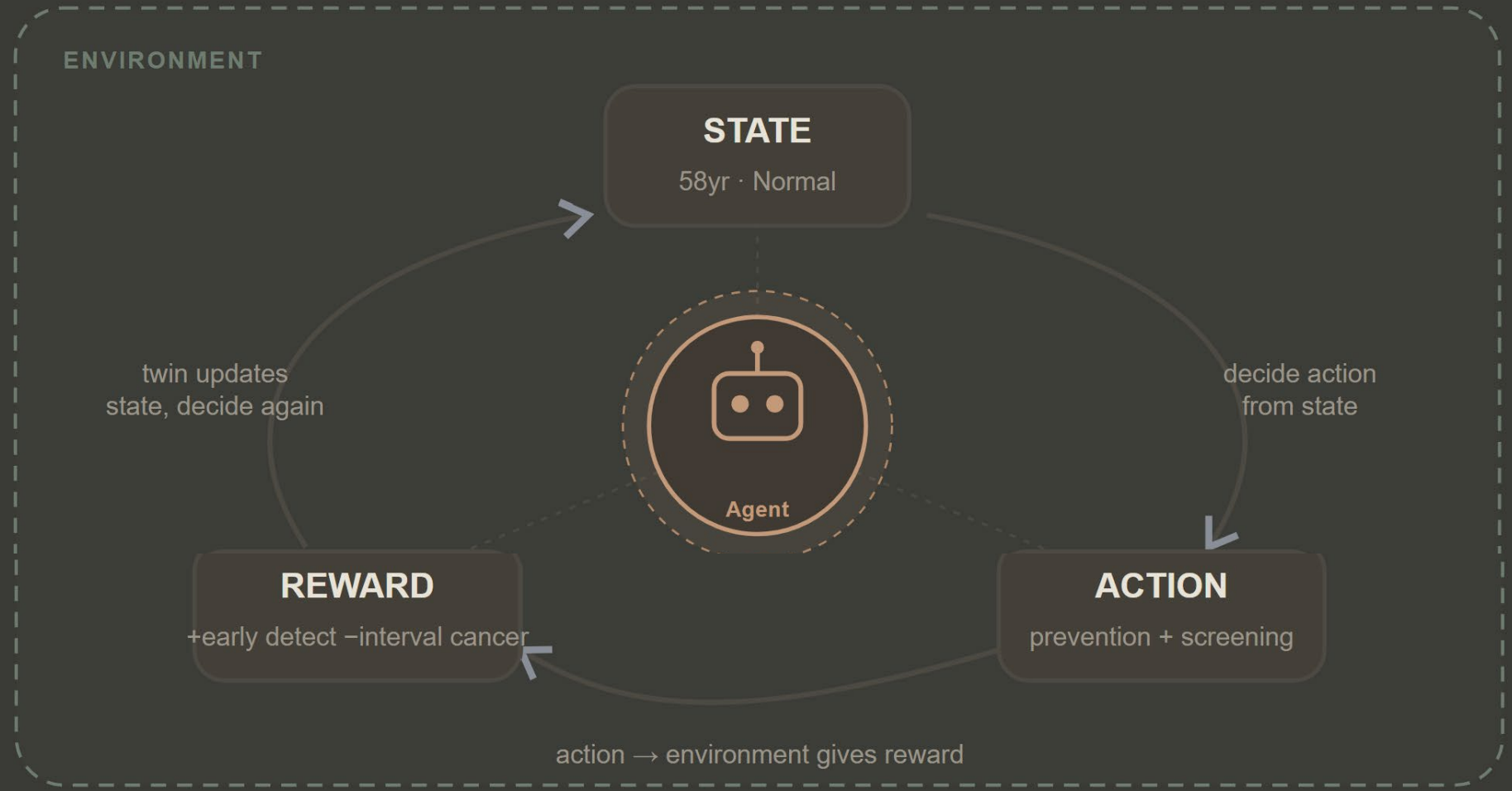
- ✓ Pick a person
- ✓ Screening History
- ✓ Stochastic twin
- ✓ Metaverse-driven Twin
- ✓ Precision Screening Evaluation
- 6 **Updated Twin**

STEP 6 / 6

Updated twin

Chang	58	F	12	F2
TW-48347	START AGE	SEX	FIT MG/G	RISK TIER

REINFORCEMENT LEARNING LOOP



4P Medicine

P1

Predictive

P2

Preventive

P3

Personalized

P4

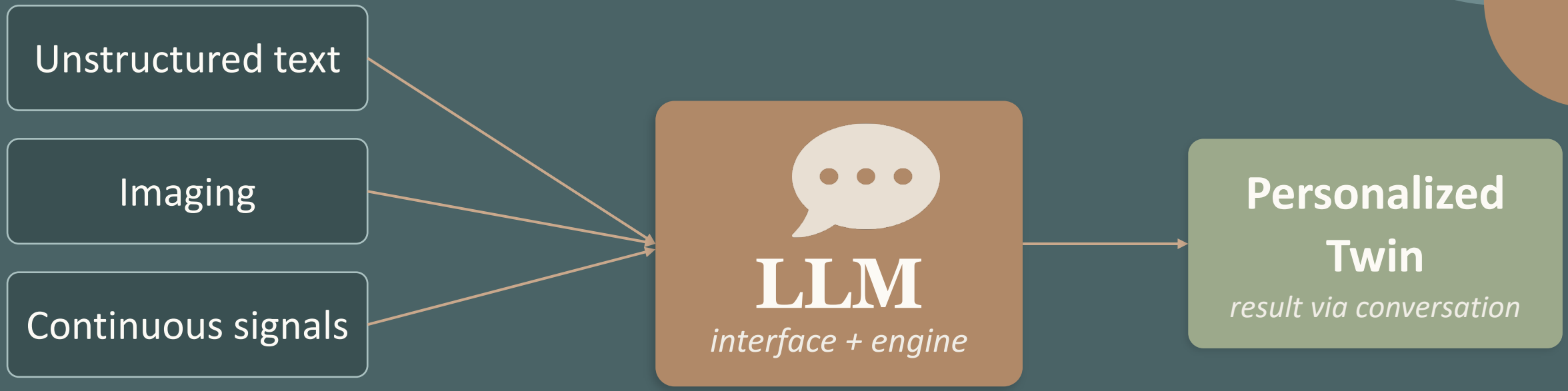
Participatory

From risk-adaptive to participatory — LLMs bridge model and person

(1) LLMs integrate multimodal inputs

(2) LLMs return personalized, plain-language responses

Multimodal Data in LLM



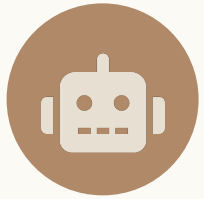
Personal information enters by conversation · multimodal data is absorbed into the prompt · the result returns as dialogue.

LLM-Guided Precision Screening Intervals

using dynamic f-Hb

My previous FIT was 5 µg/g, and my current result is 2 µg/g. What screening interval would you recommend now?

Read the contents … · LangChain workflow



1 Structured feature extraction → 2 LangChain calls ML prediction model → 3 Risk score returned → 4 Natural-language explanation

Ans:

Based on your FIT decreasing from 5 → 2 µg/g, we suggest extending your screening interval to 6 years.

LLM for Personalized Precision Intervals

personal features feed the same workflow

I am a smoker with metabolic syndrome. My previous FIT was 5 µg/g, current is 15 µg/g. What interval would you recommend?

Read the contents … · LangChain workflow

Ans:

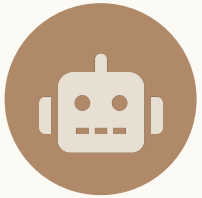
Based on your personal features and FIT rising from 5 → 15 µg/g, we suggest changing the interval **from 6-year to 2-year**.

LLM for Personalized Precision Intervals

the LLM absorbs text, imaging, and signals into the same prompt

Here are my clinic notes, my colonoscopy image, and my wearable activity data. Please update my screening plan.

Text | Imaging | Signals



1. Structured feature extraction
2. LangChain calls ML prediction model
3. Risk score returned
4. Natural-language explanation

Ans:

Combining your notes, imaging, and activity trend, we refine your risk and set a personalized 3-year interval — revised automatically as new data arrives.

Session III. Digital Twin AI for Precision Screening

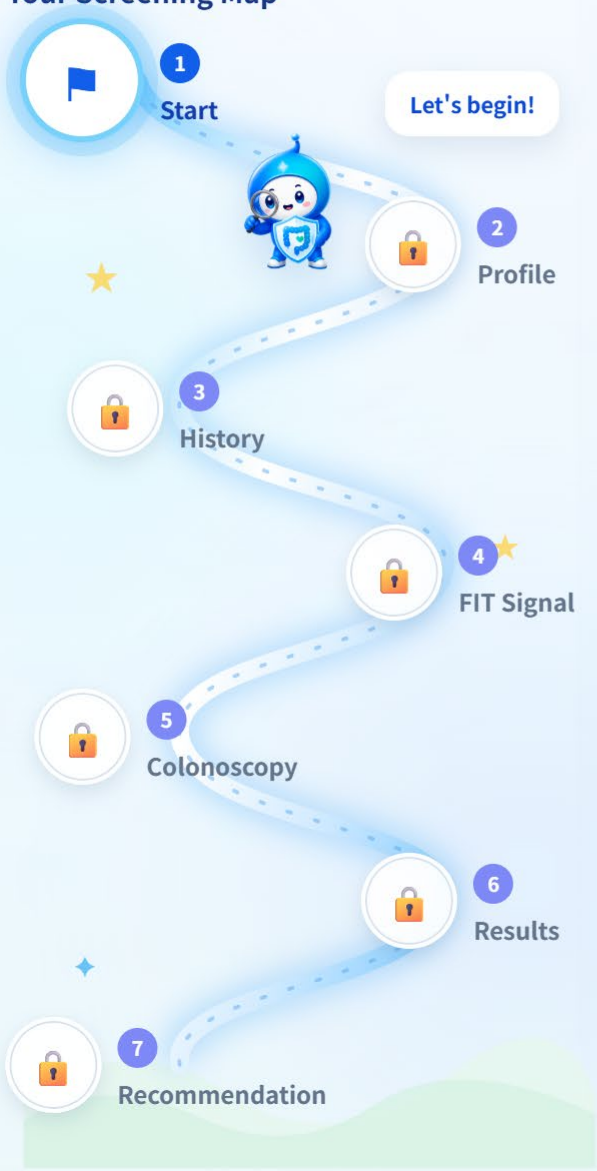
Digital Twin AI Demonstration for Precision Screening Applications

Risk-adaptive Screening Navigator ✦

Unlock your risk-adaptive, personalized screening journey

SCREENING JOURNEY

Your Screening Map



1 Start — Profile — History — FIT Signal — Colonoscopy — Results — Recommendation

I'm Aiden!

Follow me through a few simple questions to unlock your personalized screening journey!

PERSONALIZED SCREENING JOURNEY

Answer a few questions, find your next step

AI derives your personalized recommendation from your screening history and test values.

FIT Precision Screening
By f-Hb range

Risk-adaptive FIT Precision Screening
By f-Hb + Profile

Chat with AI directly

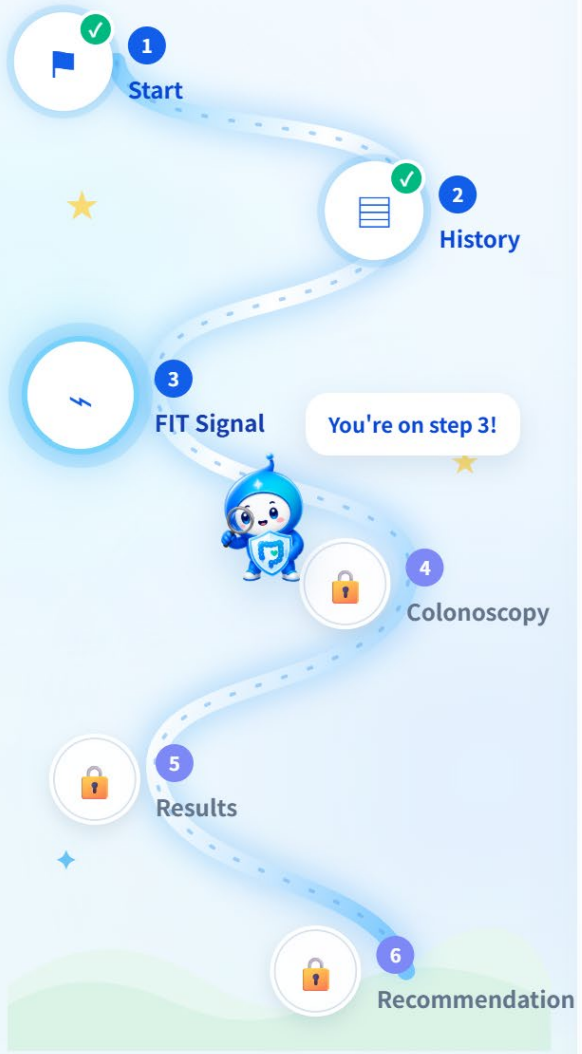
Alison Lin

Screening Navigator ✦

Personalized screening journey

SCREENING JOURNEY

Your Screening Map



Start — History — 3 FIT Signal — Colonoscopy — Results — Recommendation

I'm Aiden!

I'll use your FIT signal to help determine the next routing direction.

Step 3 • FIT Signal ✦

What was your most recent FIT result?

◇ Understanding your situation helps us give more precise advice

- ✓ **Negative** — Normal value, no referral ›
- ! **Positive** — Referred for colonoscopy ›
- # **I have a value to enter** ›

µg Hb/g | OC-Sensor | HM-Jack

f-Hb value input

8 µg Hb/g

Alison Lin

Session III. Digital Twin AI for Precision Screening

Thank you for your attention!