

# Optimizing Anemia Management: From Algorithm to Artificial Intelligence

#### **Emeritus Professor Bernard Canaud**

Montpellier University, School of Medicine, Montpellier-F & Senior Scientist, Global Medical Office FMC-France, Fresnes-F

#### Disclosure

## **Prof. Bernard Canaud**

I have the following potential conflicts of interest to report:

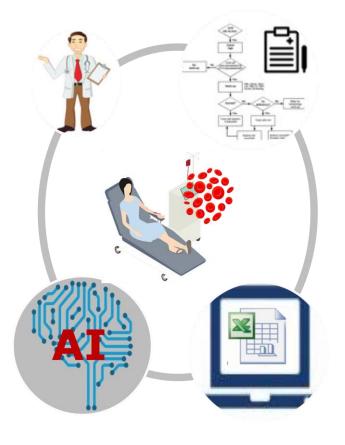
□ Scientific consultant for industry (FMC)

- □ Shareholder in a healthcare company
- Owner of a healthcare company

 $\Box$  Other(s)

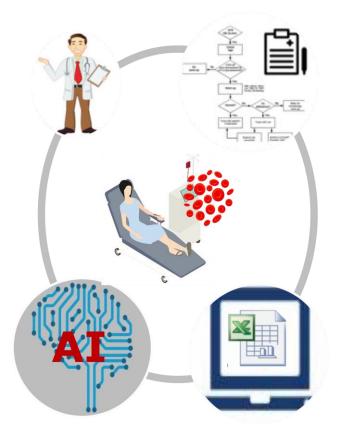
□ I do not have any potential conflict of interest

## **Agenda: From Algorithm to Artificial Intelligence**



- Renal anemia: lesson learned in few decades
- Anemia correction: ESA, as a disruptive treatment in CKD treatment
- Anemia management: from clinical to artificial intelligence support
- •Take home message: what's next

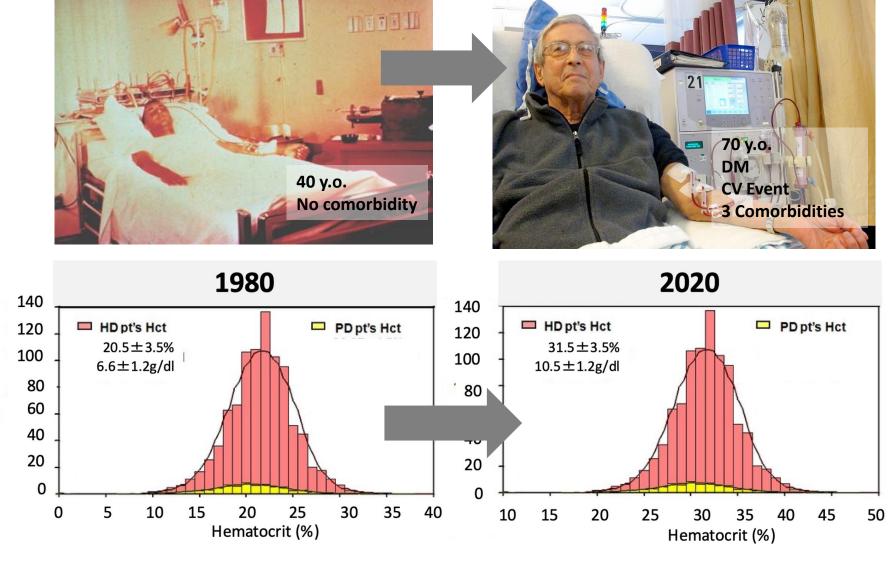
## **Agenda: From Algorithm to Artificial Intelligence**



# • Renal anemia: lesson learned in few decades

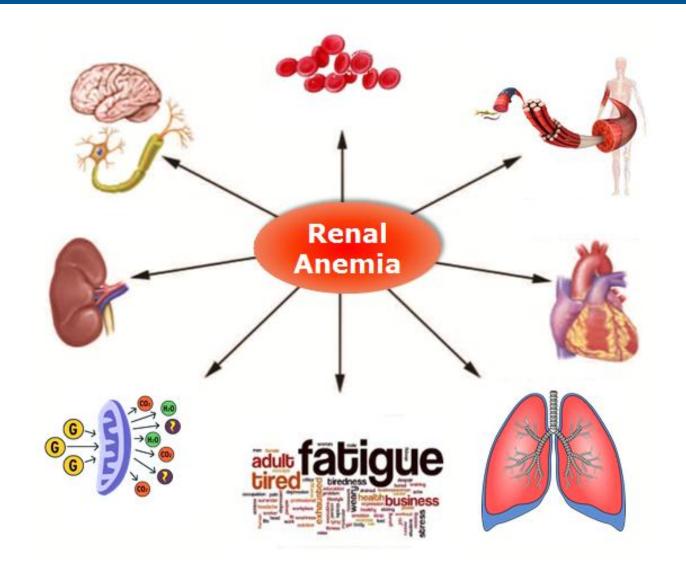
- Anemia correction: ESA, as a disruptive treatment in CKD treatment
- Anemia management: from clinical to artificial intelligence support
- Take home message: what's next

#### **Forty Years of Dialysis in Pictures**

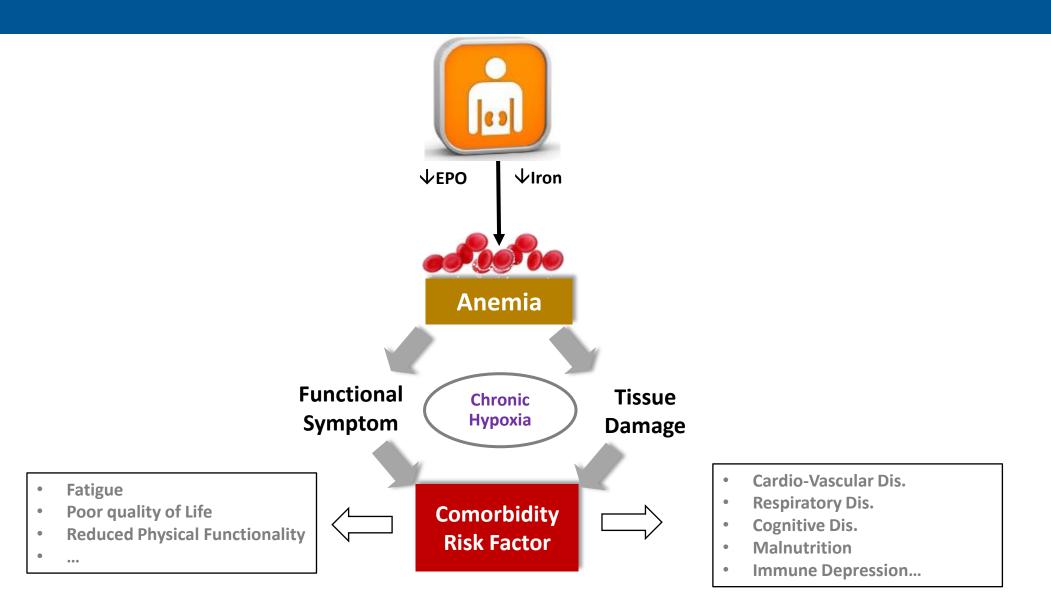


Patients x1000

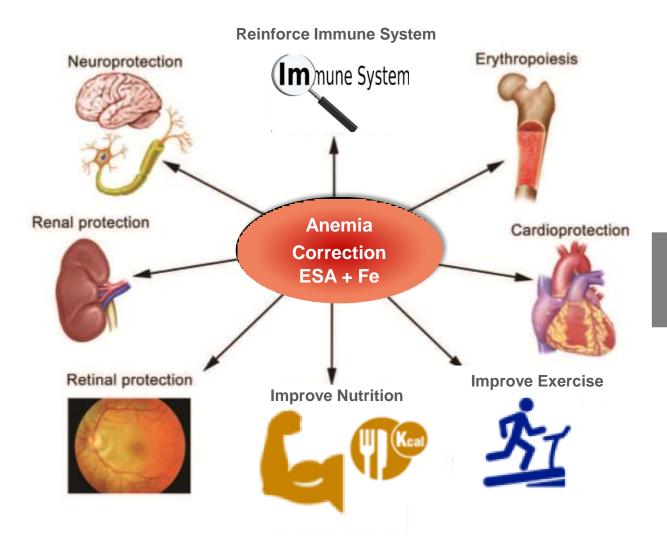
#### **Renal Anemia has Multiple Effects in CKD5D Patients**



#### Anemia is an Additional Pathogenic Factor (Hypoxia) in HD Patients



# **Correction of Anemia is Associated with Biological and Clinical Benefits in HD Patients**



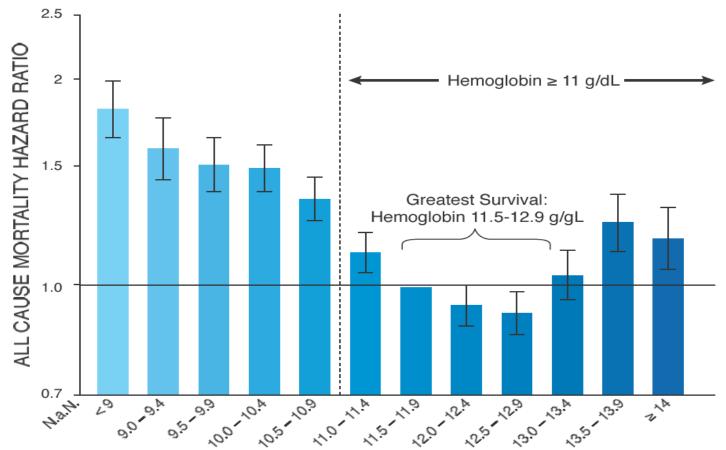
#### Improve patient outcomes

- $\uparrow$  Patient perception
- (HRQOL)
- $\downarrow$  Morbidity
- $\downarrow$  CV Mortality

#### Value based care

- Cost-Effective
- QALY

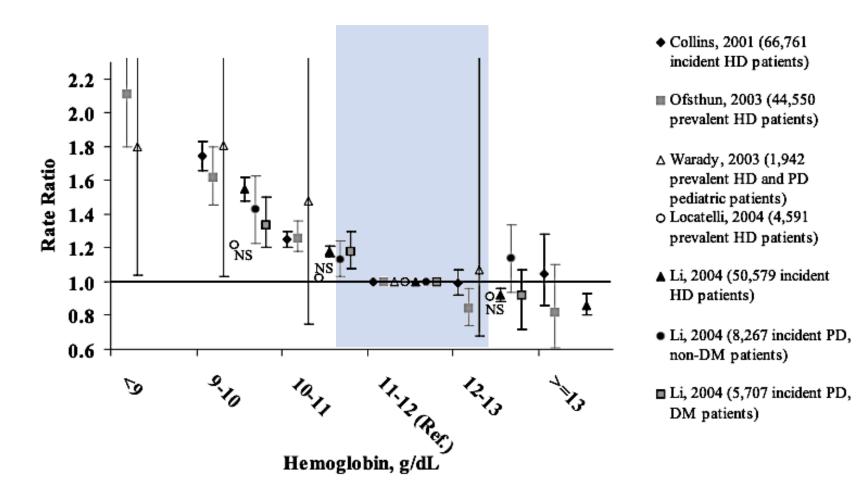
#### Hazard Ratio for All-Cause Mortality Based On Time-Dependent Hb Levels Over 8 Calendar Quarters in a LDCP



Retrospective Cohort Study (July 2001 to June 2003) 58,058 MHD patients DaVita dialysis clinics US

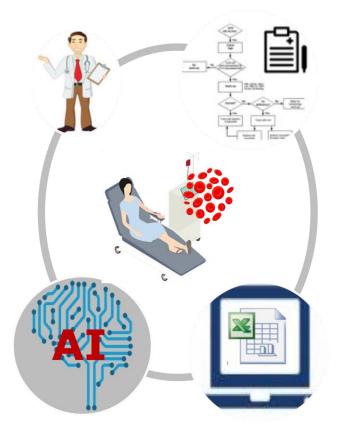
Kalantar-Zadeh K et al, J Am Soc Nephrol. 2005;16(10):3070-80.

#### **Evidence-Based Systematic Literature Review of Hemoglobin and All-cause Mortality In Dialysis Patients**



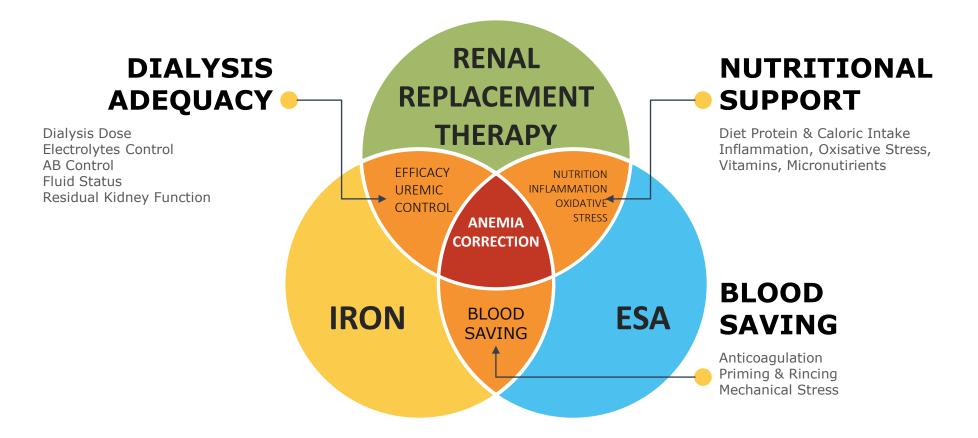
Volkova N et al, Am J Kidney Dis. 2006;47(1):24-36.

## **Agenda: From Algorithm to Artificial Intelligence**



- Renal anemia: lesson learned in few decades
- Anemia correction: ESA, as a disruptive treatment in CKD treatment
- Anemia management: from clinical to artificial intelligence support
- Take home message: what's next

## **Factors Involved in Anemia Correction of CKD5 Dialysis**

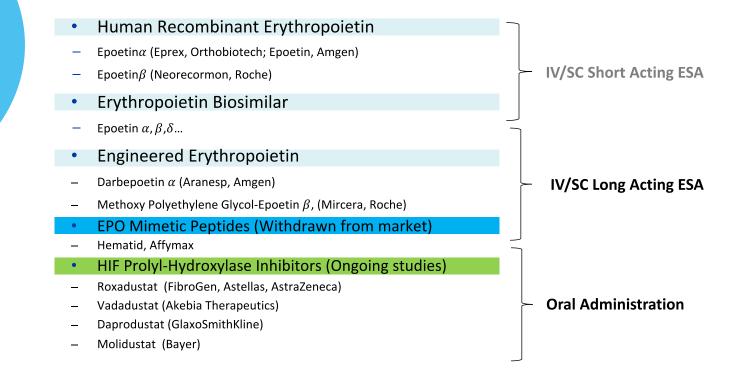


# **Erythropoietic Stimulating Agents**

ANEMIA CORRECTION

**ESA** 





# **Iron Supplementation**

#### IRON SUPPLEMENTATION

h

#### Major Oral Iron Supplements

Supplement	Elemental iron per dosage unit	Frequency						
Ferrous sulfate	65 mg/tablet <sup>a</sup>	1 tablet, 1–3 times per day						
Ferrous gluconate	38 mg/tablet <sup>a</sup>	1 tablet, 1–3 times per day						
Ferrous fumarate	106 mg/tablet <sup>a</sup>	1 tablet, 1–3 times per day						
Ferric maltol	30 mg/tablet	1 tablet, twice per day						
Ferric citrate	210 mg/tablet	1-2 tablets, 3 times per day						
Liposomal iron	30 mg/tablet	1 tablet per day						

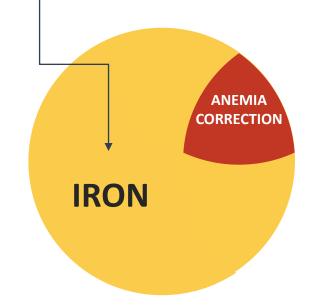
<sup>a</sup>For 325-mg tablets.

#### Major Intravenous Iron Formulations

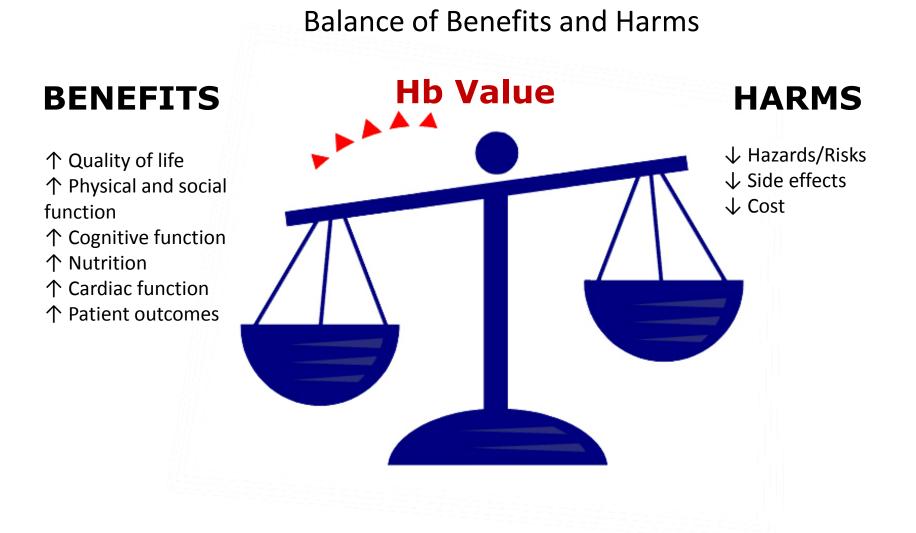
Formulation	Dosage	Frequency
Iron sucrose	200 mg	5 doses over 2 weeks
Ferumoxytol	510 mg	2 doses, 3-8 days apart
Ferric gluconate in sucrose complex	250 mg	4 doses weekly
Ferric carboxymaltose	750 mg	2 doses, 1 week apart
Iron isomaltoside	1000 mg	1 dose
Iron dextran (low molecular weight)	500 to 1000 mg	Variable

Water-Soluble Dialysate Iron Formulation

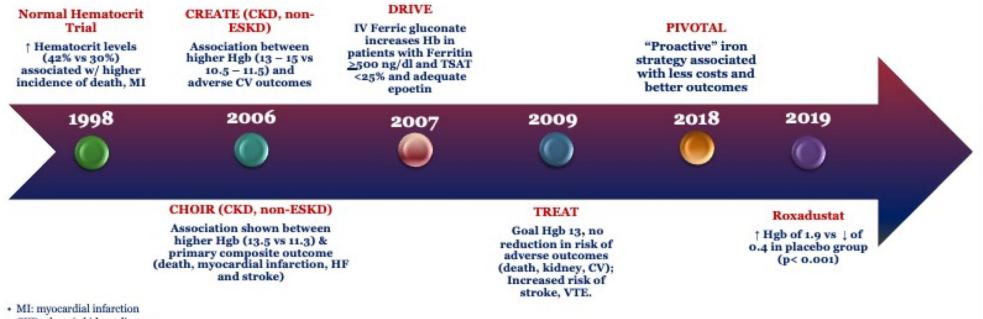
Ferric pyrophosphate citrate (FPC)



# Anemia Correction is Still a Challenge in HD Patients

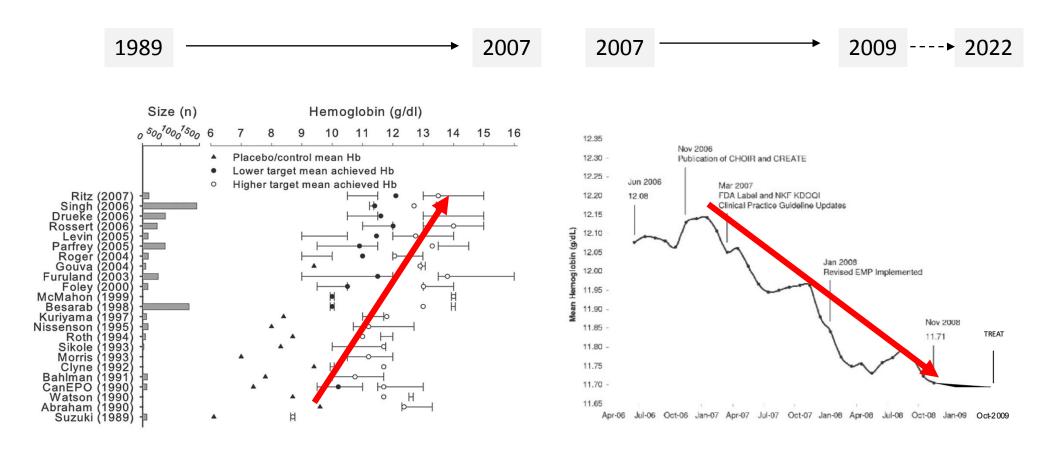


#### Landmark Trials in Anemia Treatment in Kidney Disease



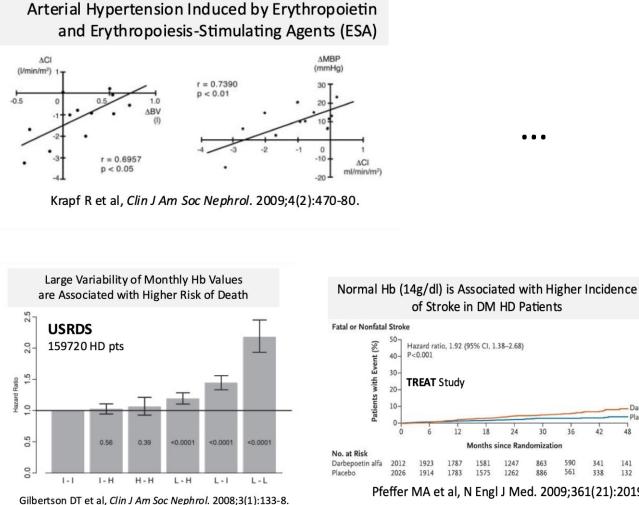
- + CKD: chronic kidney disease
- · ESKD: end-stage kidney disease
- Hgb: hemoglobin (g/dL)
- · HF: heart failure
- DM: Diabetes mellitus
- · VTE: venous thromboembolism
- · HD: hemodialysis
- IV: intravenous

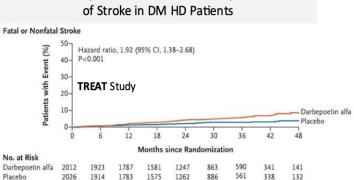
#### **Hb Target Has Changed Over Time and Results**



CHOIR, Correction of Hemoglobin and Outcomes in Renal Insufficiency CREATE, Cardiovascular Risk Reduction by Early Anemia Treatment with Epoetin Beta EMP, Erythropoiesis Stimulating Agent monitoring program - FDA, Food Drug Administration NKF KDOQI, National Kidney Foundation Kidney Disease Outcomes Quality Initiative TREAT, Trial to Reduce Cardiovascular Events with Aranesp Therapy

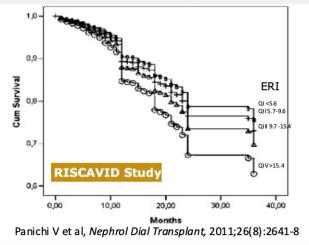
#### **Drawbacks Reported with Anemia Management...**



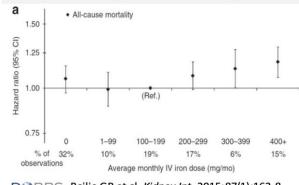


Pfeffer MA et al, N Engl J Med. 2009;361(21):2019-32.

#### High ERI is Associated with Higher Risk of Death

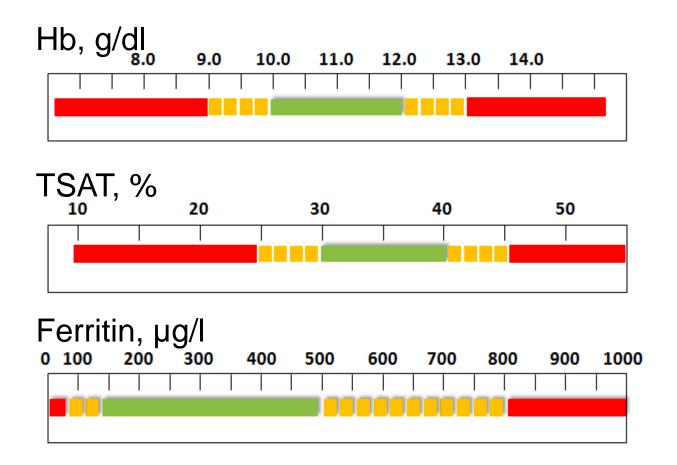


IV Iron Administration >200mg/mo. is Associated with a Higher Risk of Mortality



DGPPS Bailie GR et al, Kidney Int. 2015;87(1):162-8.

# **Optimal Targets in CKD HD Patients**



KDIGO Clinical Practice Guideline for Anemia in Chronic Kidney Disease. Kidney Int. 2012; 2(Sup 4):331-335

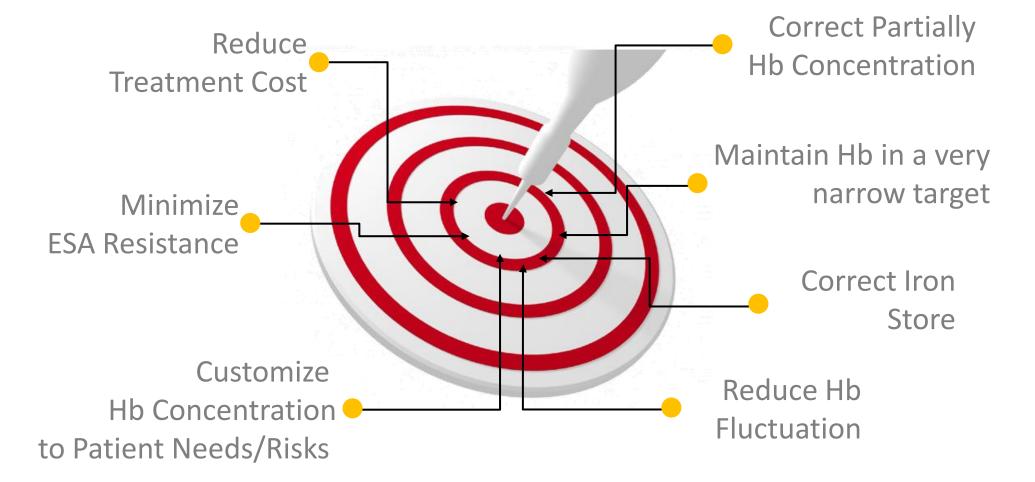
#### **Optimal Targets in CKD HD Patients** Customization is Suitable according to Patient Profile\*



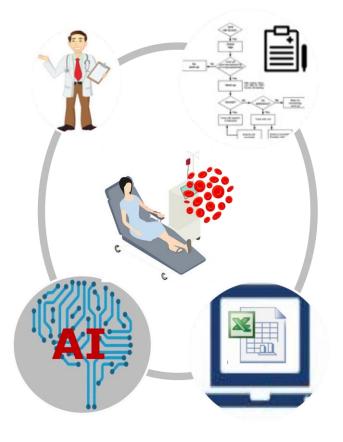
KDIGO Clinical Practice Guideline for Anemia in Chronic Kidney Disease. *Kidney Int.* 2012; 2(Sup 4):331–335

# **Anemia Correction in HD Patients Has Multiple Targets**



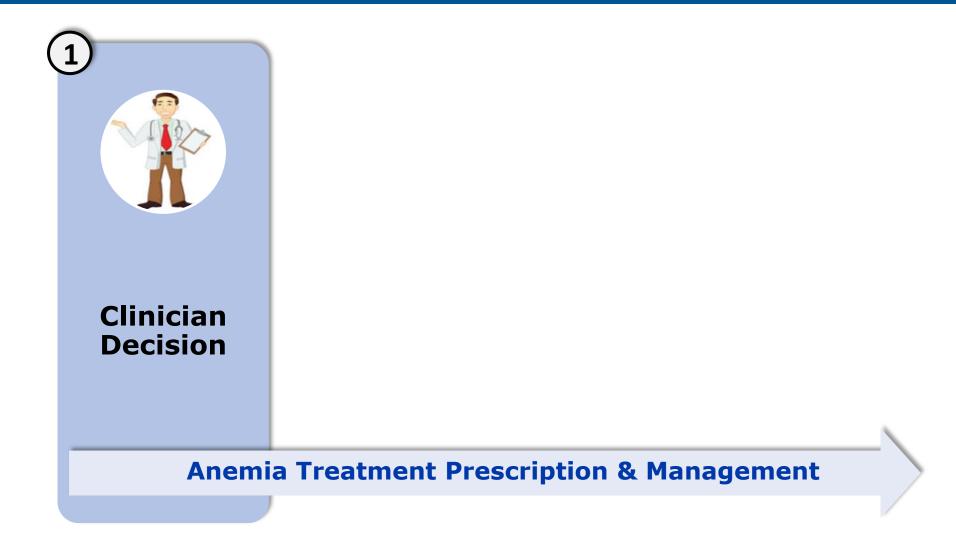


## **Agenda: From Algorithm to Artificial Intelligence**



- Renal anemia: lesson learned in few decades
- Anemia correction: ESA, as a disruptive treatment in CKD treatment
- Anemia management: from clinical to artificial intelligence support
- Take home message: what's next

# **Anemia Management in HD Patients** From Pure Clinical Decision to AI Support-Decision

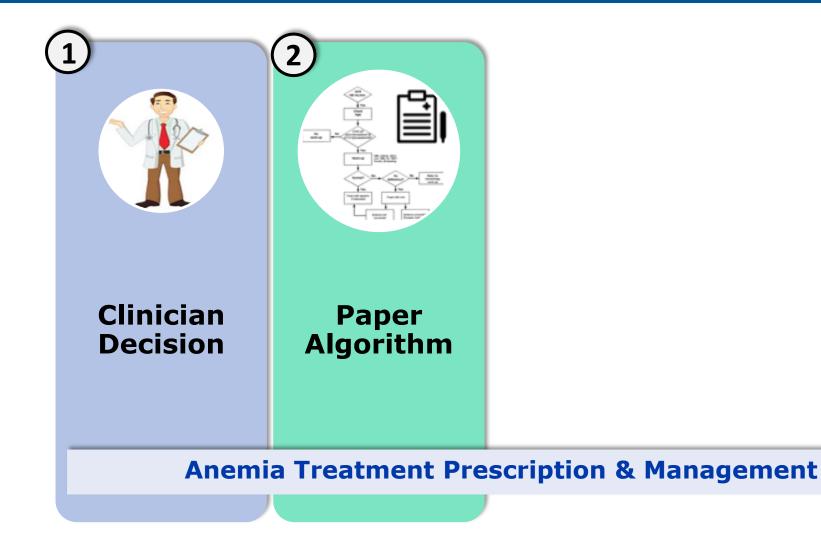


#### **Anemia Management at Patient and Facility Level** Collection of Data – Storage and Analysis (XLS)

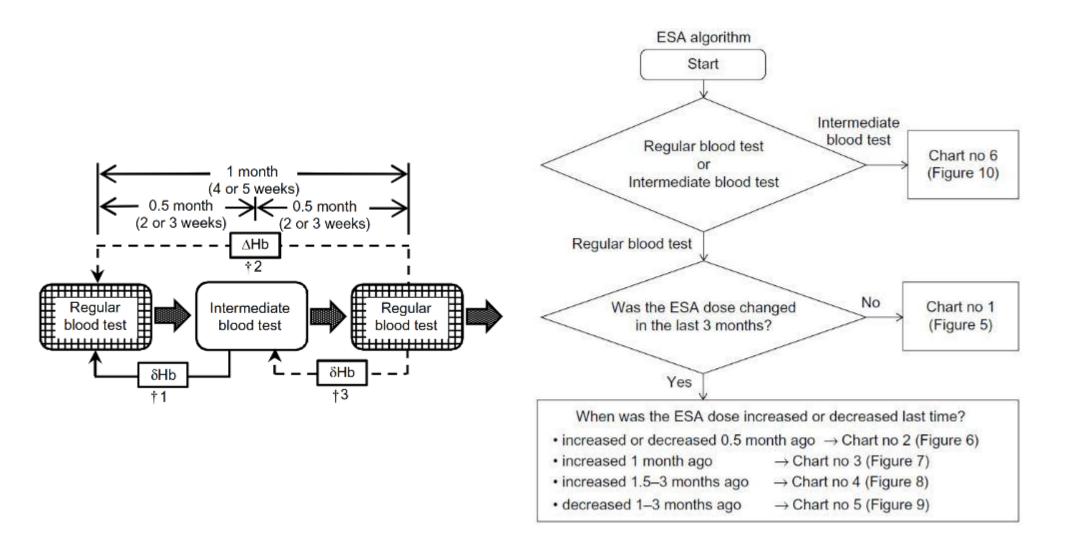
Patient Name	Code	Hb previous month	Hb current month			Darbo Alpha	Alpha, Beta EPOs	Theta Epo	Bio- similars	MPG-E beta	E	Ferritin		C- Reac. Protein	MCV	MCHC	Iron IV	Iron IV	
				×	IU/kąłwookłą × 100 ml	µq/Kq/month	1U/Kq/manth	IU/Kq/manth	IU/Kq/month	µqłKqłmonth	Tatal/Manth Frequency			×	mq/L	fI	q/L	mafmanth	µq/Kq/month
				s 15	<b>≤ 15</b>	s 1,75	<b>s</b> 350	<b>s</b> 350	\$ 350	≤ 1,75				≥20≤50	\$20	≥ 90≤ 105	≥ 32≤ 36		
	1151510107	11	11	-10,2									226	16	51,4	87	32	300	4,31
	8468648872	10,4	11,4	12,1	12,7					2,53	MPGE: 200	20;	638	49	13,6	98	33	500	6,31
	8468648227	13,2	13,7	10,7	2,9					0,7	MPGE: 50	13;	306	48	3,6	101	36	100	1,39
	8468648299	12	10,9	-2,9	6,9					1,32	MPGE: 100	21; 28;	486	30	77,4	70	31	100	1,32
	8168718842	12,4	12,7	15,8	3,5					0,78	MPGE: 50	27;	925	42	2,8	93	34		
	116171002	3,4	9,4	11,8	6,8	1,27					Darbo: 80	Monday;	761	64	18,2	101	36		
	8168718855	11	10,3	19,1	33,5					6,01	MPGE: 250	Tuesday; (every 4 weeks);	588	23	0,2	87	34	100	2,4

Folic	Vitamin	Carnitine	Age	Female	Dry	Time	Effective	Blood	Effective	OCM	V.A.	Alb.	Mean	Cardio-	iPTH	iPTH	aaCCI	Probabilit	Diabetes	Tumors	White	Platelets
Acid	B12				Body	On	veekly	Volume	Infusion	Kt/V				circolatory		Correct.	score	У			cells	
					₩eight	Dialysis	treatment	Processed	Volume				BP Pre	therapy ("				mortality				
							time		Total					ACEi/ARB)				1 year				
n	n 1	n	Year		Ką	monthr	min	L/weekly	Lłusskiy		n	qfql	mmHq	n n	parmL	parmL		×	n	n	na.ťmm'	na./mm1/1000
			>10 <100		>35 < 130		≥ 720	≥240	≥60	≥ 1,4			>60×106		≥50≤550	≥ 50 ≤ 550						≥ 100 ≤ 300
			68		69,6	61	683	322	70	2,04	AVF	3,9	89	1	237	237	4	11			9900	239
			81		79,2	50	784	334	78	1,73	AVF	3,7	68		99	33	8	25	Х		7200	240
		Х	50		71,9	26	787	415	95	2,08	AVF	4,0	96		189	189	4	11			4400	164
X			86		76,0	24	735	329	68	1,82	AVF	3,8	87		193	193	11	25	Х	Х	8400	191
			73		64,0	64	813	291	77	1,94	тс	3,6	79	2	659	659	9	25			4000	96
			67		62,8	49	460	196	56	2,25	AVF	2,7	47	1	216	216	5	27			4500	74
			31		41,6	42	726	328	68	3,00	AVF	3,7	91		30	30	5	11	Х		10200	229

# **Anemia Management in HD Patients** From Pure Clinical Decision to AI Support-Decision

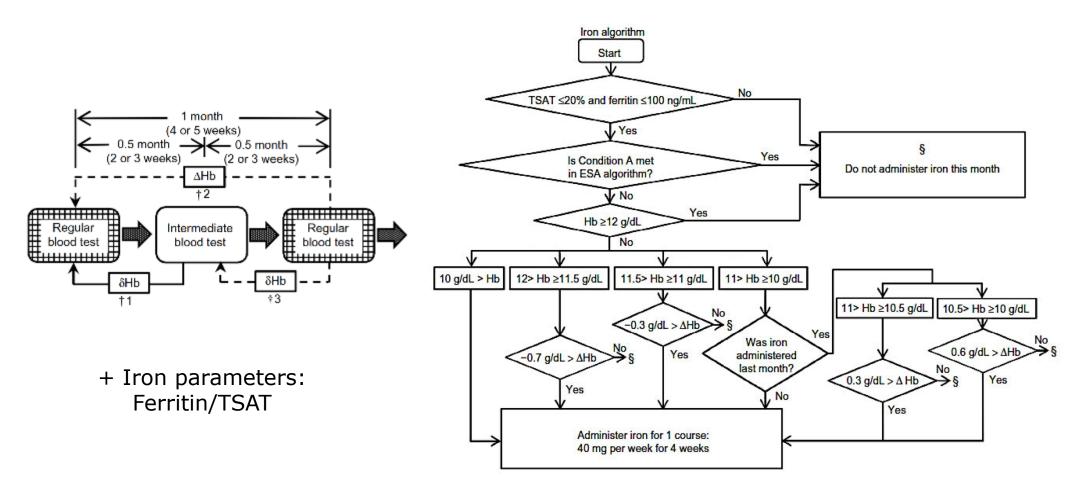


## **Creation of an Anemia Management Algorithm** ESA Administration



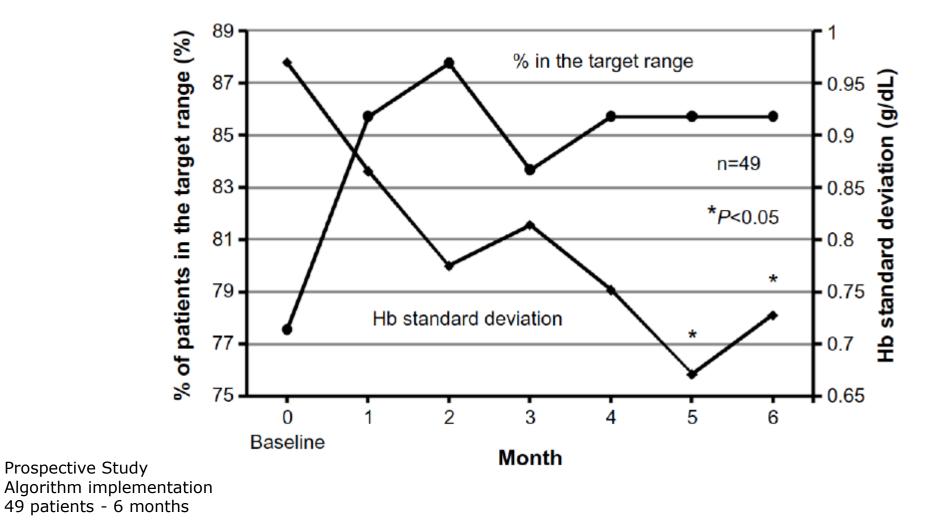
Mizutani Y et al, Int J Nephrol Renovasc Dis. 2015;8:65-75.

## **Creation of an Anemia Management Algorithm** Iron Supplementation



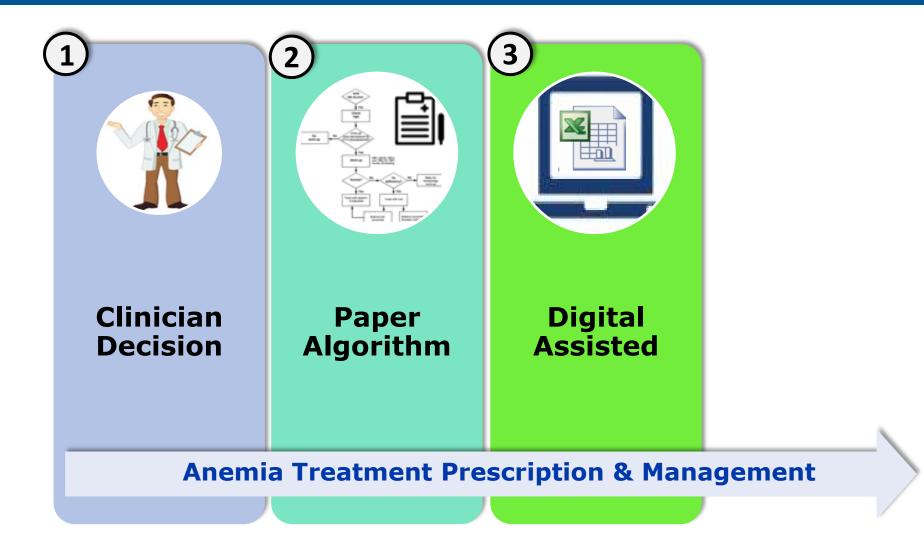
Mizutani Y et al, Int J Nephrol Renovasc Dis. 2015;8:65-75.

## Anemia Algorithm Increases Patients in Target and Reduces Hb Fluctuation

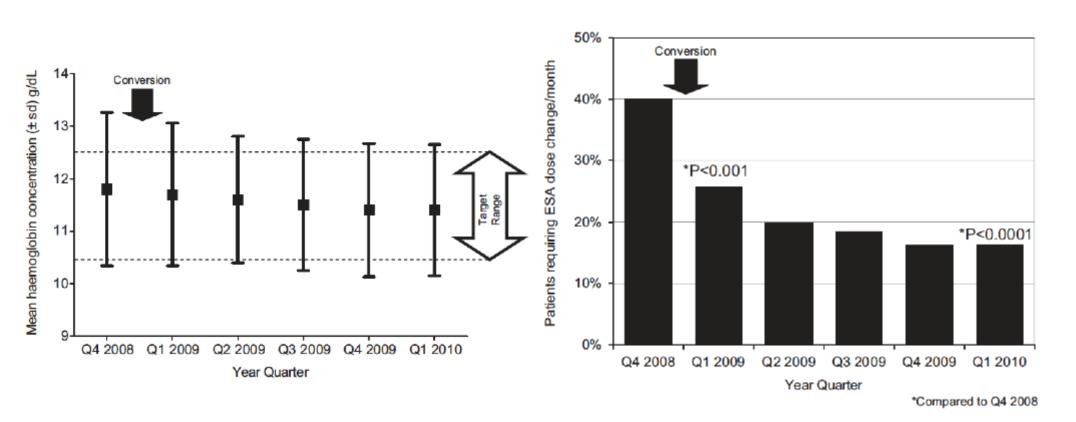


Mizutani Y et al, Int J Nephrol Renovasc Dis. 2015;8:65-75.

# **Anemia Management in HD Patients** From Pure Clinical Decision to AI Support-Decision

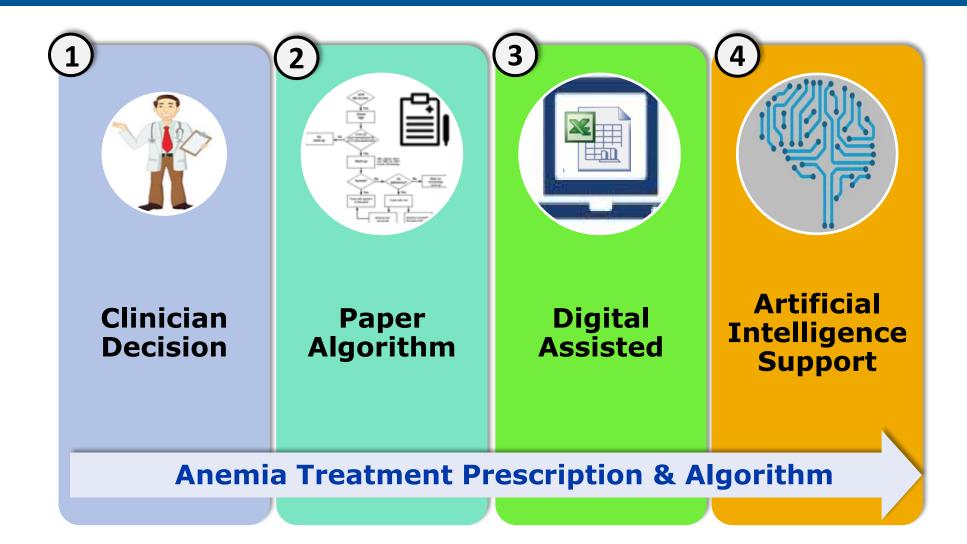


#### Algorithm for Computed-Supported Anemia Management in HD Patients Better Results For Less Work



Predictive algorithm anemia management 214 Prevalent HD Patients UK

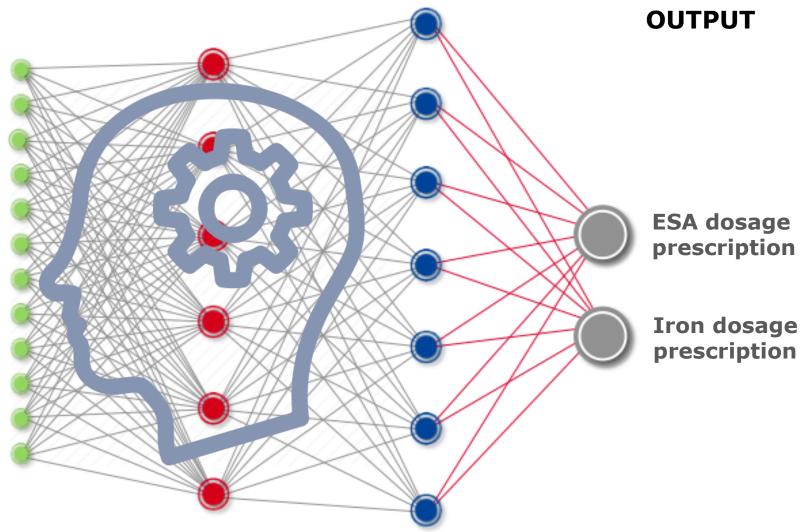
# **Anemia Management in HD Patients** From Pure Clinical Decision to AI Support-Decision



#### **Anemia Management** Conventional Way Based on Human Intelligence

#### INPUT

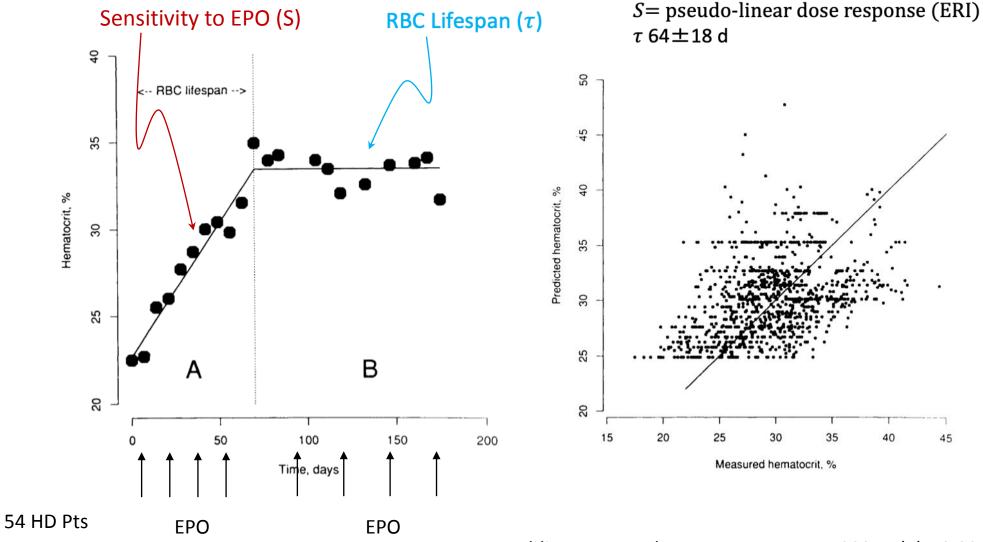
Uremia State **Dialysis Modality Biocompatibility Dialysis Fluid Purity Dialysis Efficacy** Vascular Access Nutritional Status **Patient Profile** Nephropathy **Bone Marrow** Response Erythrocytes 1/2 Life Bleeding Iron Status Anemia Management **Comorbid Profile** Intercurrent Events Unknown



"The essence of math is not to make simple things complicated, but to make complicated things simple."

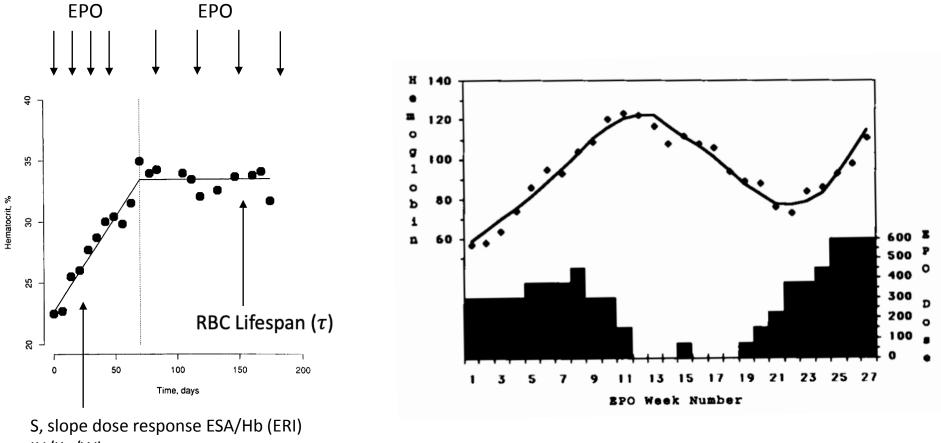
— STAN GUDDER

#### Pharmacodynamic Model of EPO Therapy in HD Patients



Uehlinger DE et al, *Clin Pharmacol Ther.* 1992;51(1):76-89.

# **Mathematical Modeling of EPO Therapy**



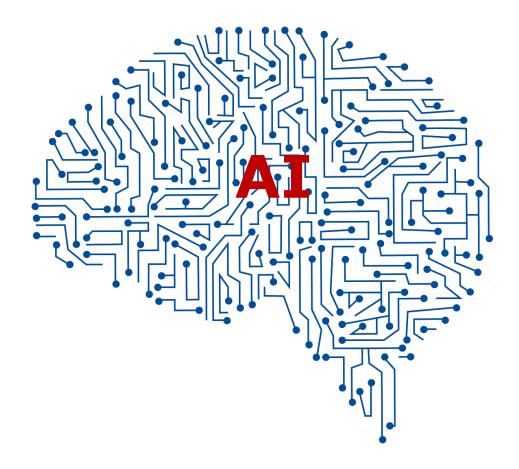
IU/Kg/Wk

 $S = 0.015 \pm 0.06 IU/Kg/wk$  $\tau = 14 \pm 4.1 \mathrm{d}$ 

#### 67 HD Pts **Canadian EPO Study**

Garred LJ et al, ASAIO Trans. 1991;37(3):M457-9.

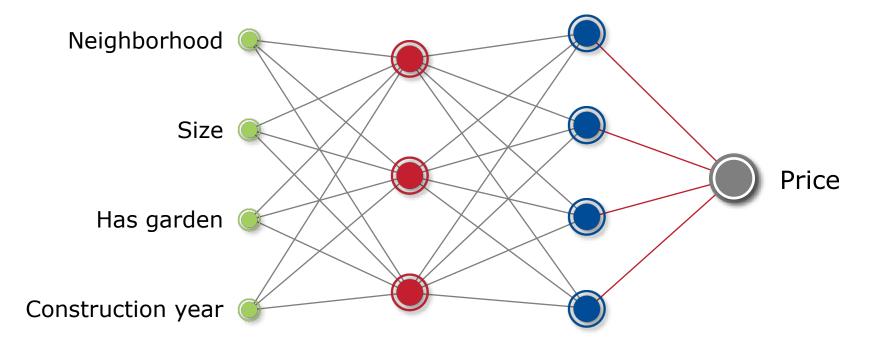
#### Artificial Intelligence is Everywhere Invades our Daily Life



# ✓ GPS

- ✓ Search engines
  - e.g., Google search
- ✓ Image recognition
- Amazon selling process
- ✓ Games e.g., PS4
- ✓ Watson, IBM
- Robotic surgery
  - e.g., «da Vinci»

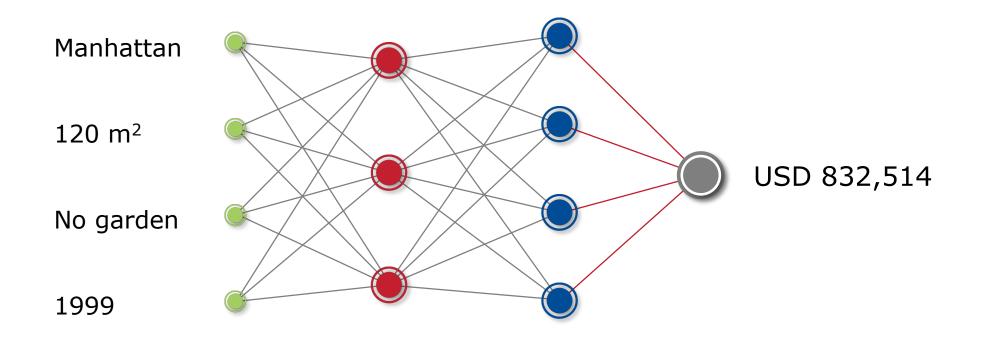
### **Artificial Neural Networks** A Practical Example: Buying a House (Real Estate)



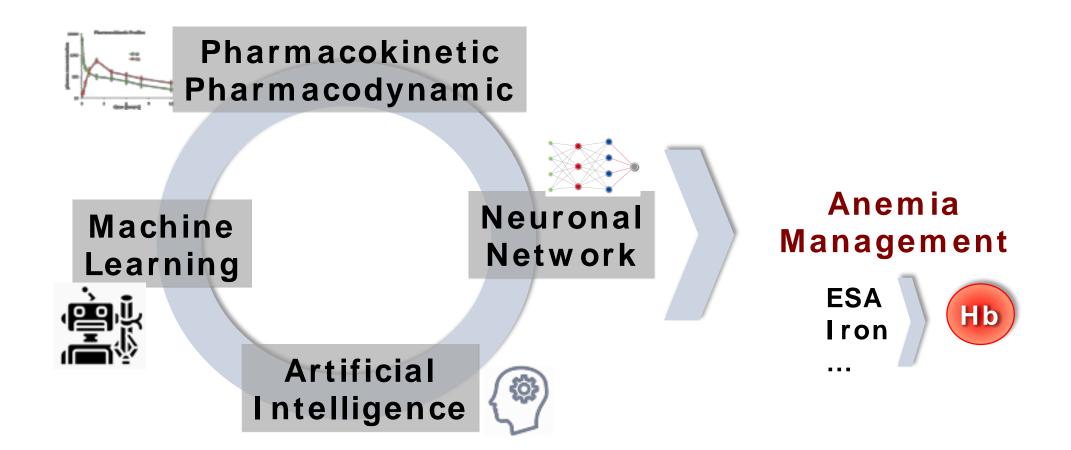
The **more pairs** of input-output data you collect, the **more accurate** the outcome will be

## Artificial Neural Networks

A Practical Example: Buying a House (Real Estate)



Once you have a trained model, you can use it for prediction. That is, on fresh new data!



### Artificial Intelligence as Support of Clinical Decision Making in Anemia Management

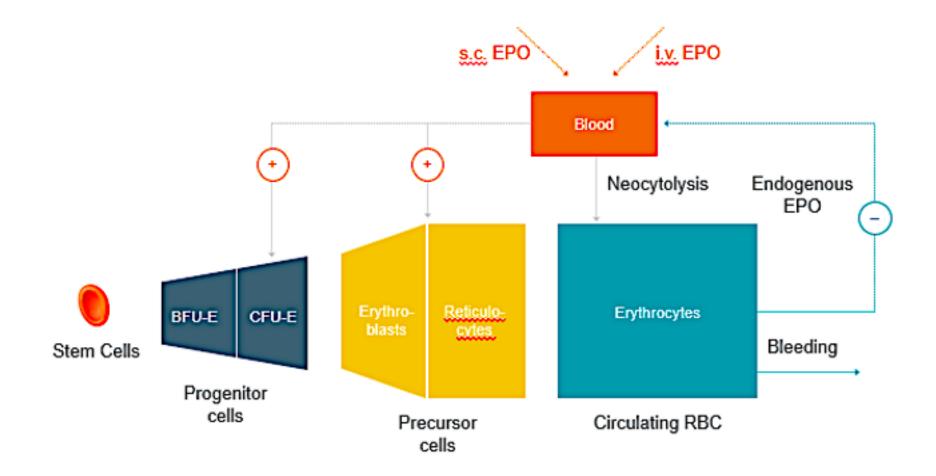
### **Mathematical Modeling**

- Knowledge of physiologic process
- Knowledge of pharmacokinetic/dynamic characteristics
- ESA sensitivity
- Erythrocytes life span
- Reticulocytosis
- Neocytolysis
- Iron availability
- Other parameters
- Formulate mathematical model
- Validate model (internal/external)
- Bigdata Advanced analytic
- Create avatar or twin-patient
- Clinical trial /superiority
- RCT versus traditional care

### **Machine Learning**

- No specific knowledge
- Bigdata input
- Machine learning
- Advanced analytics
- Training large dataset
- Validate model
- Internal/external
- Agreement
   predicted/observed
- Retrieve pharmacokinetic
- Clinical trial/superiority
- Prospective study

### A Model of Erythropoiesis in Adults with Sufficient Iron Availability



Fuertinger DH et al, *J Math Biol.* 2013;66(6):1209-40

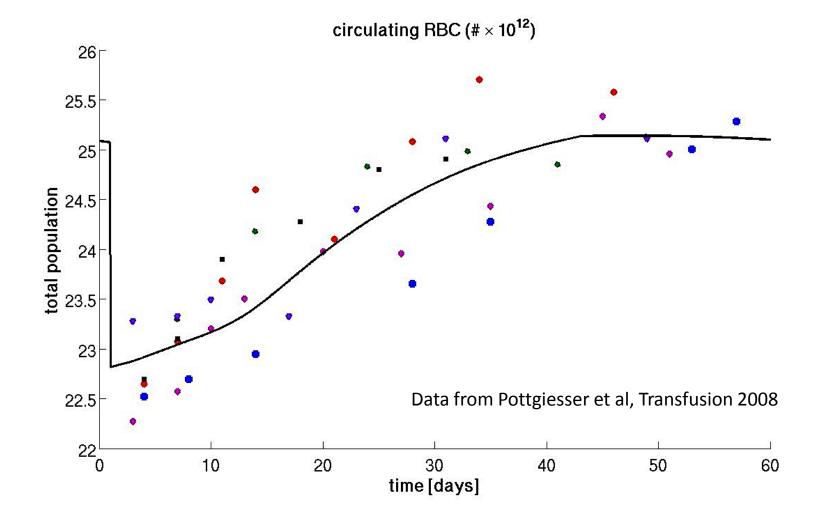
### **Formulate the Mathematical Model**

Cell proliferation, maturation velocity and apoptosis of erythroid cells are influenced by erythropoietin (EPO)

- 19145			
0 0D	BFU-E	$rac{\partial}{\partial t} p(t,x^p) + rac{\partial}{\partial x^p} p(t,x^p) = \beta^p p(t,x^p),$	
O OLOT	CFU-E	$\frac{\partial}{\partial t}q(t,x^q) + \frac{\partial}{\partial x^q}q(t,x^q) = (\beta^q - \alpha^q(E(t)))q(t,x^q),$	
	Erythoblasts	$\frac{\partial}{\partial t}r(t,x') + \frac{\partial}{\partial x'}r(t,x') = \beta'r(t,x'),$	
	BM Reticulocytes	$\frac{\partial}{\partial t}s(t,x^s) + v^s(E(t))\frac{\partial}{\partial x^s}s(t,x^s) = -\alpha^s s(t,x^s),$	
	Erythrocytes	$\frac{\partial}{\partial t}m(t,x^m)+\frac{\partial}{\partial x^m}m(t,x^m)=-\alpha^m(E(t),x^m)m(t,x^m),$	
***	endogenous Epo	$rac{d}{dt}E^{ m end}(t)=rac{1}{TBV}E^{ m end}_{ m in}(t)-c^{ m end}_{ m deg}E^{ m end}(t),$	
<b>M</b>	exogenous Epo	$\frac{d}{dt}E^{\rm ex}(t) = \frac{1}{TBV}E^{\rm ex}_{\rm in}(t) - c^{\rm ex}_{\rm deg}E^{\rm ex}(t),$	

Fuertinger DH et al, *J Math Biol.* 2013;66(6):1209-40

### **Model Validation in Blood Donation Subjects**



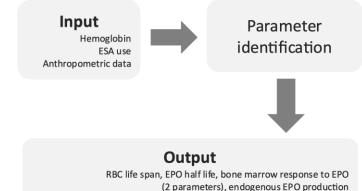
Fuertinger DH et al, *J Math Biol.* 2013;66(6):1209-40

### A Numerical Method for Structured Population Equations Modeling Control of Erythropoiesis

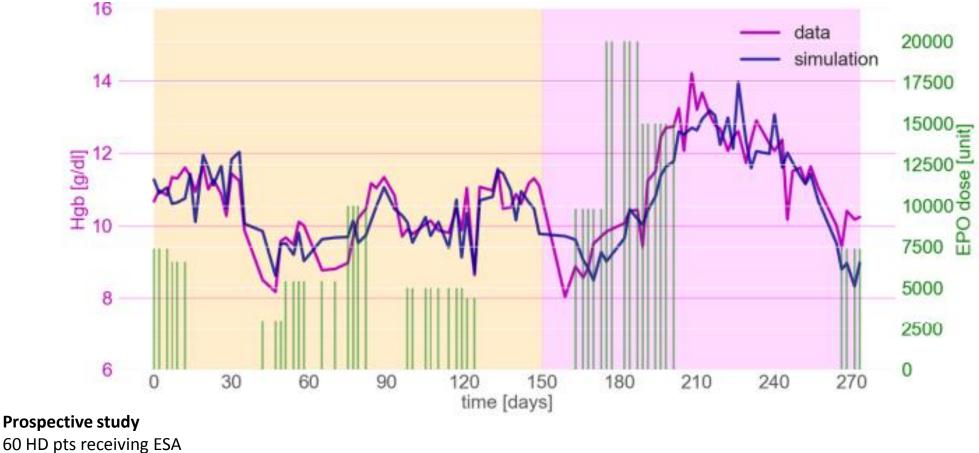
Model Adaptation to Individual Patients using Parameter Estimation: Avatar Generation

- Model includes 30 parameters
- 2 parameters are adjusted using empirical formulas
  - Data: gender, height, weight
- 5 parameters are inferred from data
  - Data: hemoglobin levels, ESA administration; anthropometric data
- Minimize a weighted least square cost functional
- Model was adapted to 60 ESRD patients

$$J(p_1, ..., p_n) = \sum_{j=1}^{N} w(t_j) (y(t_j) - \phi(\theta, t_j))^2$$

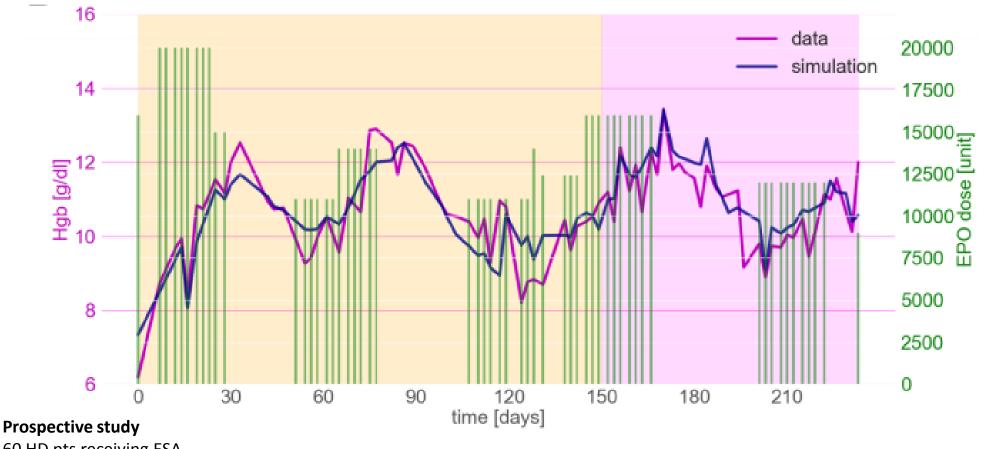


# **Comparison of Model Simulations (blue) and Empirical Data (magenta) – Selected Patient #1**



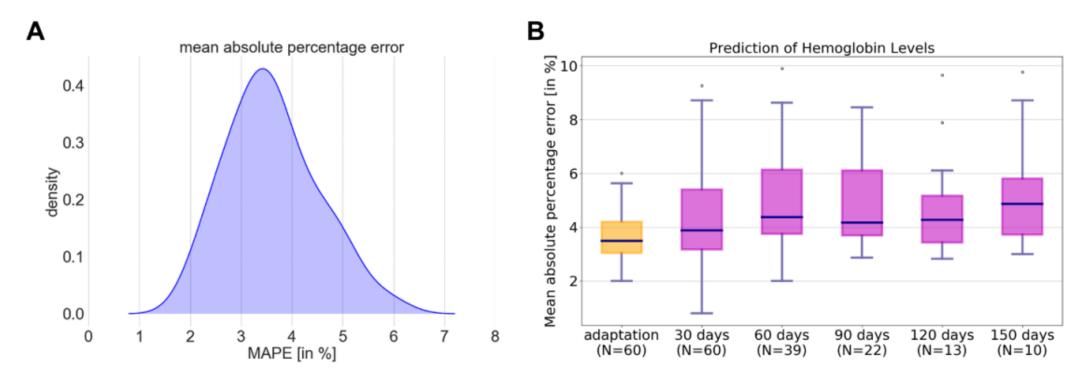
60 HD pts receiving ESA Key parameters temporal Hb data Crit-Line monitor 150d baseline period

# **Comparison of Model Simulations (blue) and Empirical Data (magenta) – Selected Patient #2**



60 HD pts receiving ESA Key parameters temporal Hb data Crit-Line monitor 150d baseline period

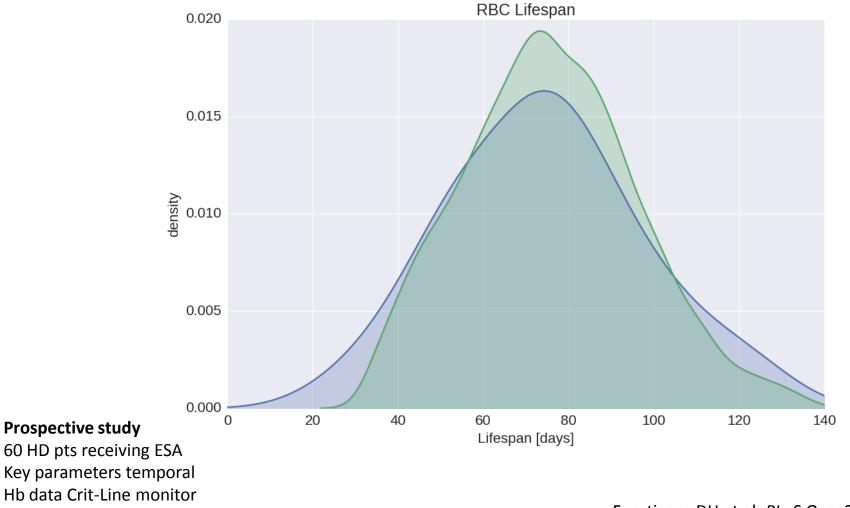
### **Prediction of Hb Values in Virtual Dialysis Clinic Avatars**



#### **Prospective study**

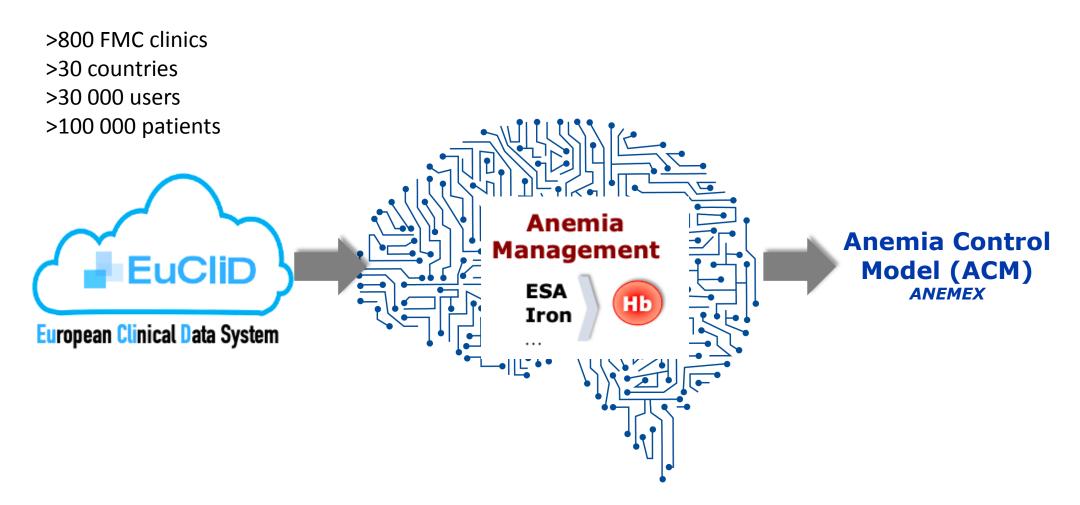
60 HD pts receiving ESA Key parameters temporal Hb data Crit-Line monitor 150d baseline period

### **Prediction of RBC Life Span In Virtual Dialysis Clinic Avatars**



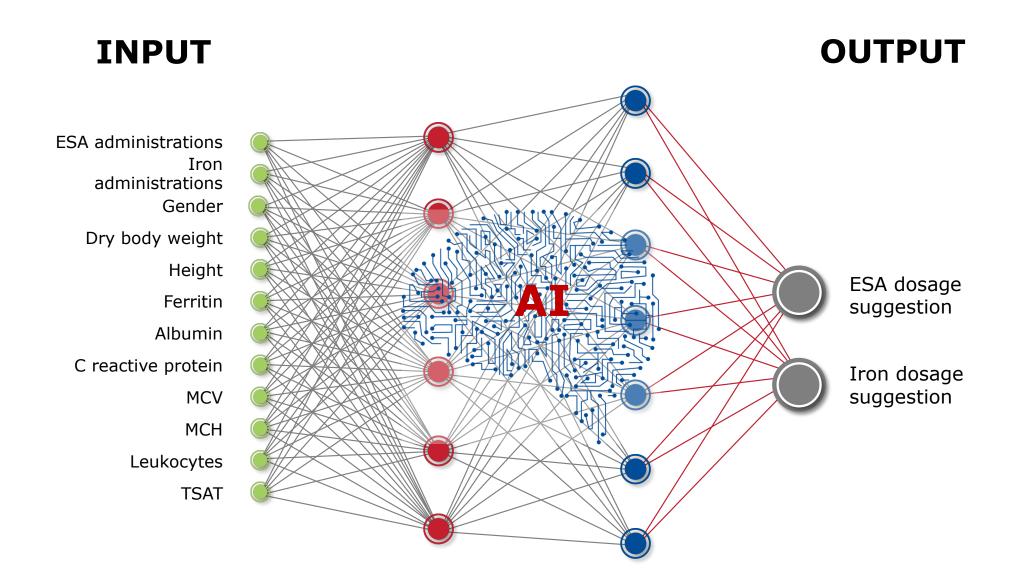
150d baseline period

### Artificial Intelligence in HD Patient Management Anemia Control Model



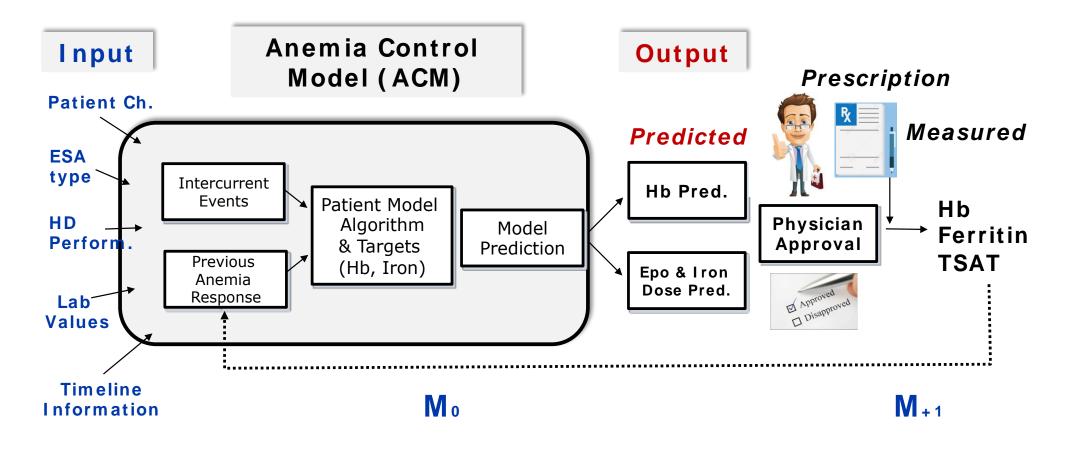
#### Anemia Control Model<sup>®</sup> (ACM) from FMC

### ACM, Euclid Dataset of FMC Clinics Trained on 950.000 Patients Records

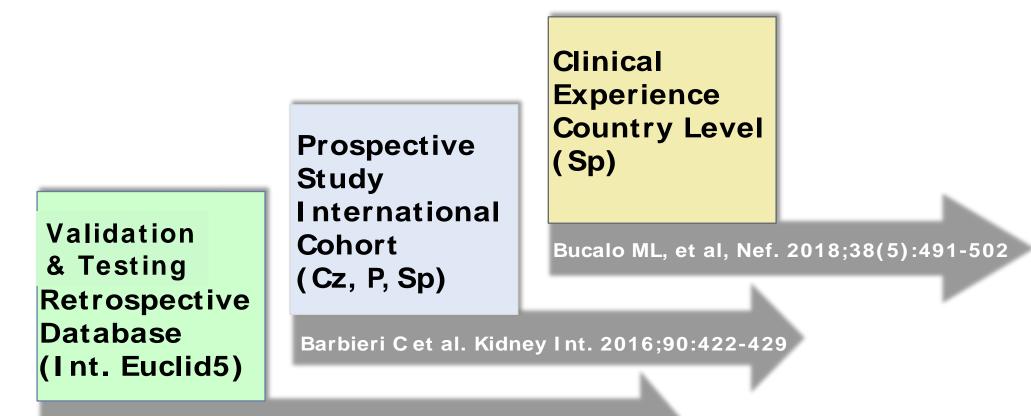


## Development of Anemia Control Model

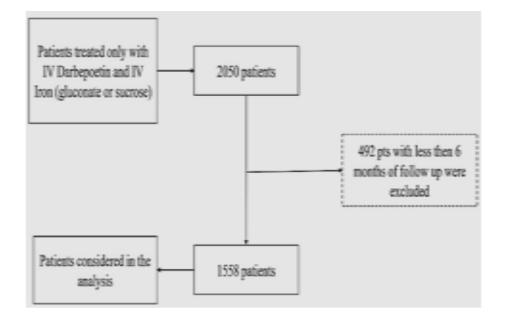
Artificial Intelligence, Neuronal Network, Algorithm & ESA Kinetic



### **Anemia Control Model (ACM)** Scientific Roadmap : Validation, Testing, Implementation



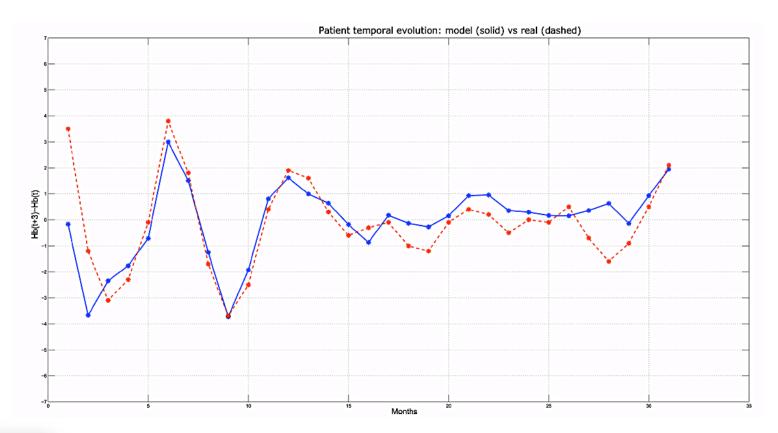
## **ACM – Model Validation** Retrospective Database Cohort



t-3 n	nonths	t t	+3 months
			_
	Past	Future	
	Administered EPO	Prescribed EPO	
	Administered Iron	Prescribed Iron	
	Labs and other parameters		
		Hb(t)	Hb(t+3)

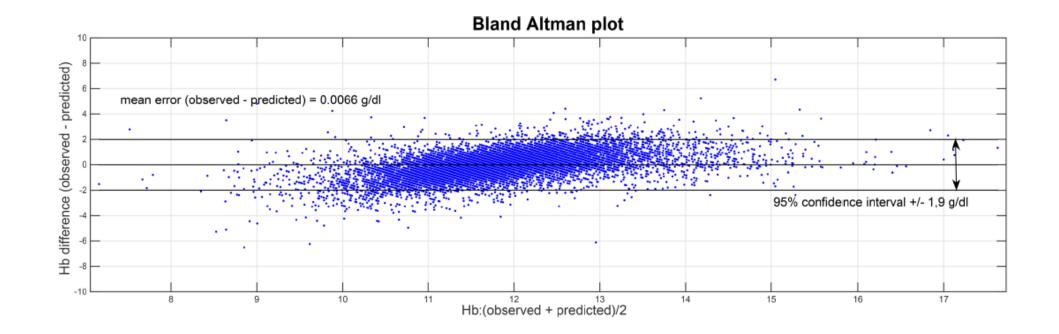
### **ACM – Model Validation** Observed versus Predicted Hb in a Typical Patient

Predicted vs. actual Hb variations for a typical patient characterized by a prediction error close to the mean absolute error on test set



ACM Anemia Control Module

### **ACM – Model Validation** Bland-Altman Analysis of Observed/Predicted Hb Values



### **Anemia Control Model (ACM) to Anemex** Scientific Roadmap : Validation, Testing, Implementation

Validation & Testing Retrospective Database (Int. Euclid5)

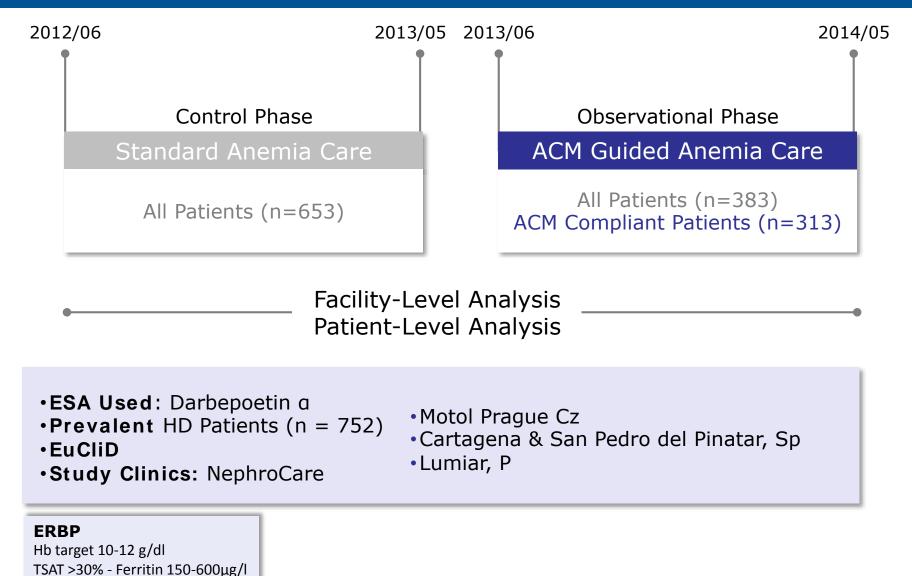
### Prospective Study International Cohort (Cz, P, Sp)

Clinical Experience Country Level (Sp)

Bucalo ML, et al, Nef. 2018;38(5):491-502

Barbieri C et al. Kidney Int. 2016;90:422-429

## **Barbieri Study** Design



## **Barbieri & al study** Patient Characteristics

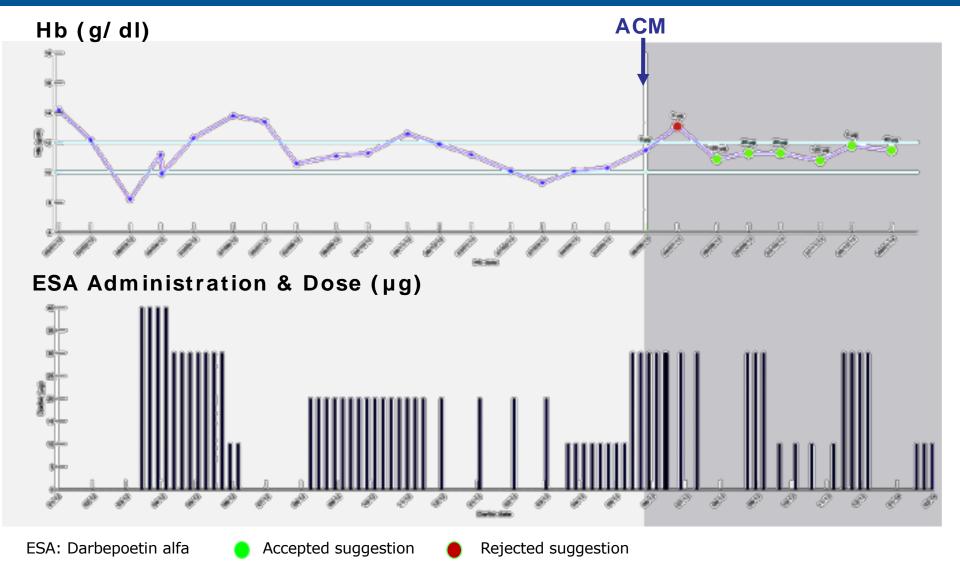
#### Patient characteristics in study

Characteristics	All patients	Chara cteristics	All patients
No. of patients Follow-up period, mo, mean ± SD Age, yr, mean ± SD Male, no. (%) Comorbidities at ACM entrance, no. (%) Coronary artery disease Congestive heart failure Peripheral vascular disease Cerebrovascular disease Chronic pulmonary disease Diabetes Charlson Comorbidity Index, mean ± SD	$\begin{array}{c} 383\\ 22.12 \pm 2.40\\ 65.18 \pm 14.89\\ 231\ (60.3)\\ \hline 33\ (8.6)\\ 82\ (21.4)\\ 114\ (29.8)\\ 71\ (18.5)\\ 58\ (15.1)\\ 87\ (22.7)\\ 6.98 \pm 3.30\\ \end{array}$	Causes of kidney disease, no. (%) Diabetes Hypertension Chronic glomerulonephritis Urinary obstruction/chronic interstitial nephritis Polycystic kidney disease Other Vascular access, no. (%): Fistula Catheter Graft Treatment modality, no. (%) HDF online High-flux HD Other	75 (19.6 69 (18.0 88 (23.0 10 (2.6) 25 (6.5) 116 (30.3 261 (68.1 59 (15.4 63 (17.2 361 (94.3 14 (3.7) 7 (1.8)

HD, hemodialysis; HDF, hemodiafiltration.

Barbieri C et al. Kidney Int. 2016;90:422-429

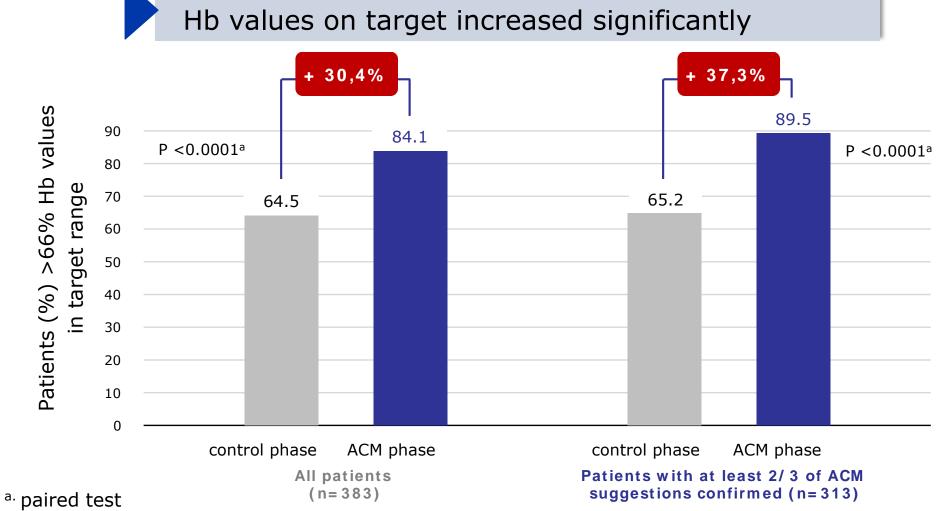
### **Hb Behavior over Time pre and post-ACM** Example of a Typical Patient



Barbieri C et al, Kidney Int. 2016;90:422-429

### **ACM Use Increased Percentage of Patients in Target**

Patients with at least two-thirds of their



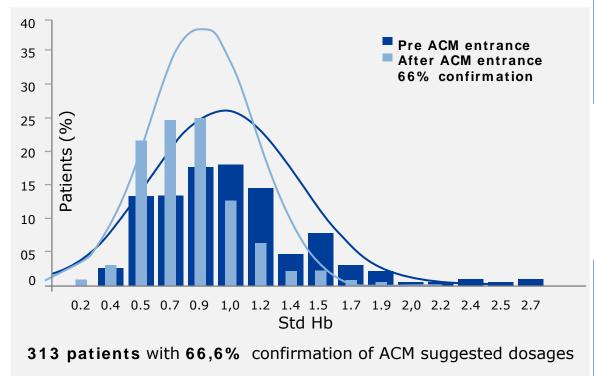
ESA Used : Darbepoetin  $\alpha$ 

Barbieri C et al. Kidney Int. 2016;90:422-429

### **ACM Use Reduced Hb Variability**

### After ACM deployment, Hb variability decreased

#### Histogram of Hb SDs before and after ACM introduction



Histogram shows the distribution of Hb standard deviations in the study phases (pre ACM entrance & after ACM entrance).

 The change in skewness, kurtosis and the distribution shift confirm that Hb variability decreased after ACM deployment.

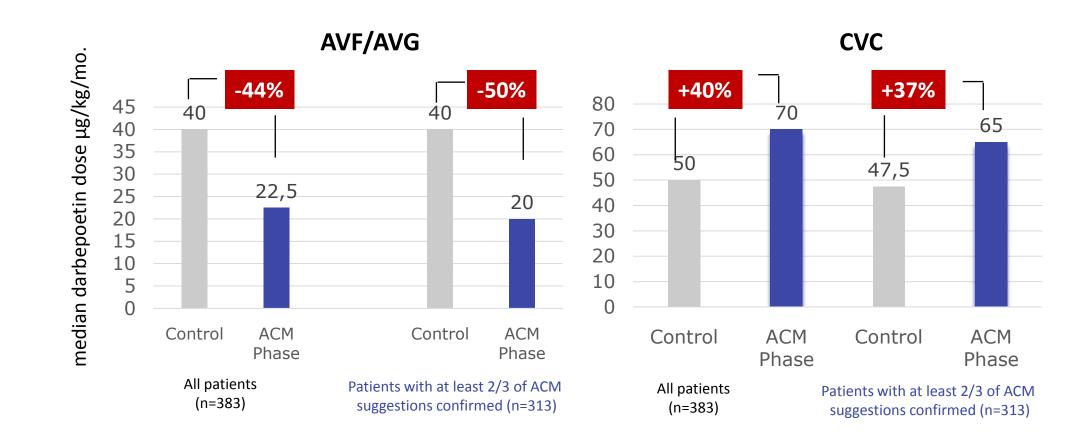
#### ESA Used : Darbepoetin $\boldsymbol{\alpha}$

### Anemia Management Supported by ACM Reduces ESA Consumption and Improves Outcomes

	Control phase	Observation phase	P-value
ACM-compliant patients ( $n = 313$ )			
Anemia outcomes			
Hb SD, g/dl, mean $\pm$ SD	$0.97\pm0.41$	$0.80\pm0.29$	< 0.001 <sup>a</sup>
Patients with >66.6% Hb within target range, no. (%)	204 (65.2)	280 (89.5)	<0.001 <sup>b</sup>
Median darbepoetin dose, µg, median (IQR)	40.00 (80.00)	20.00 (70.00)	0.001 <sup>c</sup>
Median absolute delta darbepoetin dose, μg, median (IQR) Adverse events	10.00 (25.00)	10.00 (40.00)	0.24 <sup>c</sup>
Patients with cardiovascular events, no. (%)	64 (20.4)	39 (12.5)	0.009 <sup>b</sup>
Cardiovascular events (incidence/ 1000 patient-years)	276.36	191.15	0.002 <sup>d</sup>
Hospitalization days (incidence/ 1000 patient-years)	3319.69	3348.67	0.42 <sup>d</sup>
Patients with transfusion events, no. (%)	7 (2.2)	0 (0)	0.02 <sup>b</sup>
Transfusion events (incidence/ 1000 patient-years)	54.59	0	<0.001 <sup>d</sup>



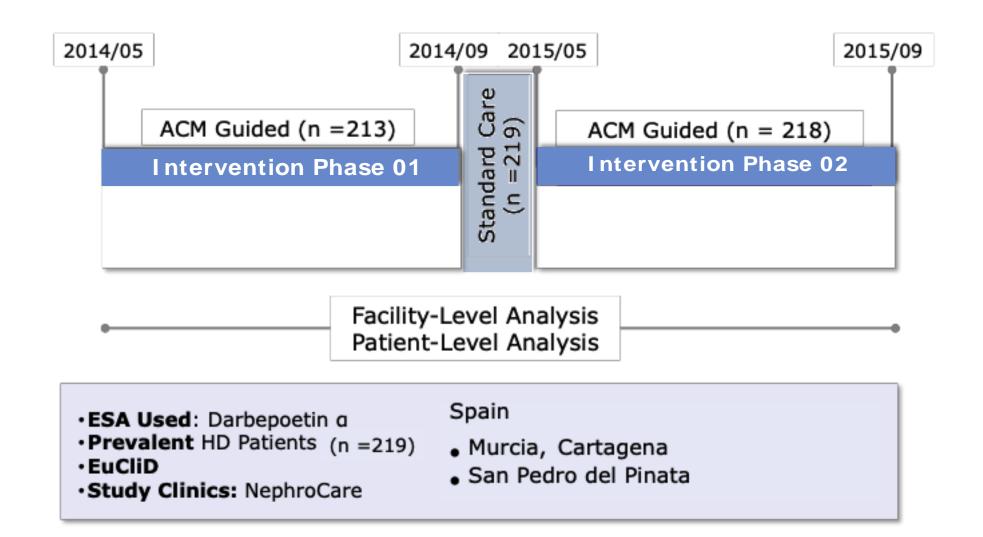
#### **Effect of Vascular Access Type on Anemia Correction** Catheters Increase ESA Consumption & Hb Variability



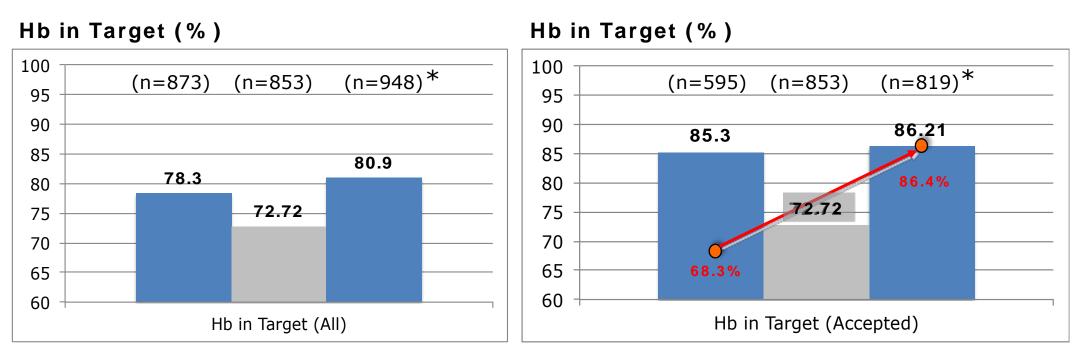
ESA Used : Darbepoetin  $\alpha$ 

Barbieri C et al. Kidney Int. 2016;90:422-429

### **ACM Used In Daily Clinical Life** Example of Spain – Study Design

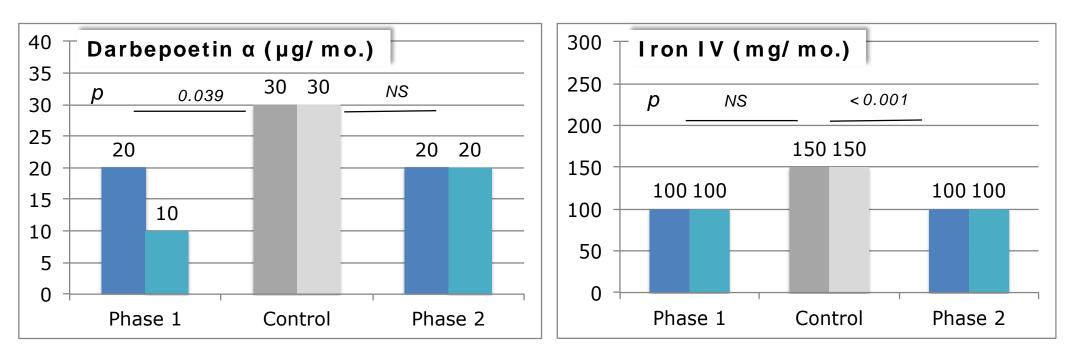


### **Primary Outcome** Hb in Target

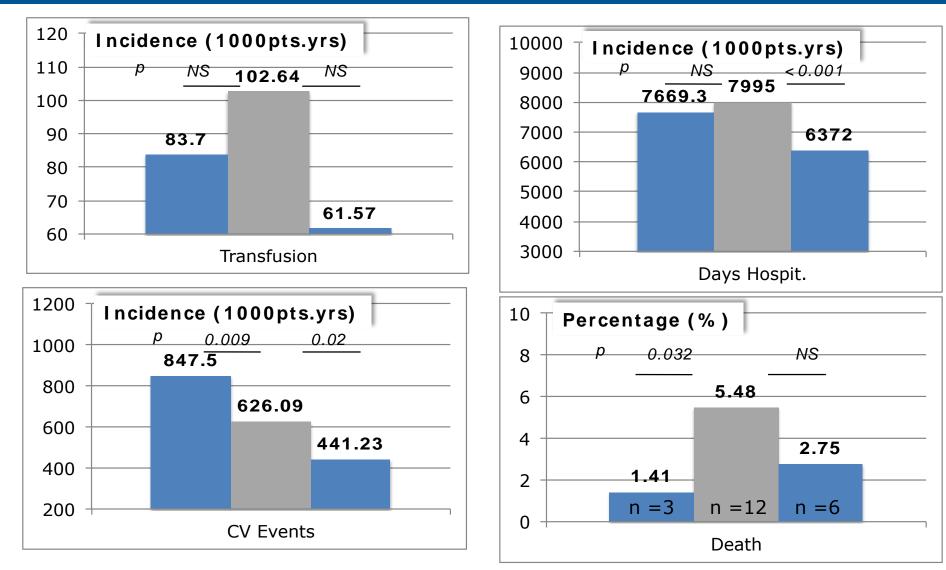


\* Number of Hb measurements

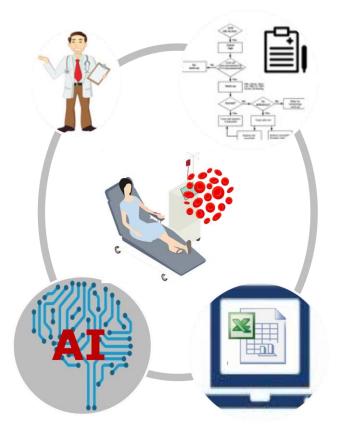
### **Secondary Outcome** ESA and Iron Consumption



### **Secondary Outcome** Transfusion – Morbidity - Mortality



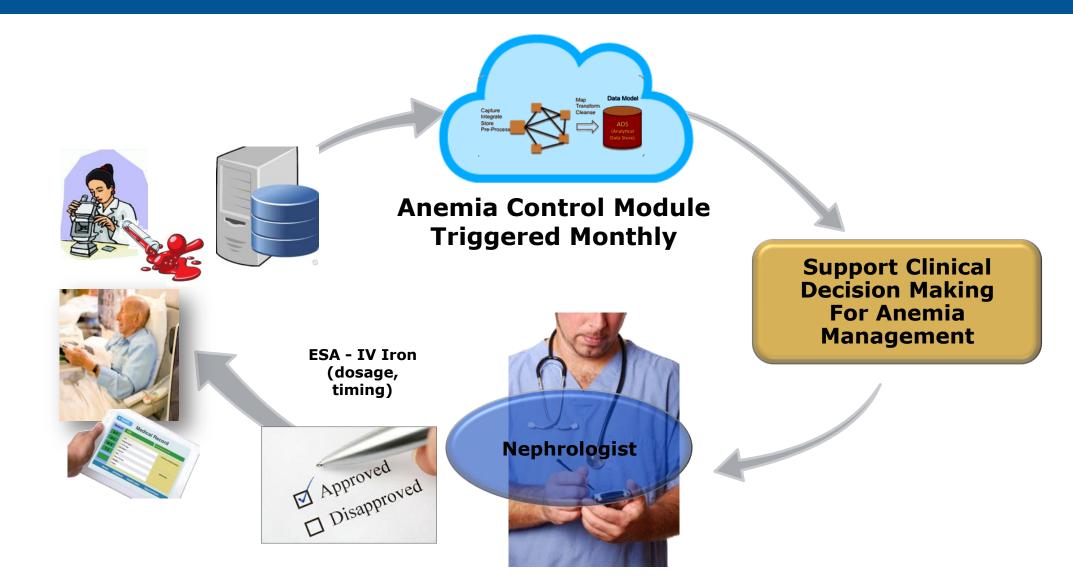
### **Agenda: From Algorithm to Artificial Intelligence**



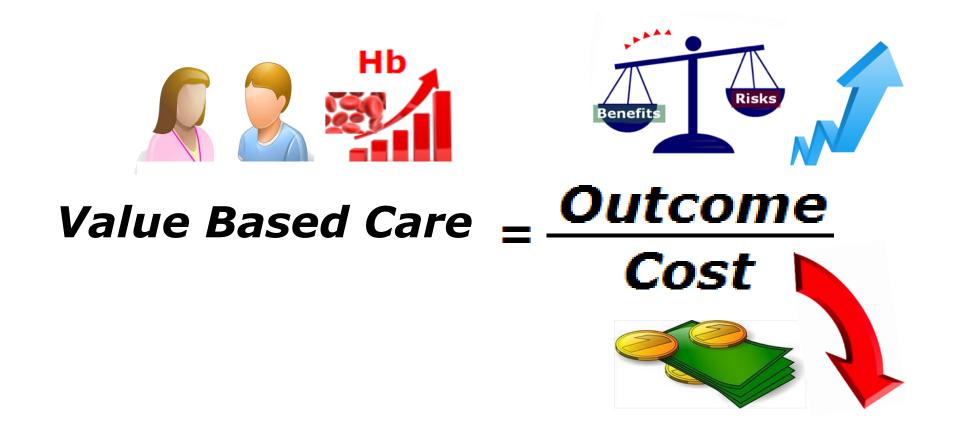
- Renal anemia: lesson learned in few decades
- Anemia correction: ESA, as a disruptive treatment in CKD treatment
- Anemia management: from clinical to artificial intelligence support
- •Take home message: what's next

### Anemia Control Module

Feedback Control Loop to Support Clinical Decision Making



### AI is a Tool that Add Value to Care of HD Patients



Porter ME. N Engl J Med. 2010;363(26):2477-81.

# In Brief... Benefits of AI in the Management of Anemia in HD Patients

- Increase number of patients in targets for Hb and iron markers
- Minimize Hb fluctuations over time
- Reduce significantly ESA and iron consumption
- Reduce variations in ESA/iron prescription
- Permit to identify potential causes of ESA resistance
- Provide information on ESA activity (sensitivity) and RBC life span (days)
- Prevent iron use imbalance (hemosiderosis) or ESA
- Reduce significantly cost associated with ESA/iron use
- Tend to reduce morbidity/mortality associated with anemia correction

### **Remaining Questions and Next Steps to be Validated**

- Software and medical device require CE certification
- Software should complying with drug prescription
- Generalizability and extension to others erythropoietic stimulating agents needs to be validated
- Economical model has to be created since it is currently out of dialysis fees
- Liability of prescription (user/software) is a new concern