

Strategies for Improving Chronic Disease Care

Paul E. Johnson

Department of Information and Decision Sciences

Research Support



Medical Industry Leadership Institute



Collaborators

Patrick O'Connor, MD, MPH

JoAnn Sperl-Hillen, MD

William Rush, PhD

Heidi Ekstrom, MA

George Biltz, MD

Gedas Adomavicius, PhD

Jaideep Srivastava, PhD

Steve Parente, PhD

Todd Gilmer, PhD

Pradyumna (Autri) Dutta

Greg Ramsey

Ryan McCabe

Background

- **Past Work**
- **Knowledge for Practice**
 - **Intervention Research**
 - **Translational Research**
- **Knowledge for Science and Practice**
 - **Interdisciplinary Framework**
 - **Mode 2 Research** — Gibbons, et al (1994)

“It can be said with complete confidence that any scientist of any age who wants to make important discoveries must study important problems. Dull or piffling problems yield dull or piffling answers. It is not enough that a problem should be ‘interesting’– almost any problem is interesting if it is studied in sufficient depth. A problem must be such that it matters what the answer is– whether to science generally or to mankind.

**P.B. Medawar
Nobel Laureate in
Medicine and Physiology
1979**

The Problem

- **18.2 million people – 6.3% of the population – have diabetes.**
- **Diabetes is the 5th leading cause of death by disease.**
- **Direct medical and indirect expenditures attributable to diabetes in 2002 were estimated at \$132 billion.**

- American Diabetes Association

More Diabetes Facts

- **Approximately 65% of deaths among people with diabetes are due to heart disease and stroke.**
- **Diabetes is the leading cause of new cases of blindness among adults 20-74 years old.**
- **In most practice settings, only a minority of adults with diabetes have achieved evidence-based goals.**

- American Diabetes Association

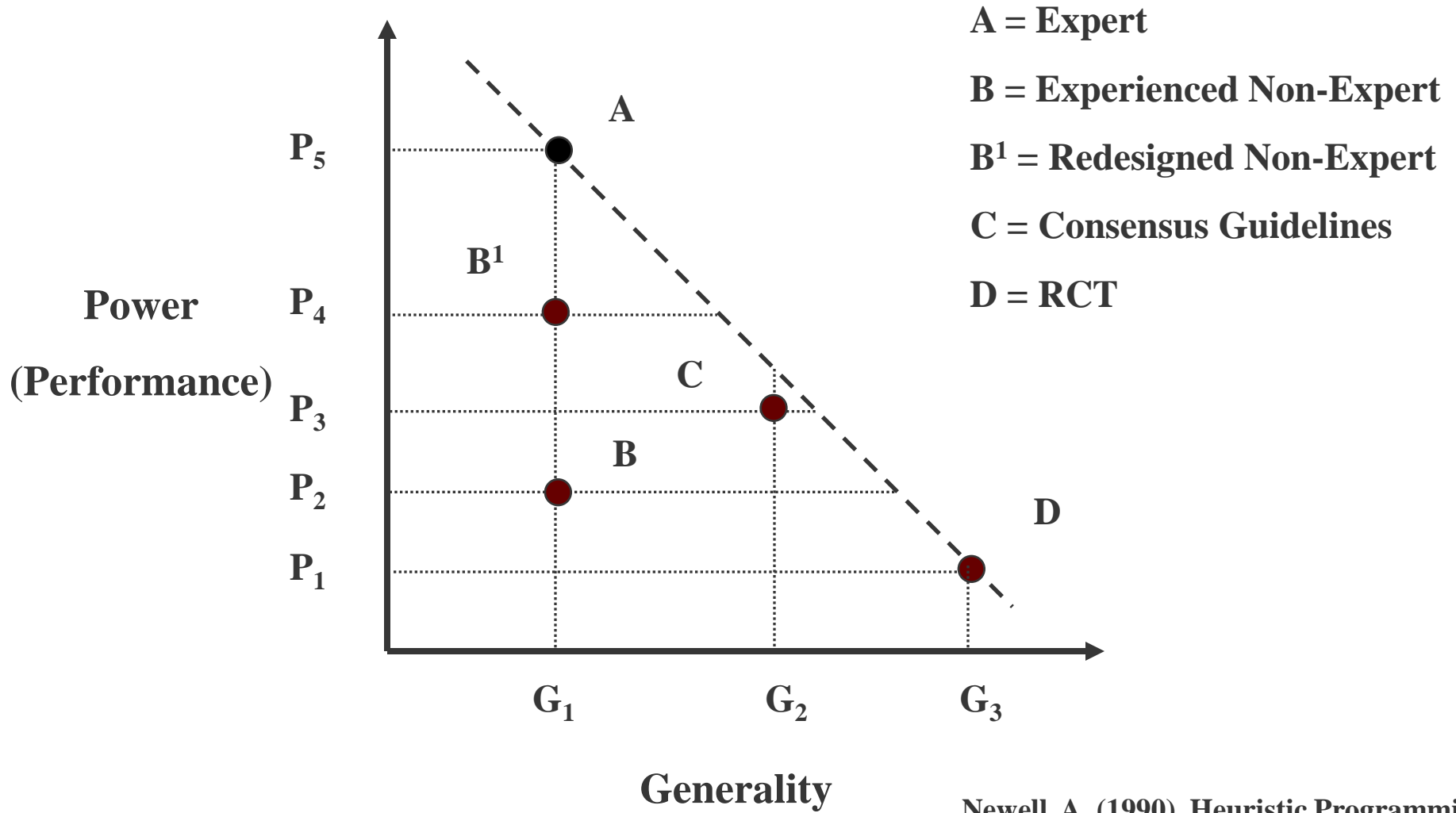
... the acute care paradigm is no longer adequate for a world, in which chronic illness is a major health challenge facing all countries. In the U.S. alone, the Centers for Disease Control and Prevention has recently estimated that chronic illness is responsible for 70 percent of all health-related deaths and 75 percent of all health care costs. The aging of the U.S. population and increases in risk factors such as obesity ensures that chronic illness will be an even greater problem in future years.

**Innovative Care for Chronic Conditions
World Health Organization, 2002**

Strategies for More Effective Diabetes Care

- **Question – Science / Practice**
- **Data – Lab / Field**
- **Simulation Tools**
- **Testing – Practice / Policy**

Issues for Theory and Practice



Newell, A. (1990). *Heuristic Programming: Ill Structured Problems*. *Progress in Operations Research*, vol. 3.

Role of Theory

- **Medicine – Understanding the Task**
- **Decision Science and Organization Theory – Decision Making and Policy Practices**
- **Cognitive Science – Explanation for Success and Failure / Methodology for Investigation**

The Task

- **Select evidence-based clinical goals**
- **Initiate therapy**
- **Titrate therapy to achieve goals**
- **Assess and manage co-morbid conditions**

Background of Empirical Work

- **Modify Physician Decisions Through Case Based Learning-(SimCare Project- AHRQ)**
- **Personalized Information for Physicians and Patients - (Project MOVES - NIH)**
- **Modify Physician Decisions Through Personalized Case Based Learning and Real Time Decision Support- (Clinical Inertia Project-NIH)**

Success and Failure in Chronic Disease Care

- **Limited Experience (Lack of Expertise)**
- **Delay of Feedback**
- **Cognitive Bias / “First Do No Harm”**
- **Clinical Inertia**
- **Nature’s Solution – A. Clark, 1998**

Knowledge in a Low Base-Rate World

- **Knowledge Production Problem**
- **Knowledge Transfer Problem**
- **Arbitrage: The Alternative Solution**

Information Arbitrage

- **“The Lexus and the Olive Tree”**
- Thomas Friedman
- **A Strategy of Knowledge Production**
- Gibbons et al
- **A Strategy for Usable/Actionable Knowledge**
- Lindbloom & Cohen

Arbitrage for the Personalization of Care

The Personalization of Care Problem

		Treatments		
		I	II	III
Patients	P ₁	c	a	b
	P ₂	c	c	c
	P ₃	c	b	c
	P ₄	a	a	b
	P ₅	b	b	b

Outcomes: a=optimal
 b=moderate
 c=weak

Ashby's Law of Requisite Variety*

Treatments

		I	II	III
Patient Types	A	b	a	C
	B	a	c	b
	C	c	b	a

Outcomes: a=optimal
b=moderate
c=weak

W.R. Ashby, (1956). Introduction to Cybernetics.

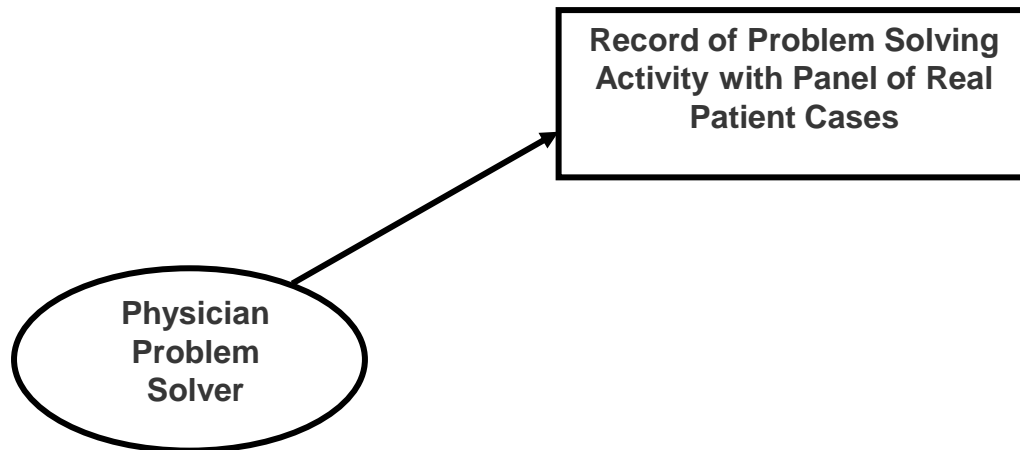
Some Example Patient Types (categories) for Type II Diabetes

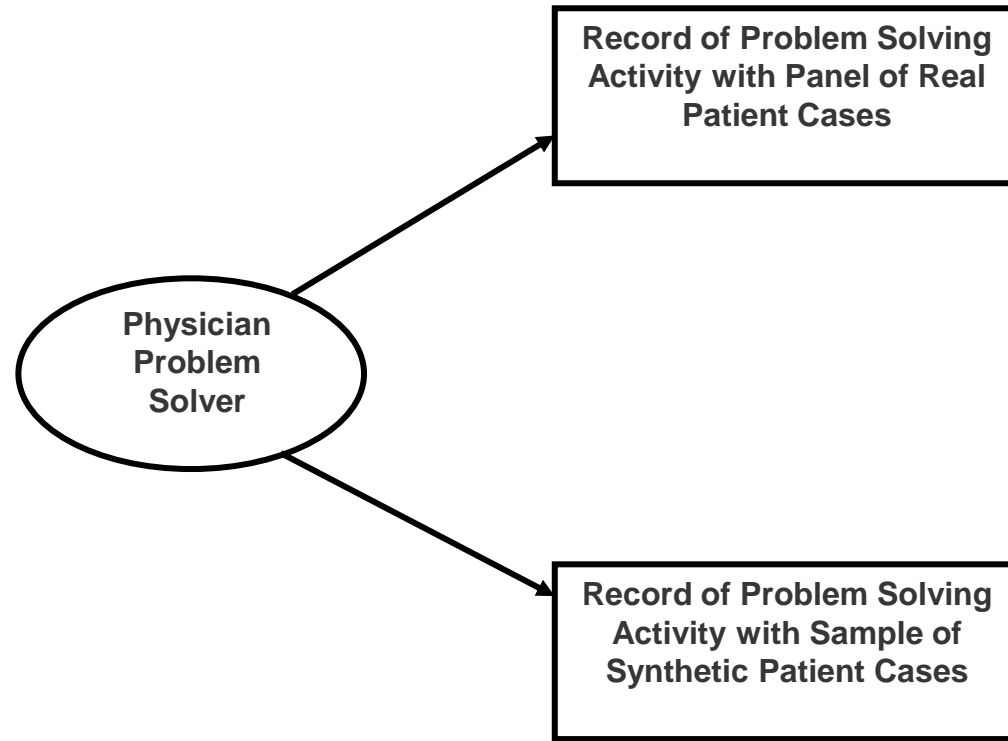
“Don’t Worry Be Happy”

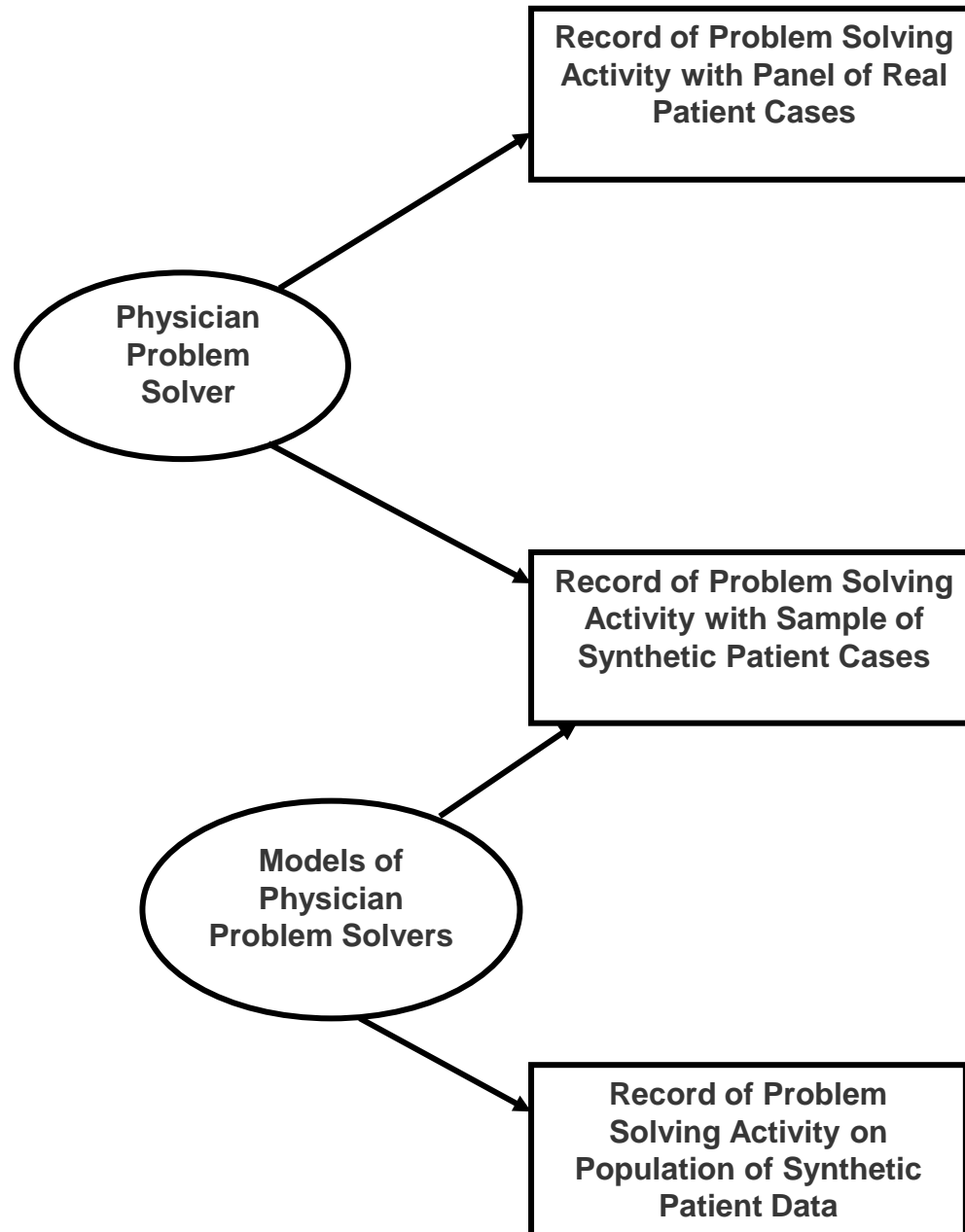
“Walking Time Bomb”

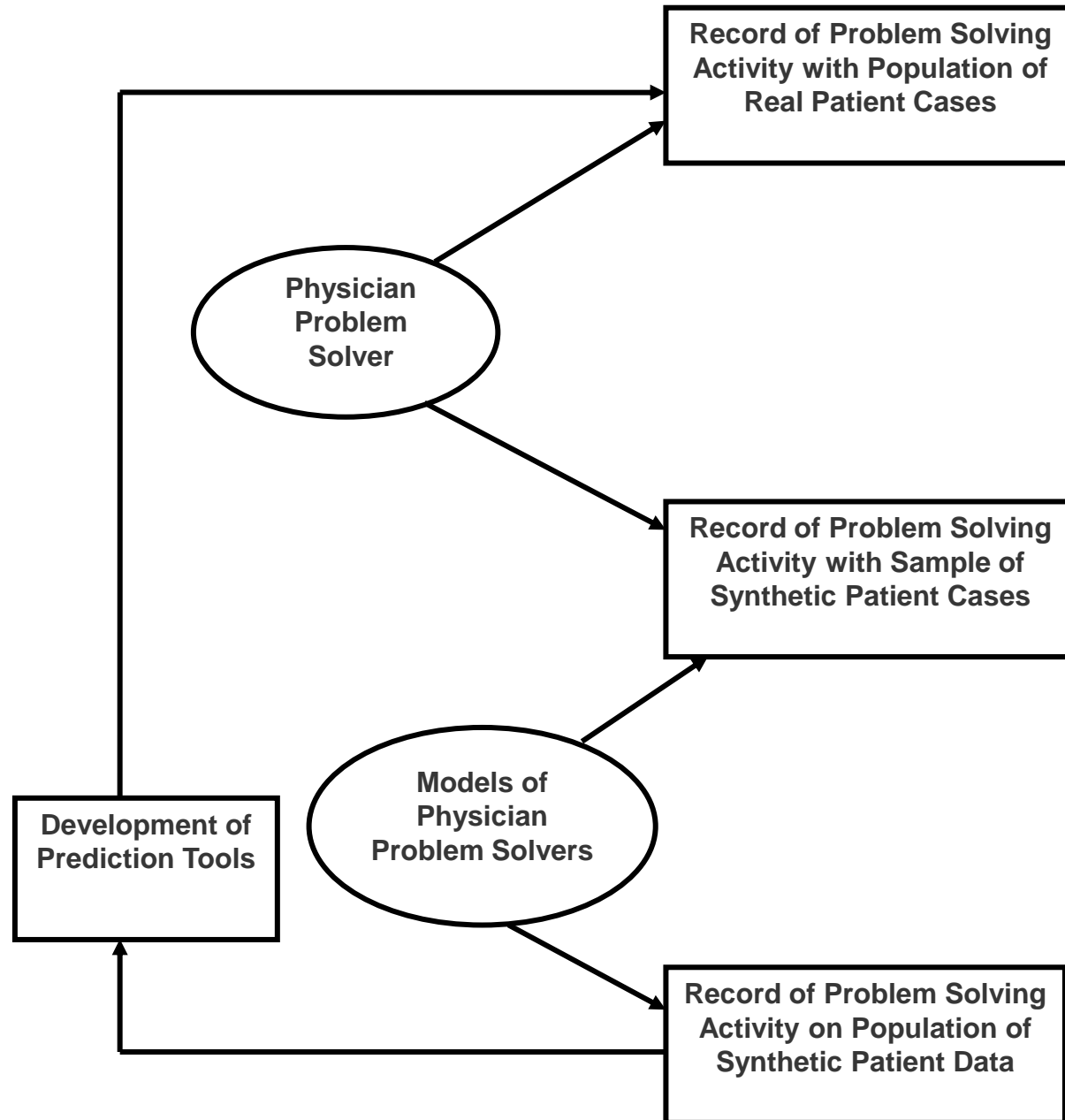
“Train Wreck”

Decision Policies for a Low Base-Rate World



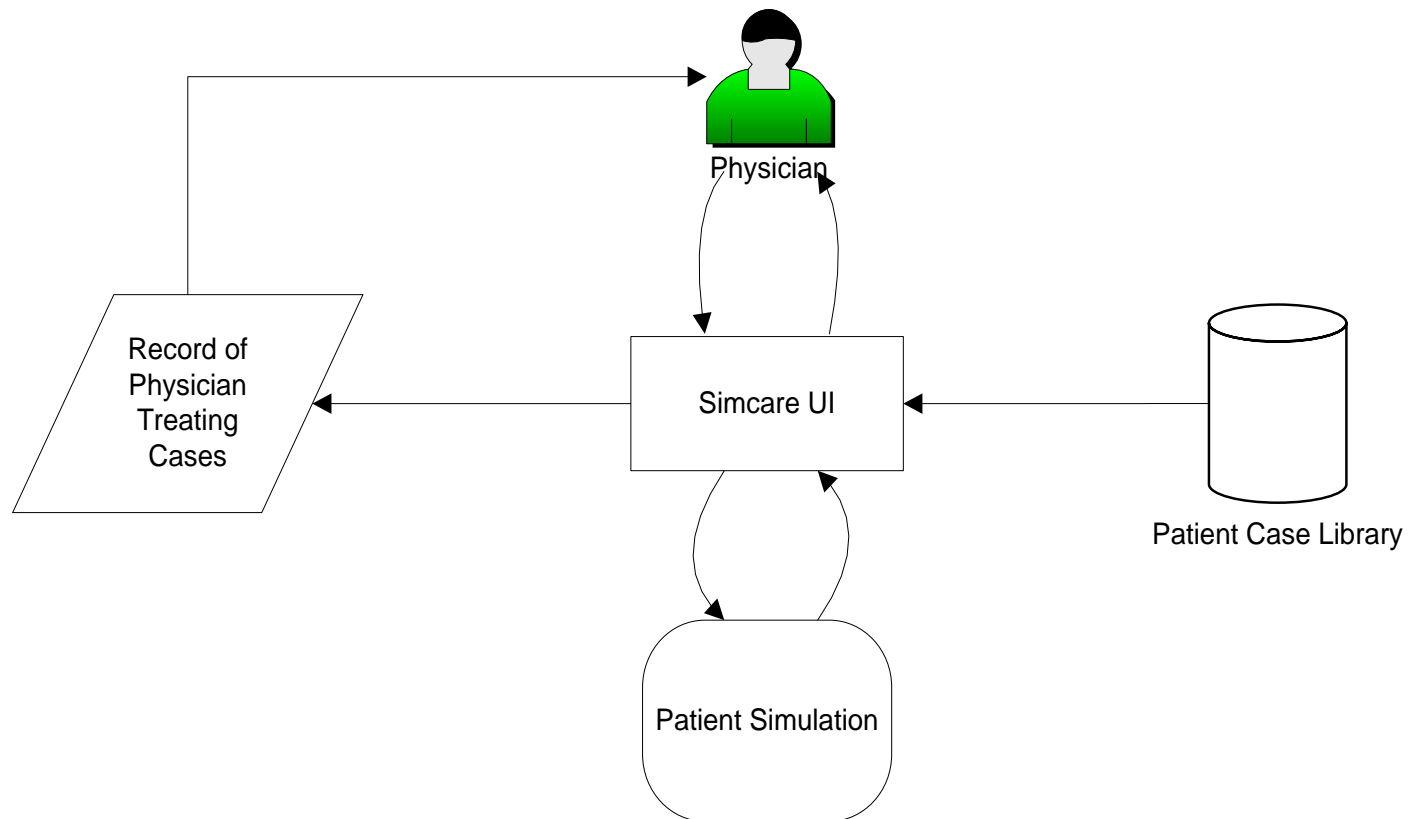




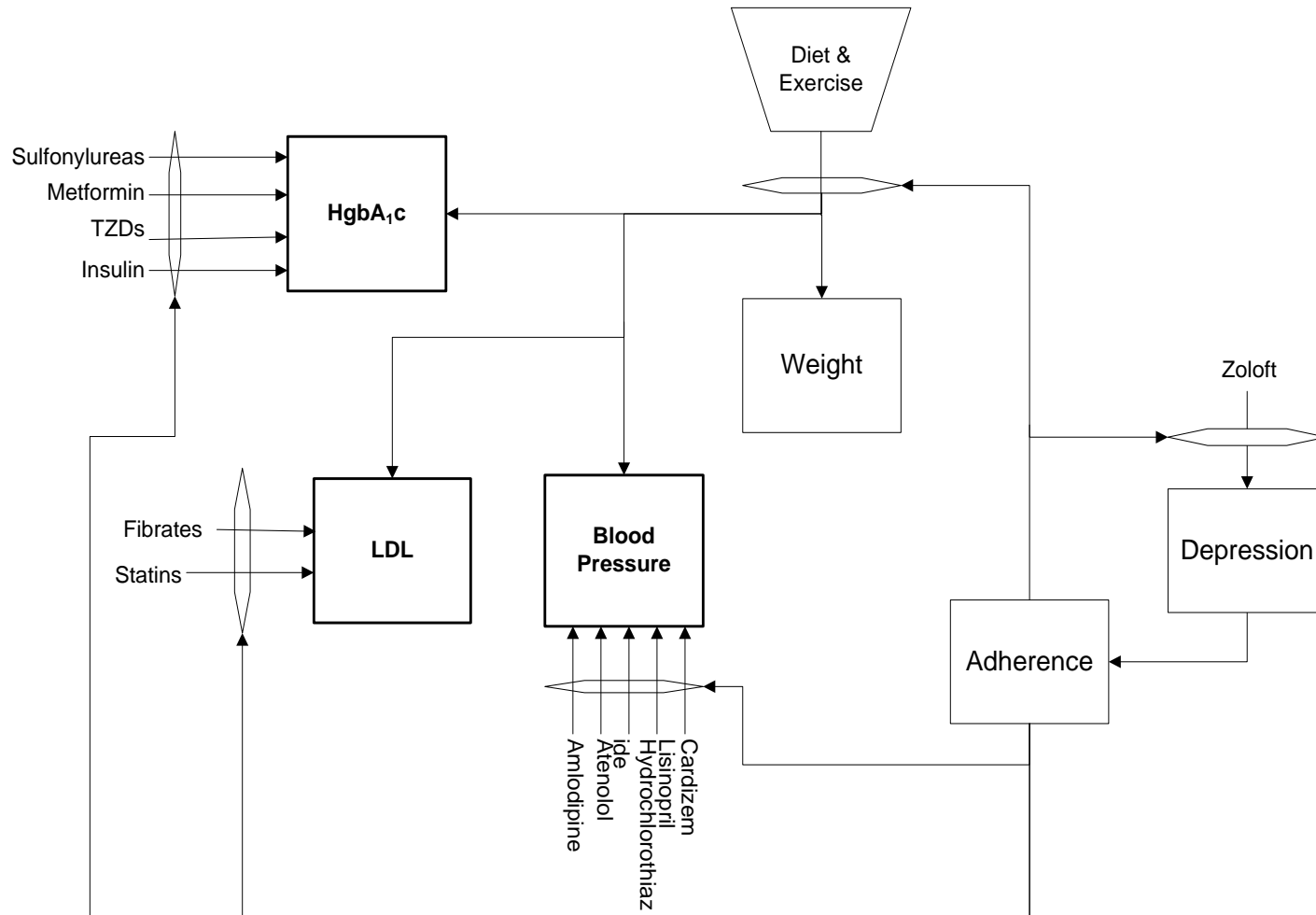


Patient Model

- SimCare Patient Simulation -

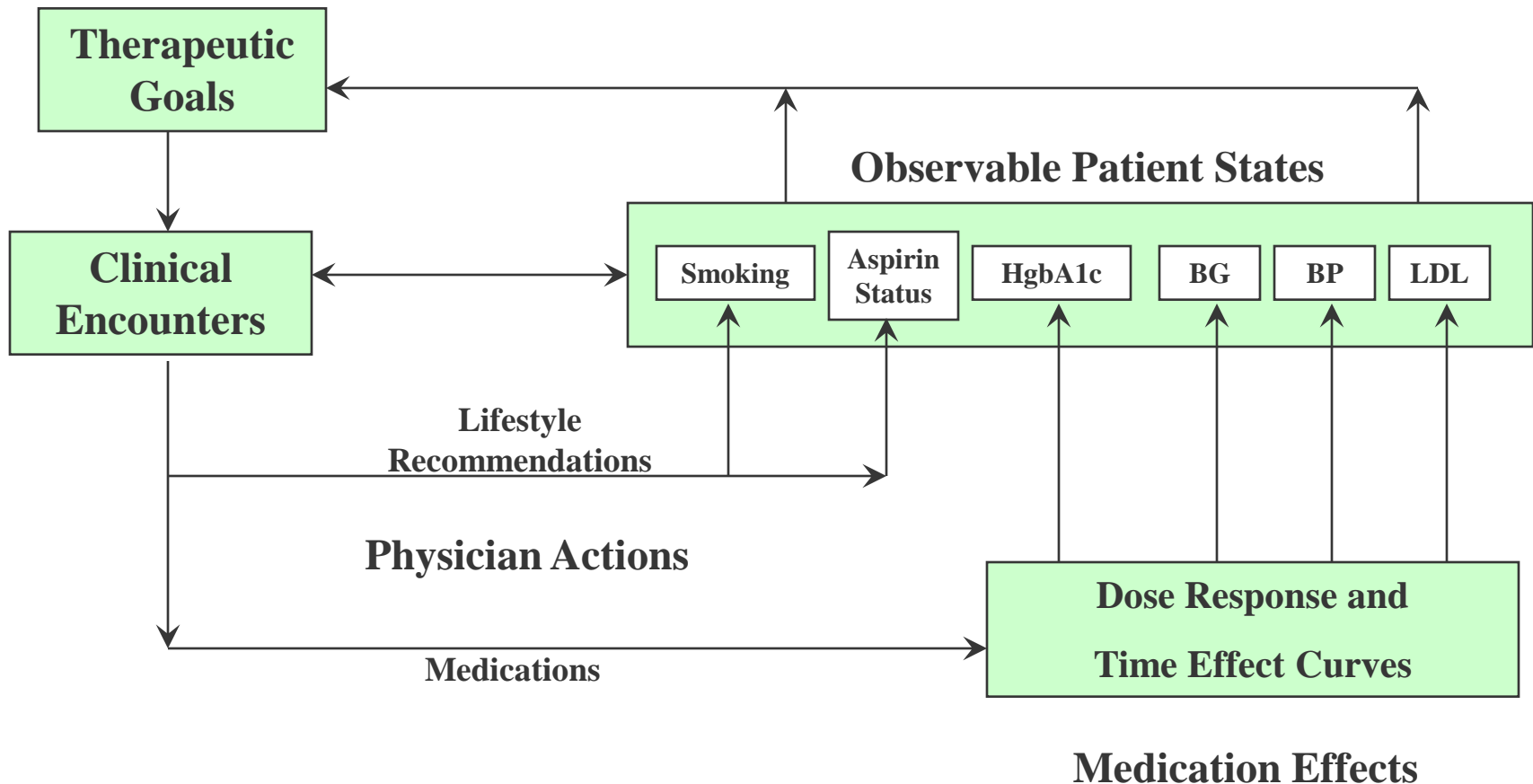


SimCare's Core Functions



From Dutta, et. al., 2004, SimCare: A Simulation Model to Investigate Physician Decision-Making in the Care of Patients with Type 2 Diabetes, in *Advances in Patient Safety: From Research to Implementation*, K. Henriksen, Battles, J.B. & Lewin, D., Editors. 2004, AHRQ Patient Safety Research Coordinating Center: Rockville, MD. (In Press)

Current SimCare/Clinical Inertia in DM Care Model - Functional Overview



The SimCare Study

40 Physicians

3 Simulated Patients

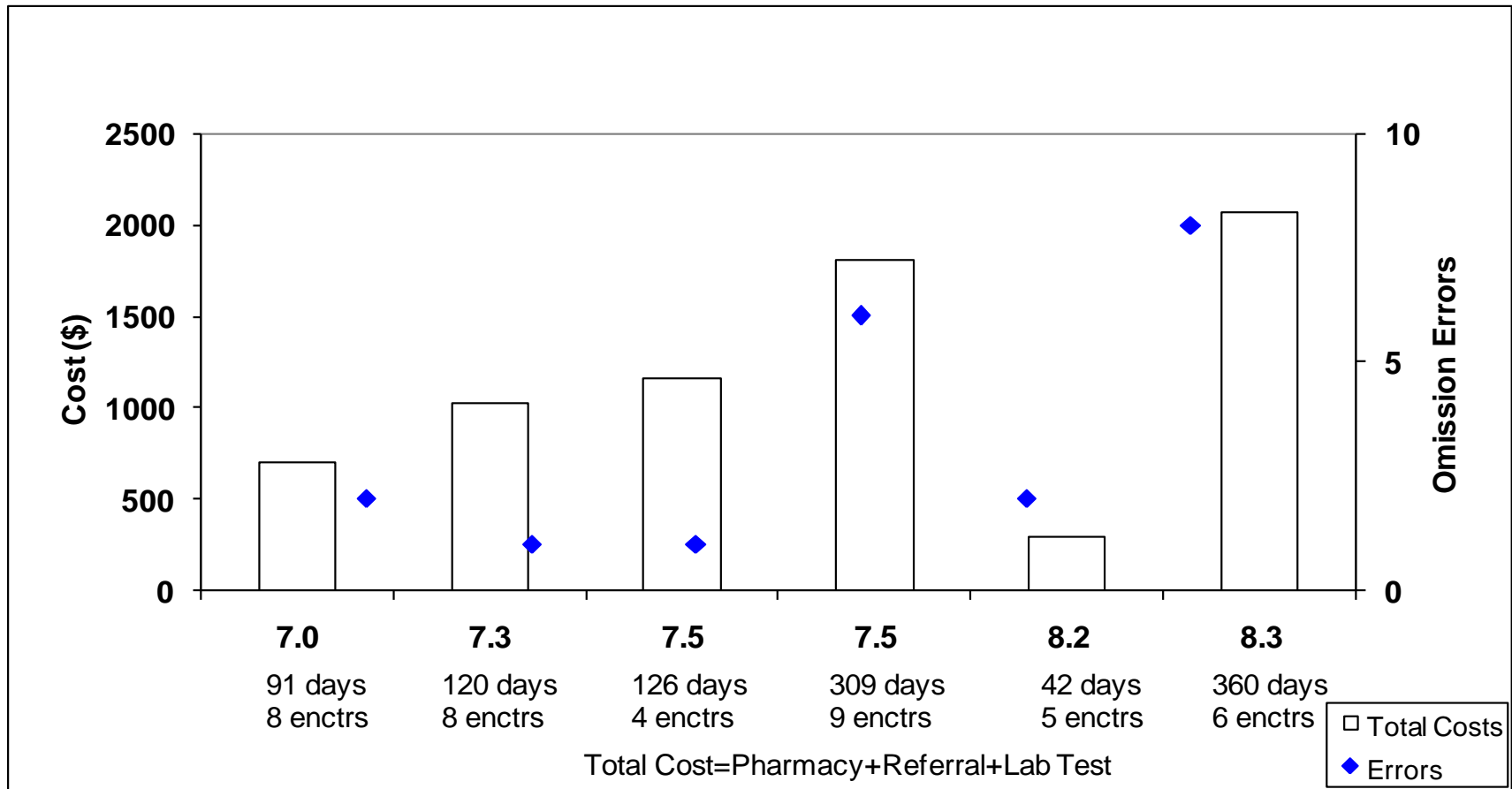
SimCare Patient Cases

- **Case 1: Initiate & titrate oral medications to reach evidence-based goals**
- **Case 2: Detect & treat depression, stop contraindicated metformin, adjust insulin once depression is treated**
- **Case 3: Recognize that metformin & glipizide are contraindicated, initiate & titrate insulin to reach evidence-based goal**

Errors in the Treatment of Chronic Disease

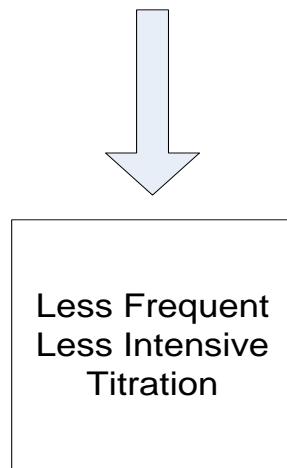
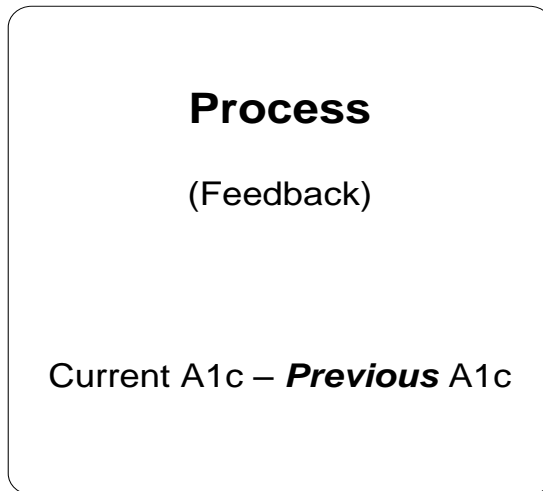
- **Omission**
 - Failure to collect information**
 - Failure to start medication**
 - Failure to titrate to goal**
- **Commission**
 - Contra indications**

Health Outcome (A1c) vs. Cost vs. Frequency of Errors (Total) for Selected Physicians on Synthetic Patient 15 (Case 1)

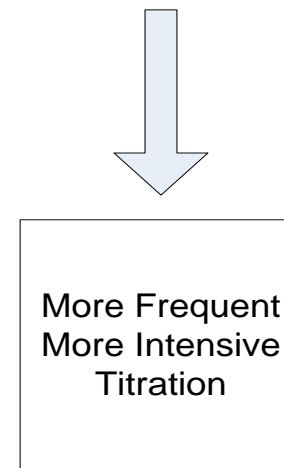
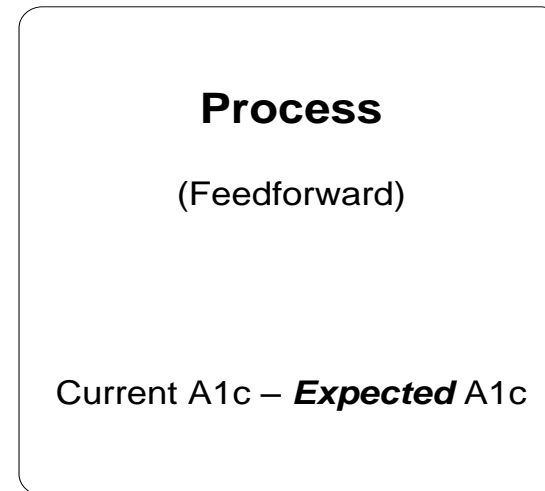


Physician Decision Making Methods

Non-Expert Physician



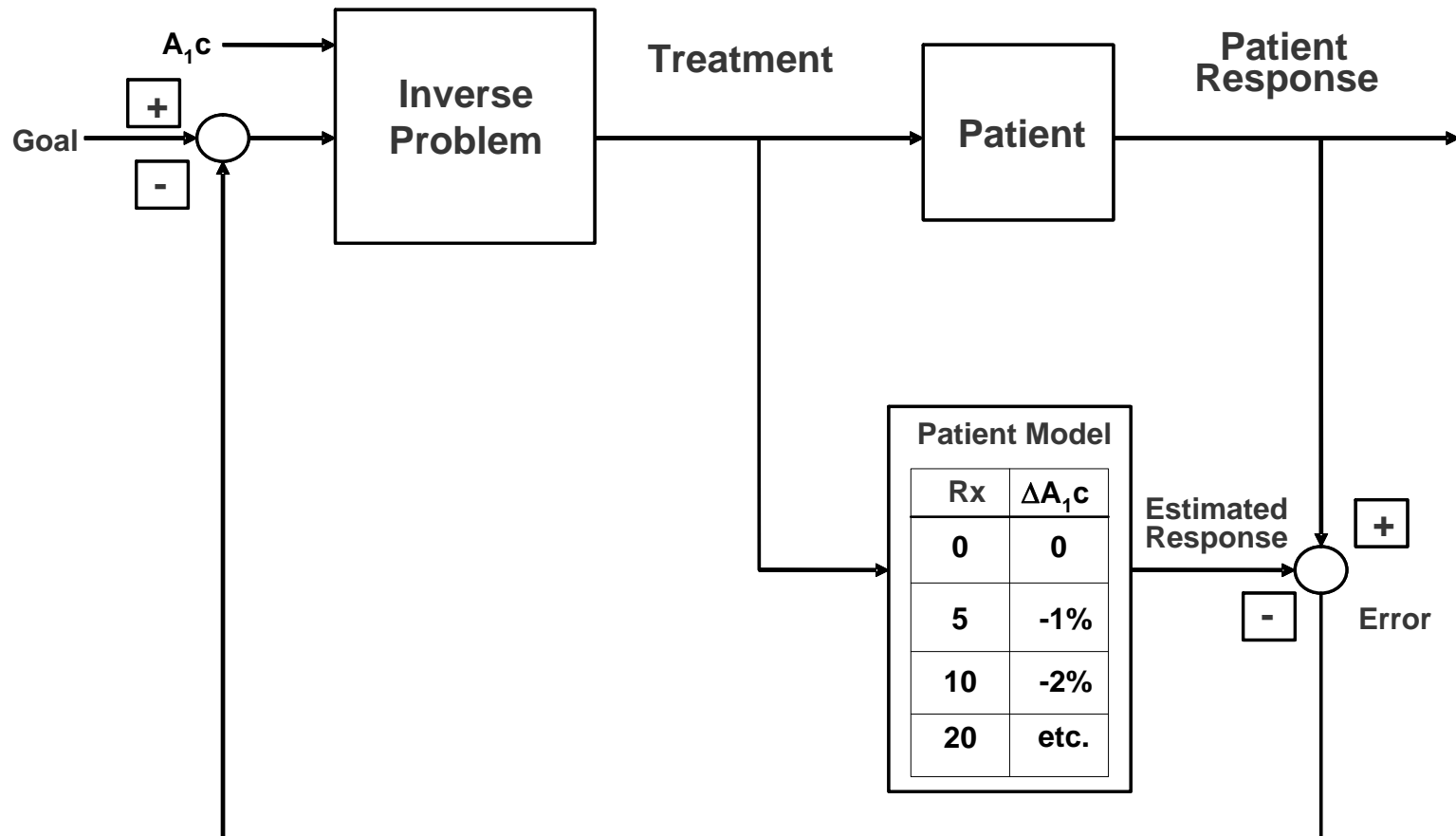
Expert Physician



Decision Making as Process Control

- **Series of Decisions**
- **Decisions are Interdependent**
- **The environment changes, both autonomously and as a consequence of previous decisions**

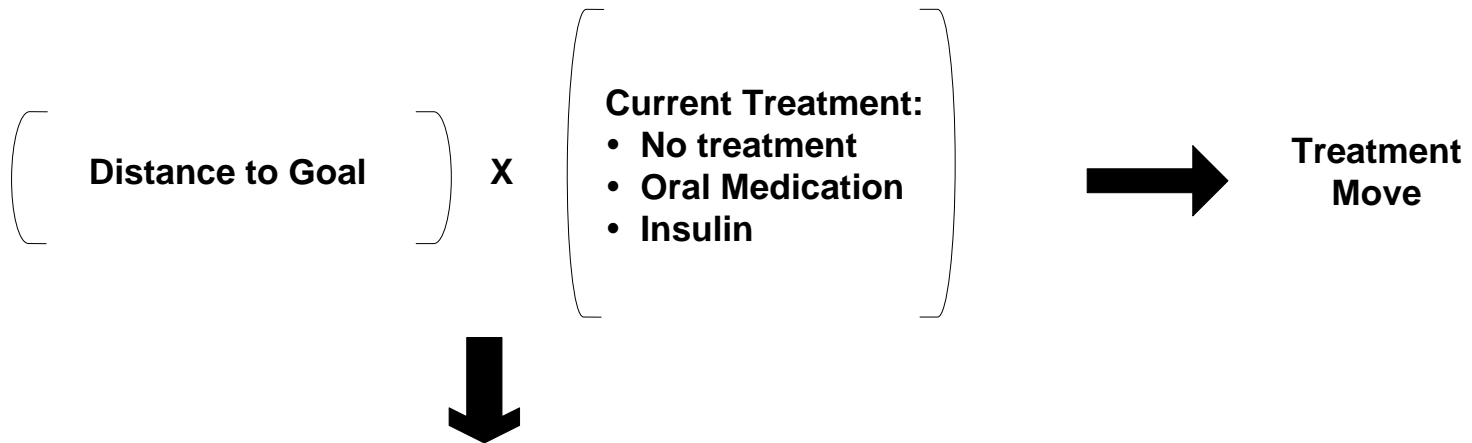
Process Control for Type 2 Diabetes



Solving the Inverse Problem

- **Reasoning From Effects to Causes**
- **The Default Strategy**
- **What the Expert Does**

Expert's Solution: Solving the Inverse Problem



Treatment needed to get the desired effect

Distance to Goal	Current Medications	Treatment Move
3	No treatment	Start 2 oral medications
3	Oral med	Increase dose, introduce 2 nd oral medication
3	Oral - max dose	Start Insulin, adjust quickly

Explaining Success

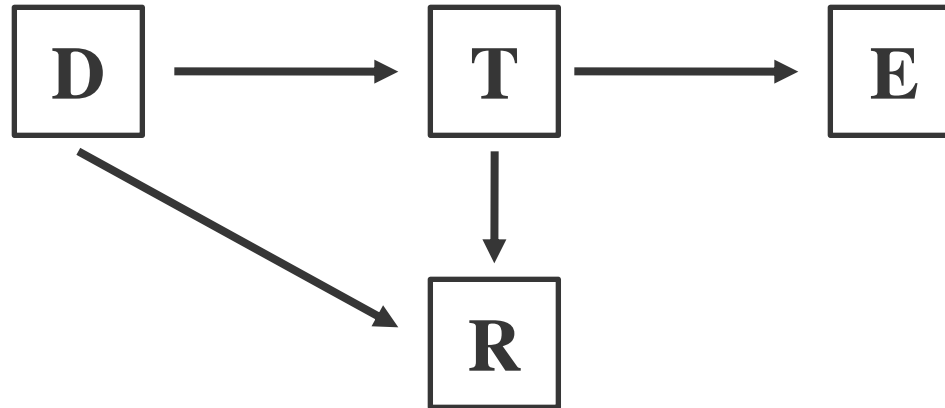
- **Process Control**
- **The Patient Model**
- **Solving the Inverse Problem**

Explaining Failure

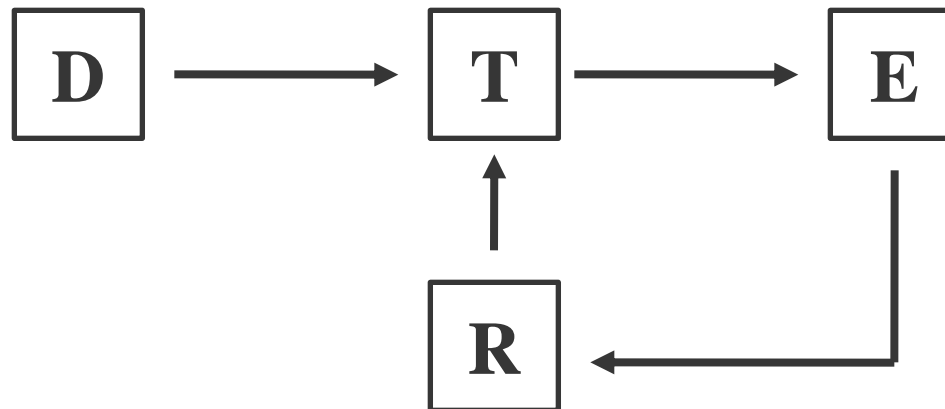
- **Slips and Mistakes**
- **Lack of Knowledge**
- **Inert Knowledge**
- **Mind Bugs**

Decision Making as Process Control

Feed Forward



Feedback



W.R. Ashby (1956). Introduction to Cybernetics

Feedback Strategy (Anchoring & Adjustment)

- **Determine Anchor (Goal or Desired Decrease in A1c)**
- **Determine Distance to Goal**
- **Select Move (Medication & Dose)**
- **Compare Observed A1c with Anchor**
- **Iterate to Goal**

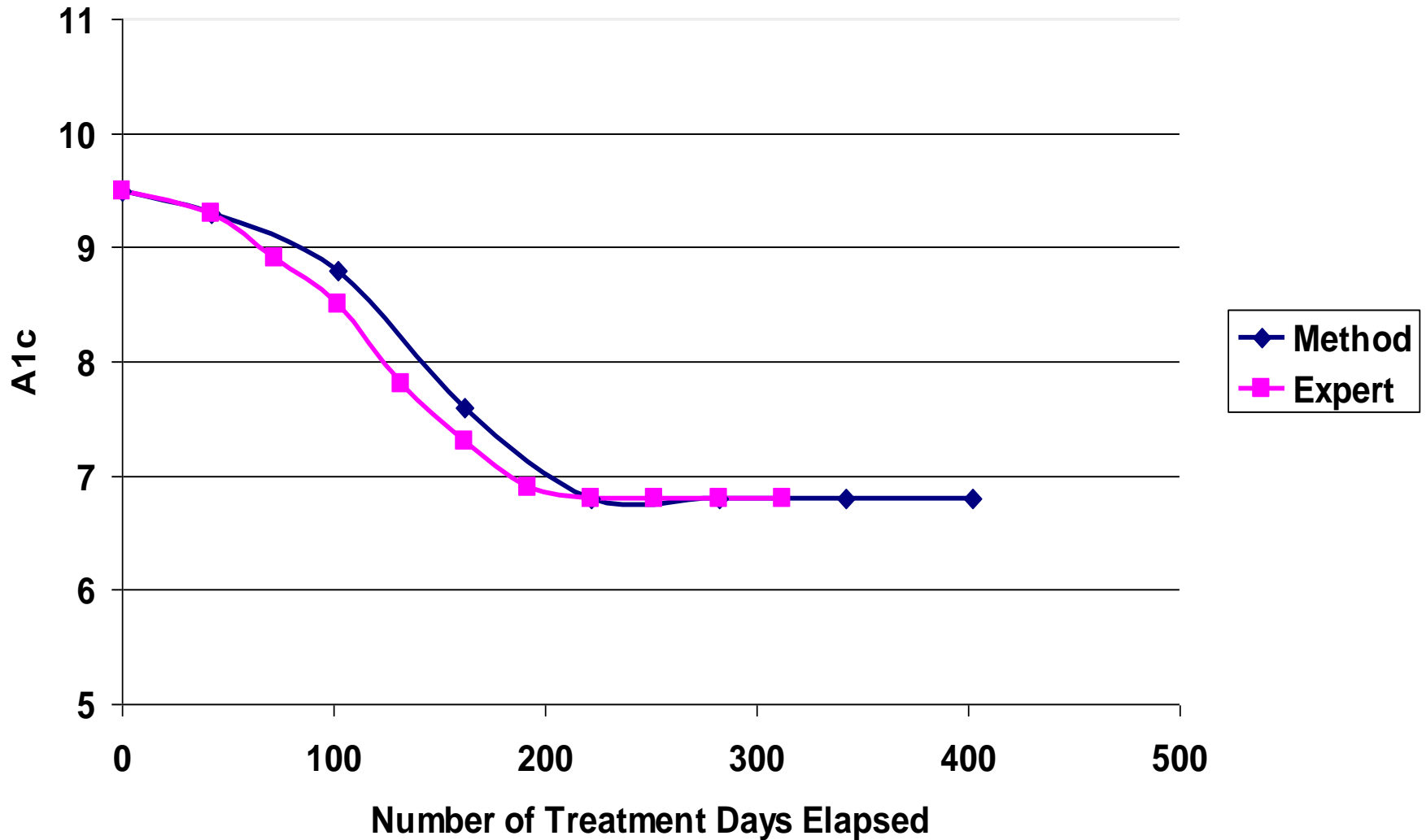
Feed Forward Strategy

- **Determine Distance and Time to Achieve Goal**
- **Determine Rate of Change (Slope) Needed to Achieve Goal**
- **Select Move (Medication & Dose)**
- **Compare Observed & Expected A1c**
- **Iterate to Goal**

Expert's Strategy

- **Determine Distance & Time to Achieve Goal**
- **Determine Rate of Change (Slope) Needed to Achieve Goal**
- **Select Move (Medication & Dose)**
- **Compare Observed & Expected A1c**
- **Determine Adjustments in Slope Needed to Achieve Goal**
- **Iterate to Goal**

Comparison of Expert and Expert's Method on Synthetic Patient 15



Performance of Physician Models on 13 Synthetic Patients

<i>Patient Characteristics (A1c)</i>	<i>Feedback</i>			<i>Feedforward</i>		
	<i>Physician</i>			<i>Physician</i>		
	4011	4018	5008	5005	4023	Expert
$7 < A1c < 12$ (13 total)	3	3	5	10	12	13
$A1c > 9$ (6 total)	2	0	0	3	5	6
$A1c \leq 9$ (7 total)	1	3	5	7	7	7

Effect of Physician Treatment Strategies on Populations of Simulated Patients

Target Population of Simulated Patients

(Number of Patients Per Cell Reflects Distribution in Real Patient Population)

Initial A1c	Adherence		Total
	High	Low	
$A1c \geq 10\%$	458	153	611
$8 \leq A1c < 10\%$	1394	284	1678
$A1c < 8\%$	6687	1024	7711
Total	8539	1461	10000

Treatment Strategies for Effective Diabetes Care



Decision Rules

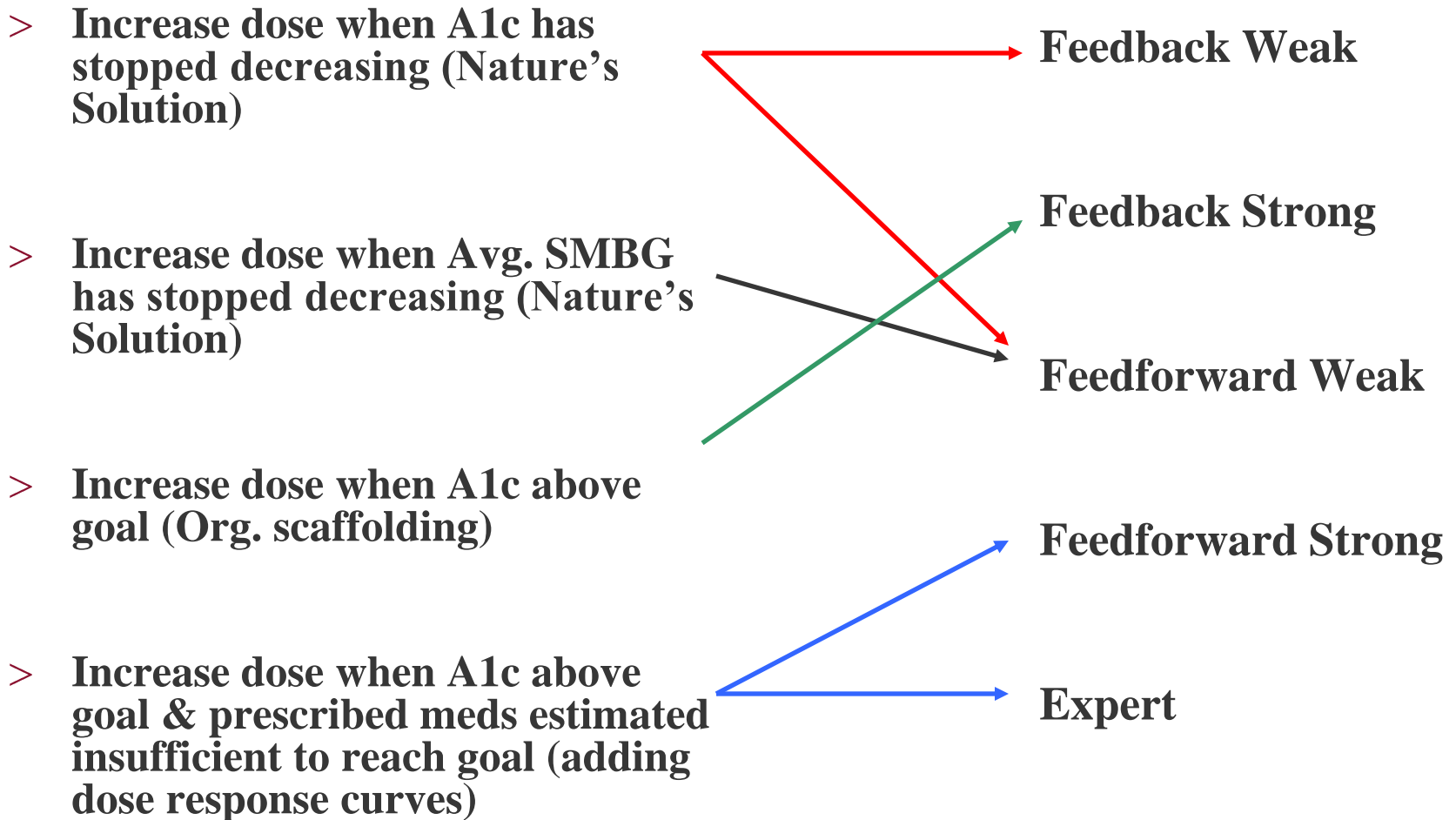
(Far From Goal)

- > **Monitor A1c level:** increase meds when patient not at goal and A1c not decreasing → **Feedback Weak**
 - > **Monitor A1c level:** increase meds when patient not at goal → **Feedback Strong**
 - > **Monitor Rate of Change (slope)** in A1c level: increase meds and/or reduce time between visits to maintain minimum rate of reduction in A1c (e.g., 0.5% per month*) → **Feedforward Weak**
 - > **Monitor Change in Slope:** increase meds and/or reduce time between visits to maintain minimum rate of reduction in A1c to meet time goal (e.g., 1 yr.) → **Feedforward Strong**
 - > **Monitor Change in Slope:** increase meds and/or reduce time between visits to maintain minimum rate of reduction in A1c to meet time goal (e.g., 1 yr.) → **Expert**
-

*compute as monthly decrease in A1c required to reach goal within a specified period of time, e.g., 1 yr.

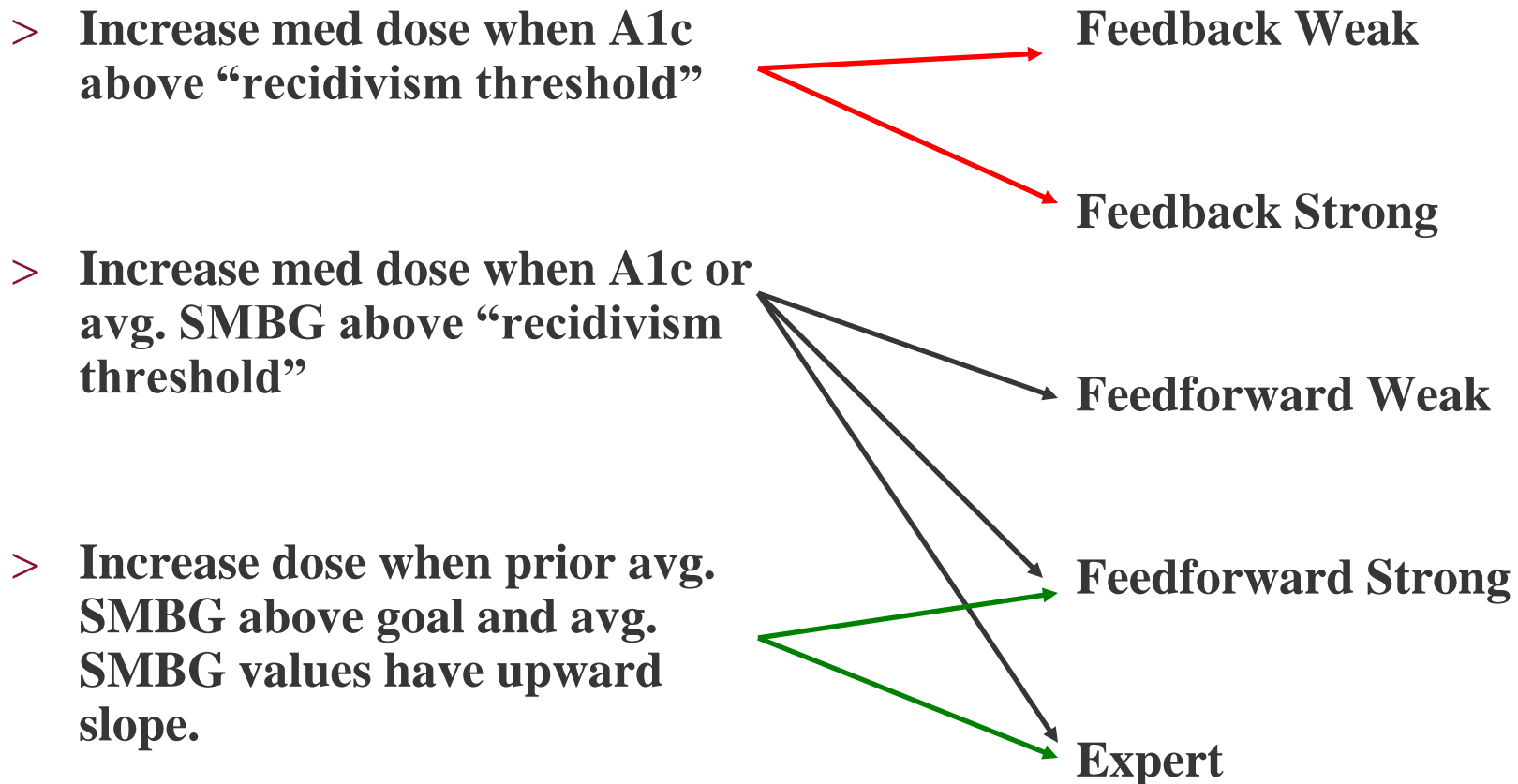
Decision Rules

(Near Goal A1c = 7.5)



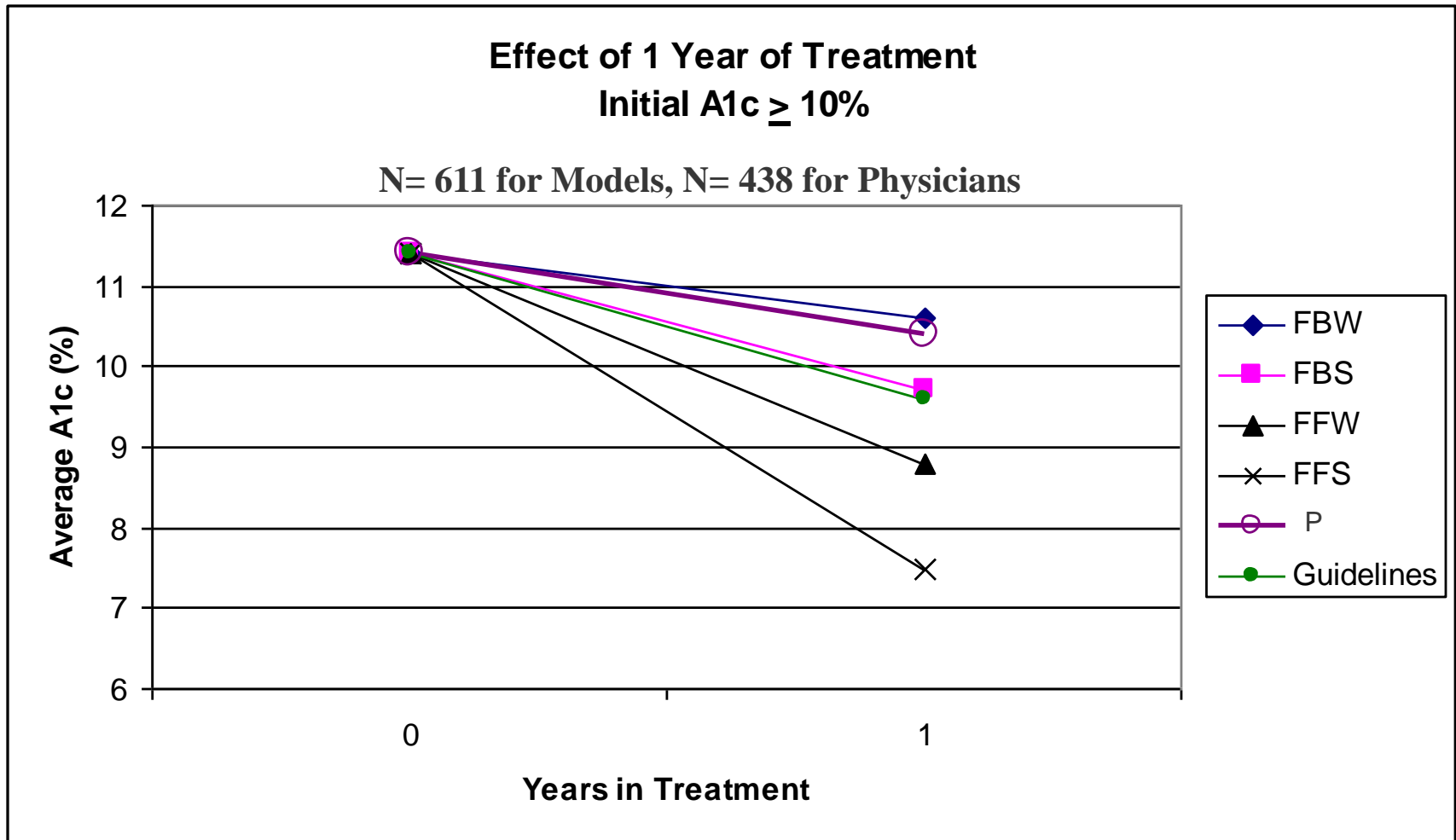
Decision Rules

(Maintaining Goal)



A1c Recidivism threshold = 7.5%
SMBG Recidivism threshold = 165 mg/dL

Effect of 1 Year of Treatment by Models, Physicians and Clinical Guidelines

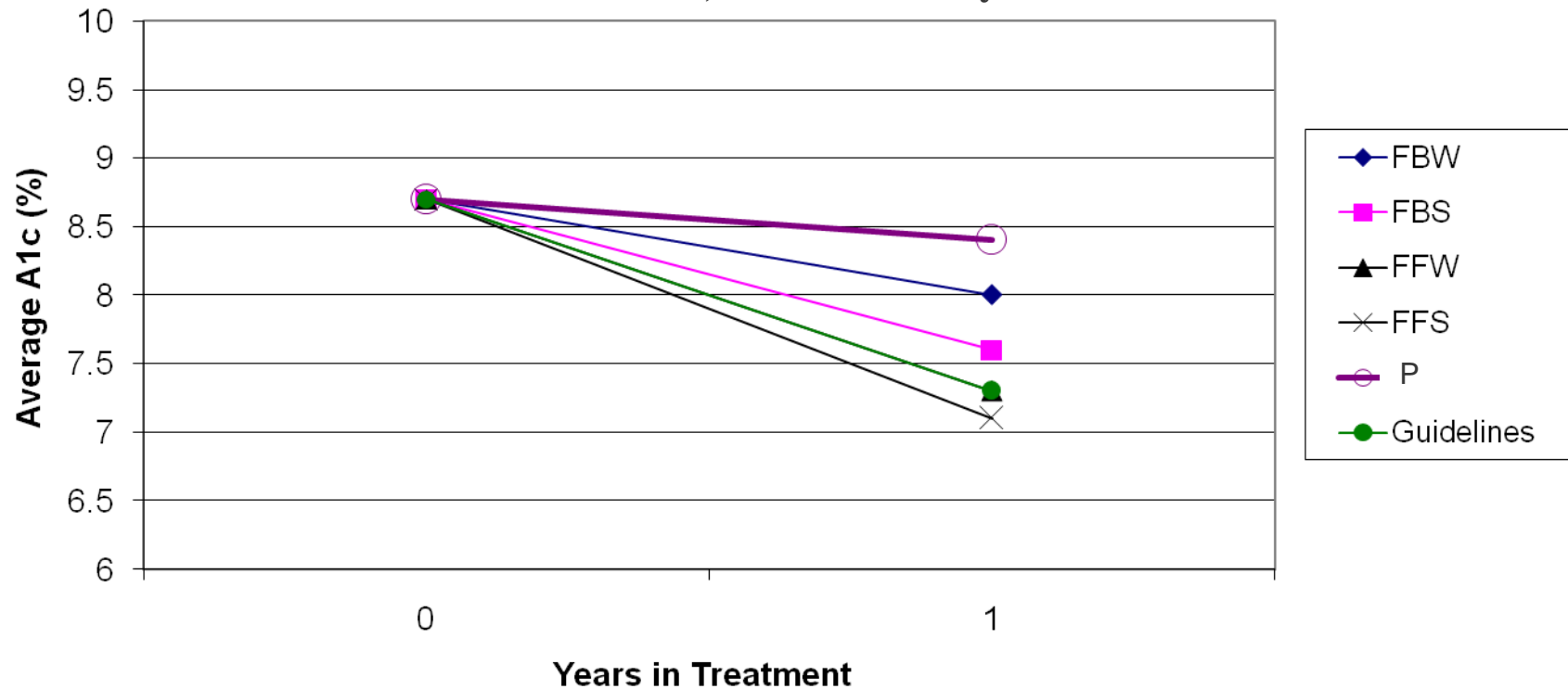


* Staged Diabetes Mgmt (SDM) Guidelines, 2005.

Effect of 1 Year of Treatment by Models, Physicians and Clinical Guidelines

Effect of 1 Year of Treatment
Initial A1c between 8% and 10%

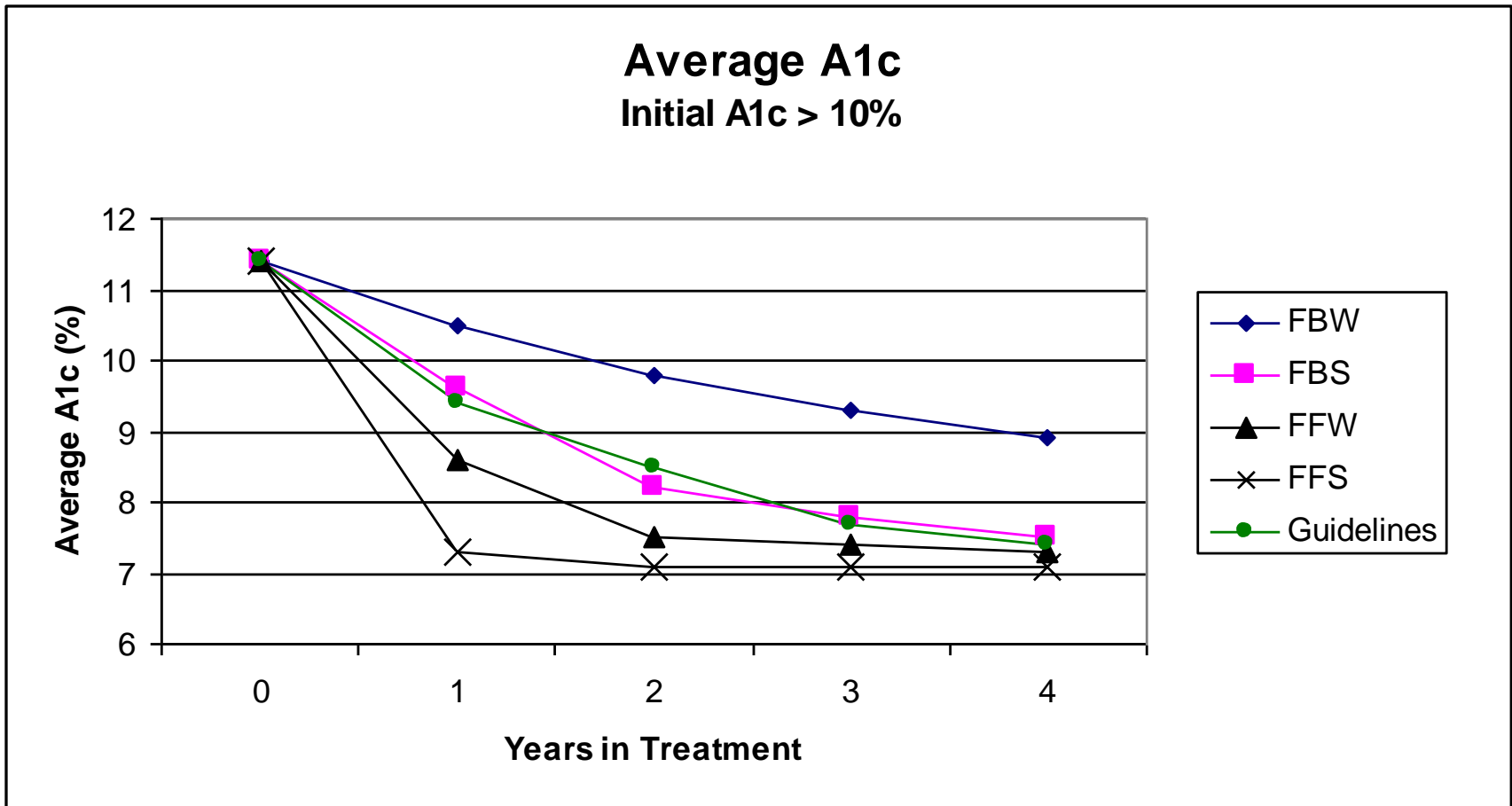
N= 1687 for Models, N= 1207 for Physicians



Effect of Treatment Strategies over Time

N= 611

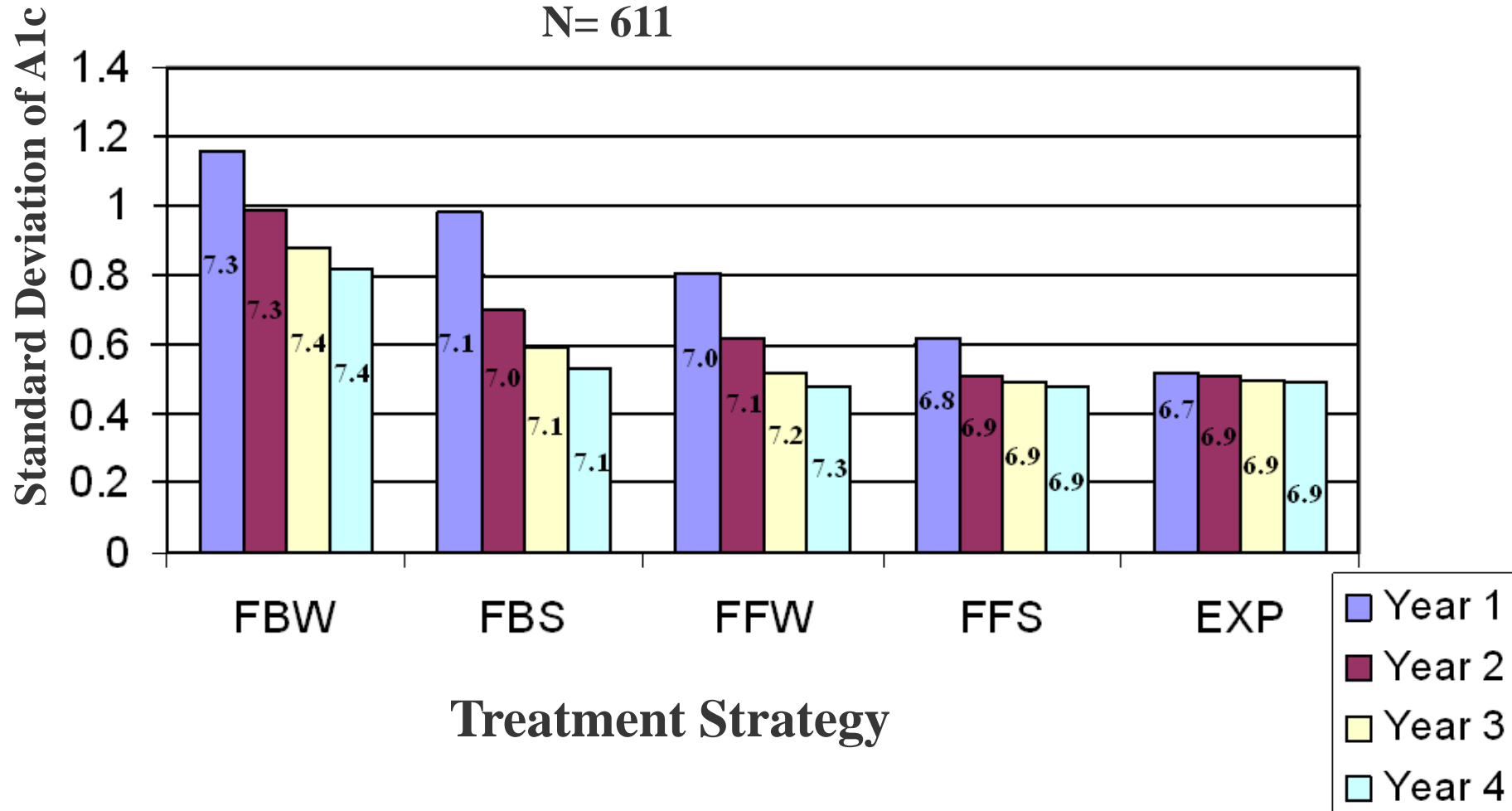
Average A1c
Initial A1c > 10%



Treatment Strategies and Variation in Patient State

(Initial A1c Values $\geq 10\%$)
(Average A1c Value in Bars)

N= 611



Cost to Bring Patients to A1c Goal - Year 1

Strategy	Pt Type (# Pts)	% of Pts at Goal	\$ PMPM
FBW	LH (6687)	88	186
FBS		95	179
FFW		100	180
FFS		100	191
EXP		100	192
FBW	MH (1394)	11	2822
FBS		43	831
FFW		76	509
FFS		94	504
EXP		98	502
FBW	HH (458)		
FBS		3	14660
FFW		15	3094
FFS		65	1014
EXP		93	821

PMPM =
Per Member
Per Month

Cost to Bring Patients to A1c Goal - Year 2

Strategy	Pt Type (# Pts)	% of Pts @ Goal	\$ PMPM
FBW	LH (6687)	95	712
FBS		100	542
FFW		100	718
FFS		100	548
EXP		100	553
FBW	MH (1394)	41	3958
FBS		84	2230
FFW		95	3492
FFS		100	2355
EXP		100	2206
FBW	HH (458)	2	33146
FBS		30	5234
FFW		67	3216
FFS		95	2877
EXP		99	2960

PMPM =
Per Member
Per Month

Cost to Reduce A1c by 0.5% - Year 1

Strategy	Pt Type (# Pts)	% of Pts with 0.5% Change	\$ PMPM
FBW	LH (6687)	6	2807
FBS		10	1745
FFW		13	1410
FFS		16	1160
EXP		17	1140
FBW	MH (1394)	63	503
FBS		86	419
FFW		96	407
FFS		96	494
EXP		97	507
FBW	HH (458)	74	466
FBS		91	458
FFW		98	474
FFS		100	663
EXP		100	767

PMPM =
Per Member
Per Month

Cost to Reduce A1c by 0.5% - Year 2

Strategy	Pt Type (#Pts)	% of Pts with 0.5% Change	\$ PMPM
FBW	LH (6687)	2	13184
FBS		3	12266
FFW		2	17217
FFS		9	3803
EXP		9	4147
FBW	MH (1394)	42	1558
FBS		36	2014
FFW		12	6492
FFS		10	8689
EXP		8	10936
FBW	HH (458)	67	1073
FBS		83	1146
FFW		70	1528
FFS		28	4863
EXP		8	18827

PMPM =
Per Member
Per Month

Personalization: Exploiting Variety

- **Use predictive models to match patients and physicians**
- **Types of predictive models**
 - **Statistical (e.g., UKPDS risk engine)**
 - **Machine Learning (e.g., decision tree)**

Experiment: Switch Patients to Low Cost FBW Strategy for Maintenance

- **Treat patients $A1c > 10\%$ and $A1c < 8\%$ with FBS, FFW, FFS, Expert strategies for 1 year**
- **For all patients that reached goal at end of 1 year:**
 - **maintain by using existing strategies**
 - **maintain by switching to FBW strategy**

Experiment: Number of Patients at Goal by Year 1

Strategy	Pt Type (# pts)	Pt Count
FBS	LH (6687)	6344
FFW		6666
FFS		6682
EXP		6686
FBS	HH (458)	13
FFW		69
FFS		299
EXP		428

Experiment: Cost to Treat Year 2

Strategy	Pt Type (# pts)	Avg Monthly Cost to Maintain Tracked Pts	
		Maintained by Initiating Strategy (\$)	Maintained by FBW Strategy (\$)
FBS	LH (6687)	312	301
FFW		331	325
FFS		354	339
EXP		355	340
FBS	HH (458)	1083	1078
FFW		1097	1095
FFS		1234	1232
EXP		1443	1448

Cost Savings Associated with Switching Treatment Strategies in Year 2

Initial Strategy (# pts at goal)	Pt Type (# pts)	Cost* Savings per Year (\$) when switched to FBW Strategy
FBS (6344)	LH (6687)	837,408
FFW (6666)		479,952
FFS (6682)		1,202,760
EXP (6686)		1,203,480
FBS (13)	HH (458)	780
FFW (69)		1,656
FFS (299)		7,176
EXP (428)		(25,680)

*Cost = Cost of year 2 treatment for tracked patients minus cost of year 2 treatments for those same pts when tested in year 2 with FBW strategy.

The Problem of Risk

The UKPDS (Prospective Diabetes Study) Risk Engine*

- **Model for predicting absolute risk of CHD**
- **Based on RCT of 4540 newly diagnosed Type 2 diabetes patients followed for 10 years.**
- **Independent variables: age, gender, ethnicity, smoking, A1c, SBP, cholesterol**
- **Statistical model composed of survival probability equations**

*Stevens et al., (2001). The UKPDS risk engine: a model for the risk of coronary heart Disease in Type II diabetes (UKPDS 56). *Clinical Science*, 101:671-679.

Risk of Coronary Heart Disease (CHD): 1 Year of Treatment

Strategy	Pt. Type (# pts)	% Risk of Adverse Event within 10 Yrs	
		CHD Event	Fatal CHD
Untreated	LH (6687)	22	18
FBW		20	16
FBS		19	15
FFW		19	15
FFS		19	15
EXP		19	15
Untreated	MH (1394)	29	24
FBW		23	19
FBS		21	17
FFW		19	15
FFS		18	15
EXP		18	15
Untreated	HH (458)	42	37
FBW		32	28
FBS		30	25
FFW		23	19
FFS		19	15
EXP		19	15

Best Practice Strategies: Low Risk (of CHD) and Lowest (PMPM) Cost

- **A1c < 8% – Expert**
- **A1c between 8% and 10% – Feedforward Weak**
- **A1c > 10% – Feedback Strong**

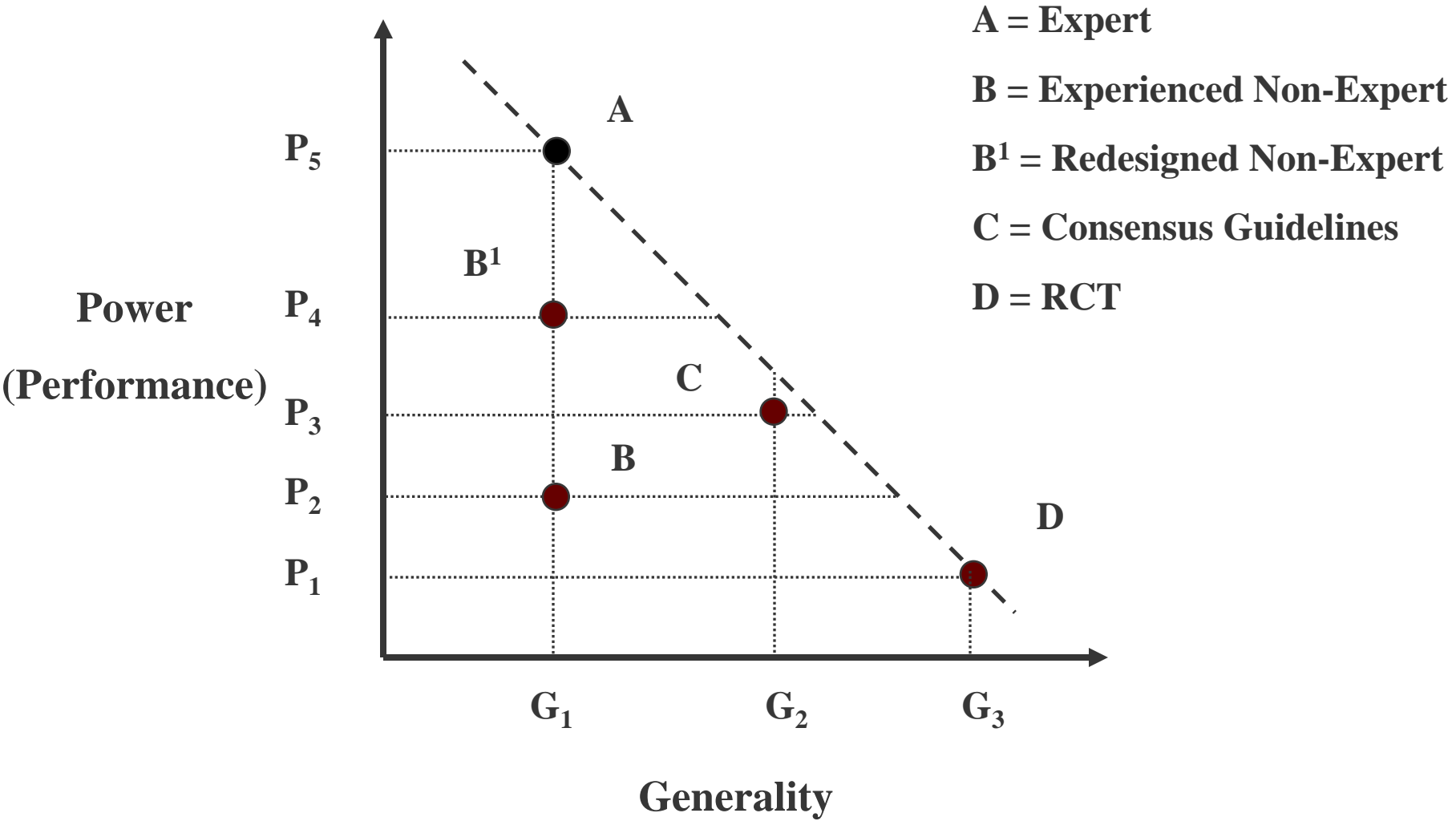
Explaining Best Practice Strategies

- **A1c < 8%: *Expert*** – makes more moves than other strategies, identifies patients for moves via slope and level of average SMBG.
- **A1c between 8% and 10%: *Feedforward Weak*** – Makes more moves than feedback models because of scheduling practices (higher # patients with 0.5% decrease) and fewer than other feedforward models (lower cost than these models) because of smooth landing rule.
- **A1c > 10%: *Feedback Strong*** – This strategy has lower costs because it starts fewer patients on insulin (compared to oral meds insulin is costly)

Issues for Requisite Variety in the Treatment of Chronic Illness

- **Regulation** (with Respect Patient Categories)
- **Personalization** (with Respect to outcome, cost, risk)
- **Converting Theory into Practice**

Issues for Theory and Practice



Summary and Conclusions

- **Modeling for Decision Making & Treatment Outcomes**
 - **Comparative Effectiveness Studies**
 - **Prioritization of Care**
 - **Policy Development**
- **Personalization of Care**
 - **Explanatory vs Predictive Modeling**
 - **Changing Practice- Training vs Decision Support**
 - **Redesign of Treatment Policies**
- **Unsolved Problems**

The Way Forward

... To address the rising rates of chronic conditions, an evolution in health care systems is imperative. Acute care will always be necessary (even chronic conditions have acute episodes), but at the same time health care systems must embrace the concept of caring for long-term health problems.

Patients, health care organizations and decision-makers have to recognize the need to expand systems to include new concepts...

**Innovative Care for Chronic Conditions
World Health Organization, 2002**

It remains to be seen whether work that combines knowledge from fields as diverse as computer science, decision making and the management of clinical care, can contribute to the development of such concepts.

**But as Sherlock Holmes said to Watson
“... the game is afoot...”**