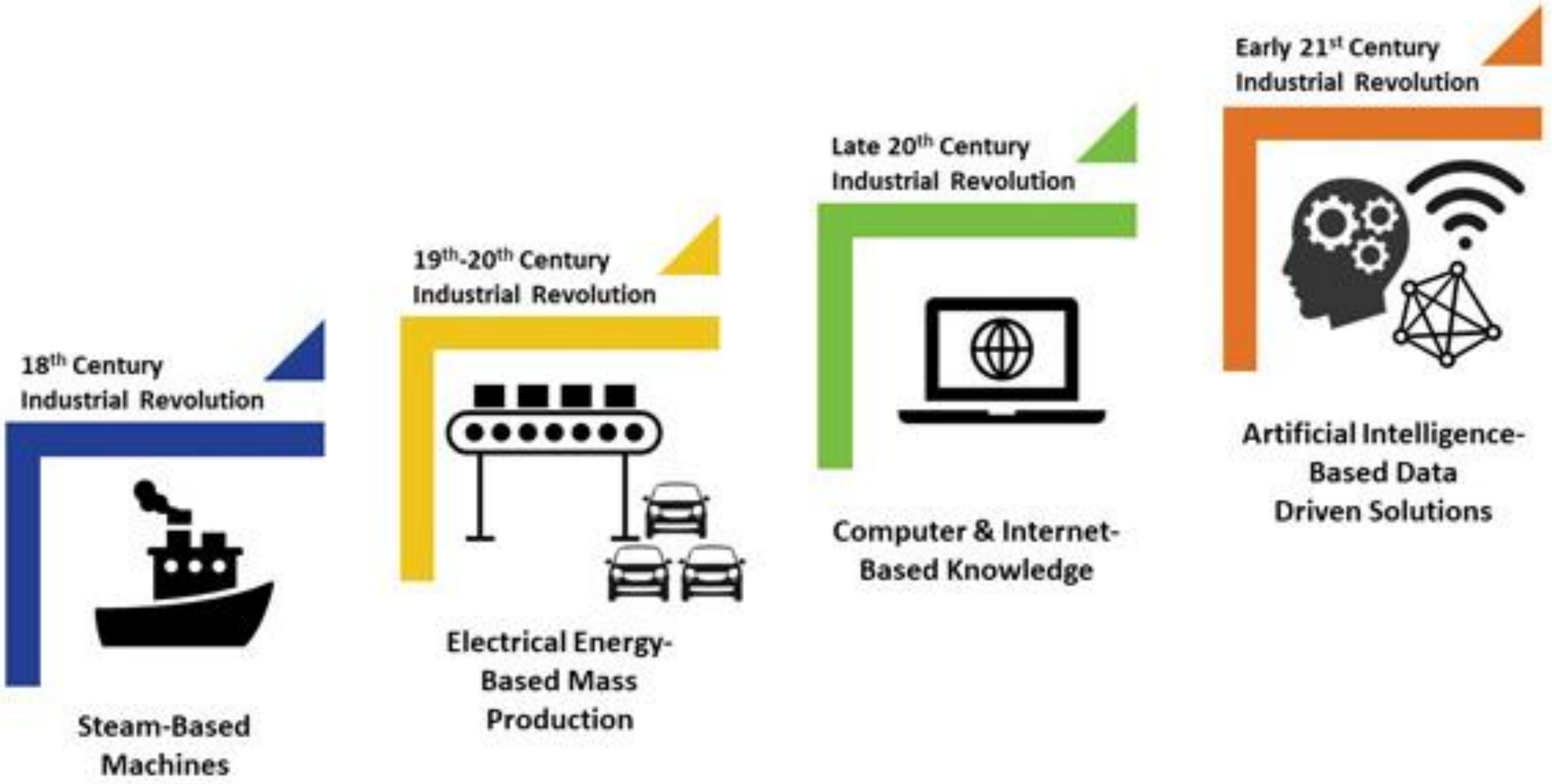
ΤΕΧΝΗΤΗ ΝΟΗΜΟΣΥΝΗ ΣΤΗΝ ΕΞΩΝΕΦΡΙΚΗ ΚΑΘΑΡΣΗ

ΑΝΑΣΤΑΣΙΟΣ Χ. ΦΟΥΝΤΟΓΛΟΥ

MD, MSc, PhD student

“The development of full artificial intelligence could spell **the end of the human race**....It would take off on its own, and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn’t compete, and would be superseded.”

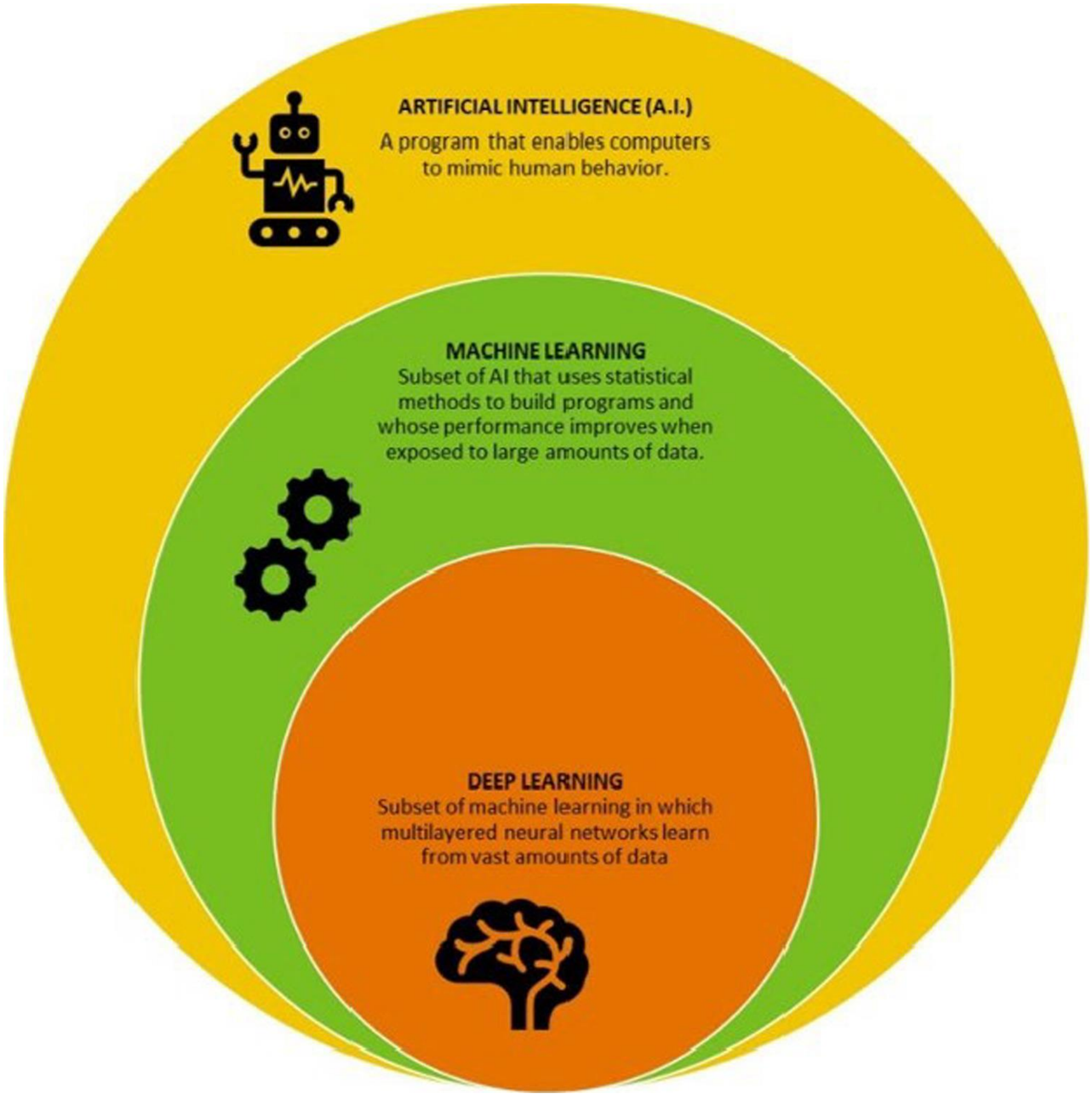
Stephen Hawking told the BBC

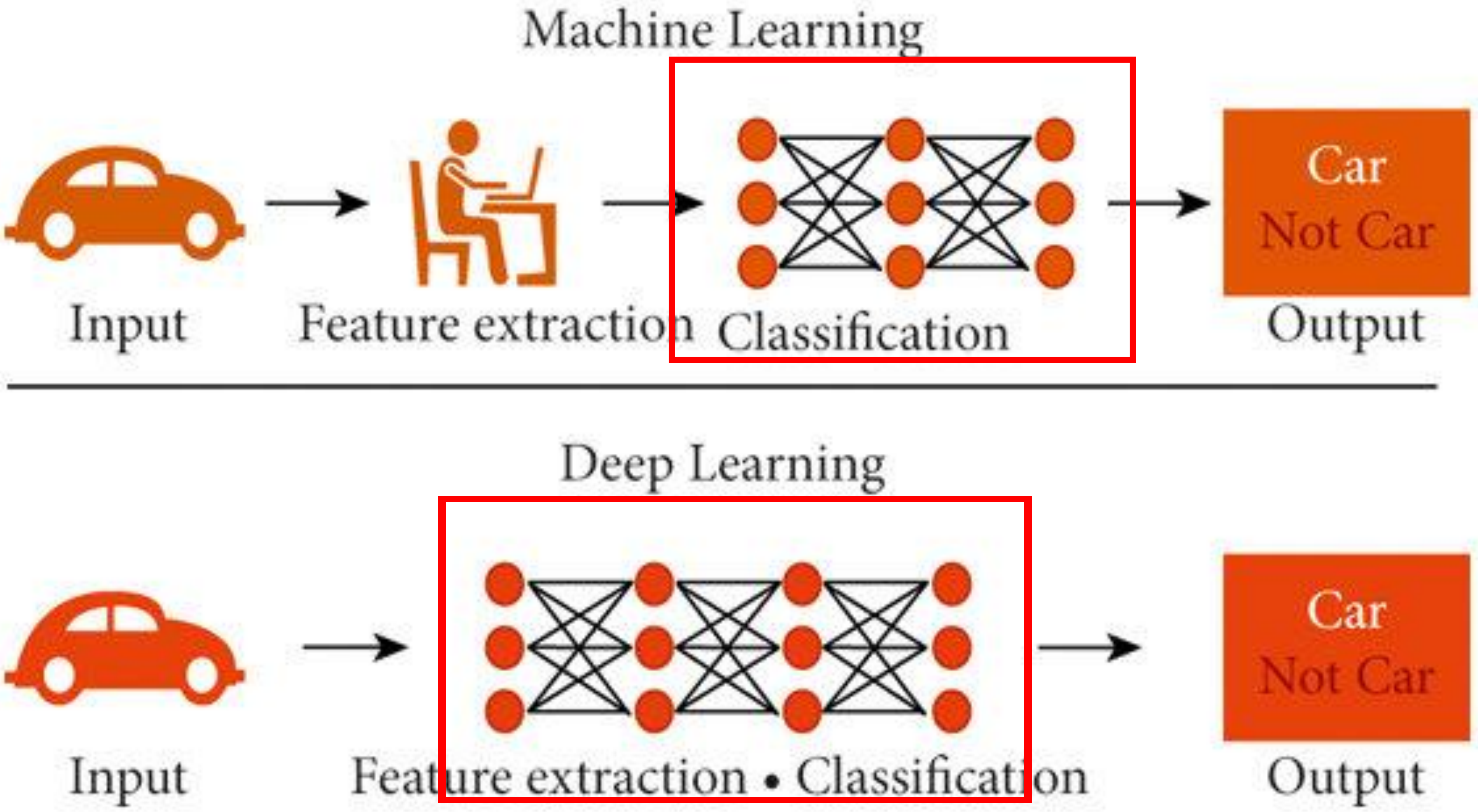

18th Century Industrial Revolution
Steam-Based Machines
19th-20th Century Industrial Revolution
Electrical Energy-Based Mass Production
Late 20th Century Industrial Revolution
Computer & Internet-Based Knowledge
Early 21st Century Industrial Revolution
Artificial Intelligence-Based Data Driven Solutions

τι είναι;

- η τεχνητή νοημοσύνη αναφέρεται στην ικανότητα μιας μηχανής να αναπαράγει τις γνωστικές λειτουργίες ενός ανθρώπου, όπως είναι η μάθηση, ο σχεδιασμός και η δημιουργικότητα.
- η τεχνητή νοημοσύνη καθιστά τις μηχανές ικανές να 'κατανοούν' το περιβάλλον τους, να επιλύουν προβλήματα και να δρουν προς την επίτευξη ενός συγκεκριμένου στόχου.
- τα συστήματα τεχνητής νοημοσύνης είναι ικανά να προσαρμόζουν τη συμπεριφορά τους, αναλύοντας τις συνέπειες προηγούμενων δράσεων και επιλύοντας προβλήματα με αυτονομία.

Η Βαθιά Μάθηση (Deep Learning) είναι ένα υποσύνολο της Μηχανικής Μάθησης (Machine Learning), η οποία με τη σειρά της, είναι ένα υποσύνολο της Τεχνητής Νοημοσύνης (Artificial Intelligence).




Machine Learning
Input
Feature extraction
Classification
Car
Not Car
Output
Deep Learning
Input
Feature extraction • Classification
Car
Not Car
Output

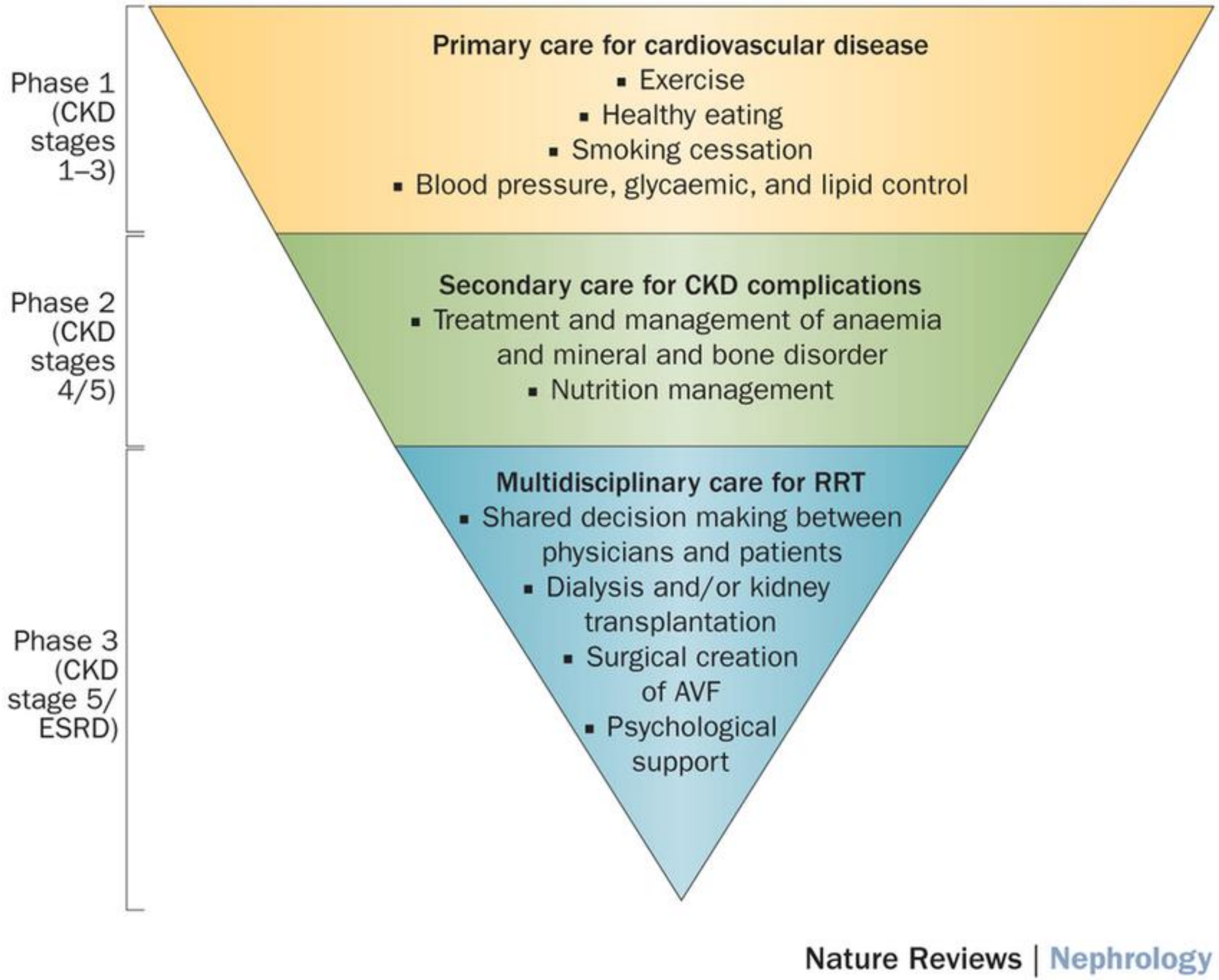
γενική χρήση στον τομέα της υγείας

- μία από τις βασικές εφαρμογές των συστημάτων τεχνητής νοημοσύνης αφορά την υποστήριξη της κλινικής απόφασης.
- έχοντας τη δυνατότητα ταχείας ανάλυσης μεγάλου όγκου δεδομένων, οι αλγόριθμοι της τεχνητής νοημοσύνης μπορούν να εντοπίζουν μοτίβα για διάφορες καταστάσεις υγείας και να βοηθούν τους επαγγελματίες υγείας στην τελική διάγνωση και λήψη απόφασης για τη θεραπεία

ειδικές χρήσεις στον τομέα της υγείας

- βελτίωση της διαγνωστικής ικανότητας
- έγκαιρη πρόγνωση
- η κατάλληλη θεραπεία στον κατάλληλο ασθενή
- ανάπτυξη νέων φαρμάκων
- ευκολότερη πρόσβαση του ασθενούς στο σύστημα υγείας
- αποδοτικότερη κατανομή διαθέσιμων πόρων

Η έννοια της ολοκληρωμένης φροντίδας στην ΧΝΝ


Phase 1 (CKD stages 1–3)
Primary care for cardiovascular disease
▪ Exercise
▪ Healthy eating
▪ Smoking cessation
▪ Blood pressure, glycaemic, and lipid control
Phase 2 (CKD stages 4/5)
Secondary care for CKD complications
▪ Treatment and management of anaemia and mineral and bone disorder
▪ Nutrition management
Phase 3 (CKD stage 5/ ESRD)
Multidisciplinary care for RRT
▪ Shared decision making between physicians and patients
▪ Dialysis and/or kidney transplantation
▪ Surgical creation of AVF
▪ Psychological support
Nature Reviews | Nephrology

πως την διαχειρίζεται ο ανθρώπινος εγκέφαλος;

ΔΕΔΟΜΕΝΑ → **ΑΛΓΟΡΙΘΜΟΙ** → **ΑΠΟΦΑΣΕΙΣ**

- ΕΡΓΑΣΤΗΡΙΑΚΕΣ ΕΞΕΤΑΣΕΙΣ
- ΒΙΟΔΕΙΚΤΕΣ
- ΑΠΕΙΚΟΝΙΣΤΙΚΑ ΕΥΡΗΜΑΤΑ
- ΟΙΚΟΓΕΝΕΙΑΚΟ ΙΣΤΟΡΙΚΟ
- ΑΤΟΜΙΚΟ ΙΣΤΟΡΙΚΟ
- ΦΑΡΜΑΚΑ

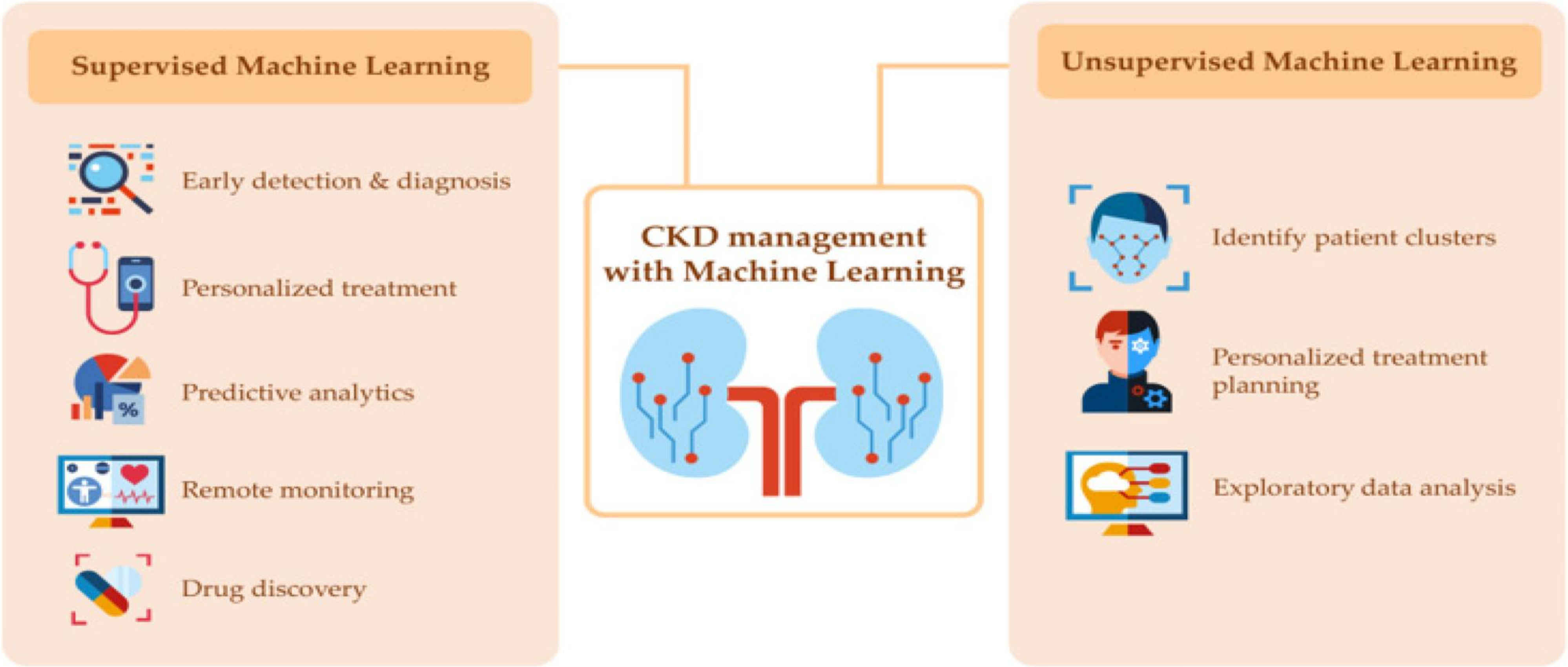
KDIGO
KIDNEY DISEASE IMPROVING GLOBAL O

KDOQI
KIDNEY DISEASE OUTCOMES QUALITY INITIATIVE
National Kidney Foundation

- ΔΙΑΓΝΩΣΗ
- ΠΡΟΓΝΩΣΗ
- ΘΕΡΑΠΕΙΑ

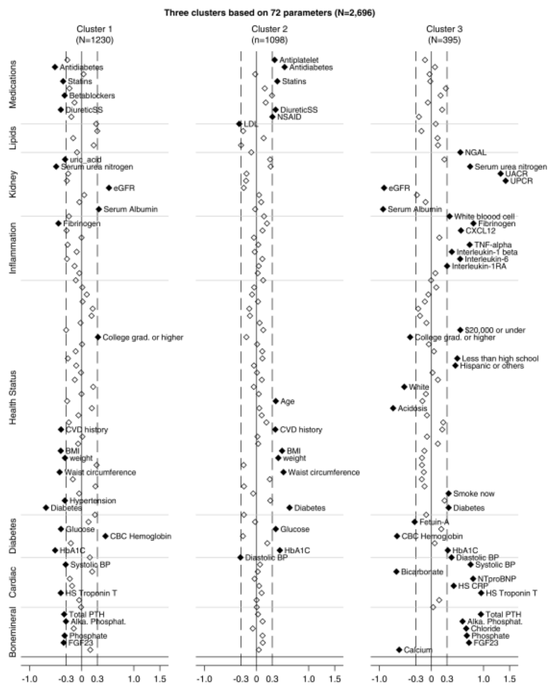
αλλά.....

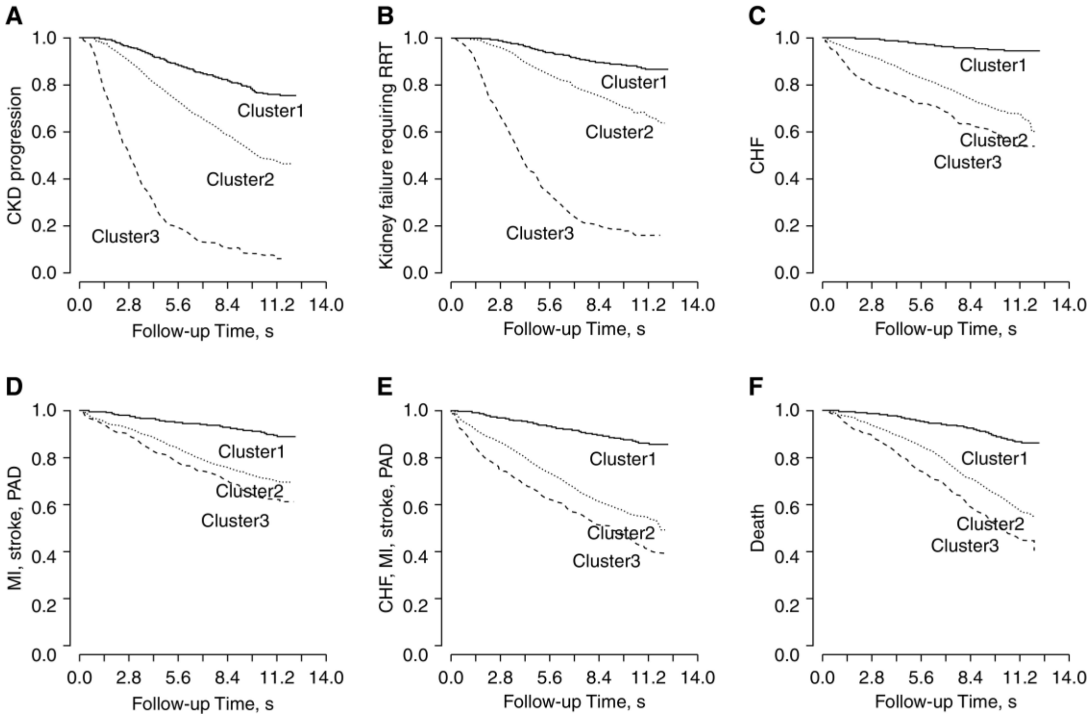
πως μπορεί να τη διαχειριστεί η τεχνητή νοημοσύνη;

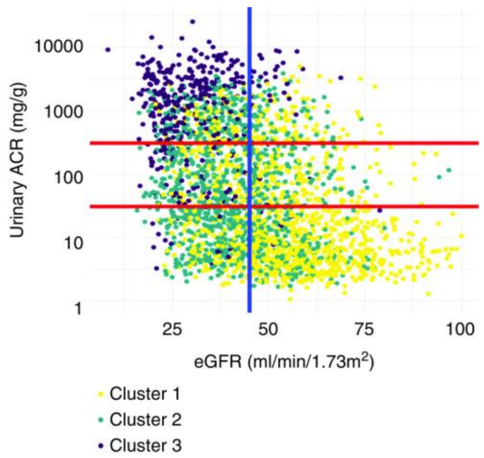

Supervised Machine Learning
Early detection & diagnosis
Personalized treatment
Predictive analytics
Remote monitoring
Drug discovery
CKD management
with Machine Learning
Unsupervised Machine Learning
Identify patient clusters
Personalized treatment
planning
Exploratory data analysis

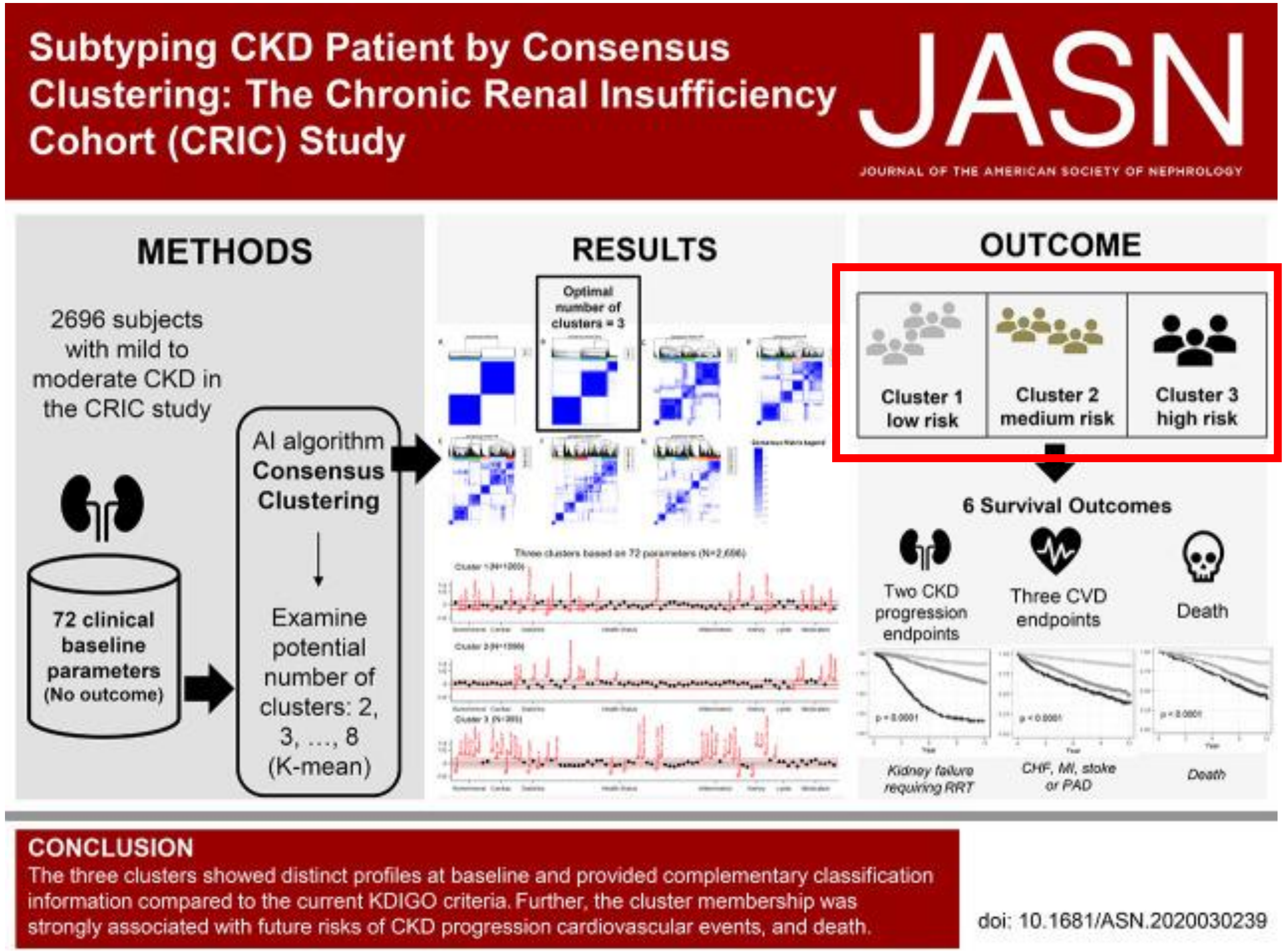
CKD	Chan et al. (2021) [40]	Prediction: patients (n = 1146) with prevalent DKD (G3a–G3b with all grades of albuminuria (A1–A3) and G1 and G2 with A2–A3 level albuminuria)	Prediction risk of ESKD in patients with CKD and type 2 diabetes mellitus Combination of novel biomarkers and data extracted from EHR (KidneyIntelX score). Comparison with traditional models	ML Random forest model	AUC for composite kidney endpoint 0.77 compared with an AUC of 0.61 (95% CI 0.60–0.63) for the clinical model	Missing data for urine results
	Hermsen et al. (2019) [41]	Diagnosis: use of kidney transplant biopsies and nephrectomy samples	Multiclass segmentation of digitized kidney tissue sections Facilitation of the histological study of samples using digital analysis and comparison of this approach with the performance of expert pathologists	Deep learning: CNN	The best segmented class was glomeruli. The mean intraclass correlation coefficient for glomerular counting performed by pathologists versus the network was 0.94	This work focused only on the segmentation of glomeruli and refers to a small sample size
Glomerular disease	IgAN-tool (Asia) [22]	Prediction: patients with IgAN from multiple centers in China (n = 2047) Multicenter, retrospective	ESKD prediction for IgAN patients Model based on 10 clinical, laboratory, and histological variables	XGBoost algorithm	High discriminatory power: C-statistic of 0.84 (95% CI 0.80–0.88) for the validation cohort	Study only performed in Asian patients
	IgAN-tool (EU) [42]	Prediction: IgAN patients (n = 948). Retrospective. Follow-up 89 months	ESKD prediction for IgAN patients Model based on seven clinical and histological variables including MEST-C score	Cox regression for variable selection DL: ANN	AUC 0.82 at 5 years AUC 0.89 at 10 years	Developed and tested in retrospective cohorts Therapeutic interventions not included
Inherited kidney disease	Jefferies et al. (2021) [43]	Diagnosis: de-identified health records from a cohort of patients with confirmed Fabry disease (n = 4978) Patients from 50 US states	Diagnosis of Fabry disease using EHR. ICD-10 codes used AI tool (OM1 Patient Finder^{TM}) (OM1 Inc., Boston, MA)	ML (model not specified)	AUROC 0.82 Testing in males only: AUROC 0.83 Testing in females only: AUROC 0.82	Missings in health records Gender imbalance Not validated in external cohorts outside the USA
	Potretzke et al. (2023) [18]	Diagnosis/prediction: Patients with ADPKD undergoing MR imaging between November 2019 and January 2021 (N = 170) 1 center: Mayo Clinic	Evaluate performance in clinical practice of an AI algorithm for MR-derived total kidney volume in ADPKD	DL: CNN	AI algorithm TKV output mean volume difference −3.3%. Agreement for disease class between AI-based and manually edited segmentation high (five cases differed)	Prospective study in different centers to evaluate whether the algorithm is generalizable remains to be elucidated

CHRONIC RENAL INSUFFICIENCY COHORT STUDY





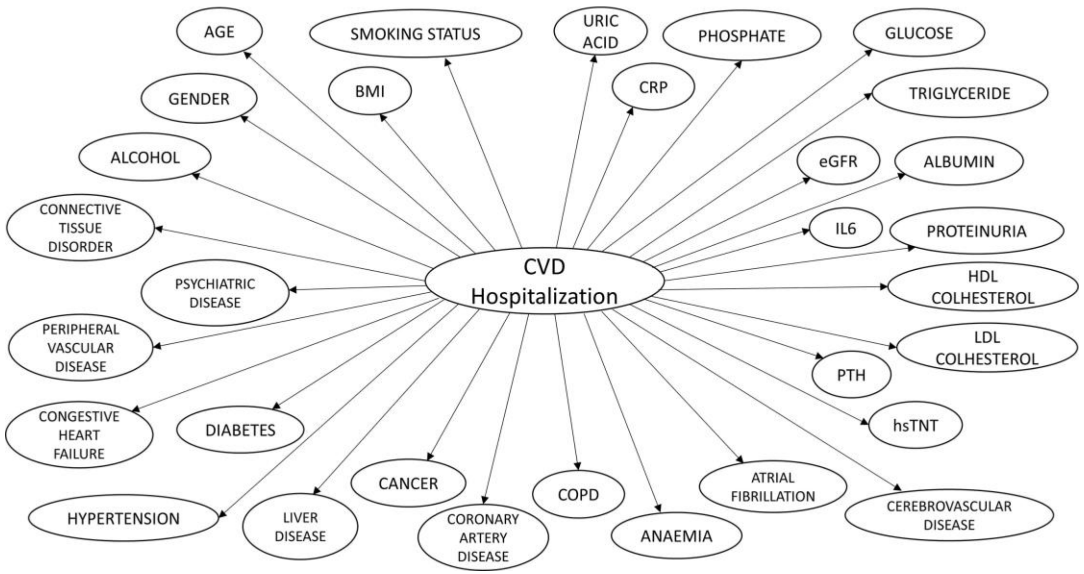




Subtyping CKD Patient by Consensus Clustering: The Chronic Renal Insufficiency Cohort (CRIC) Study
JASN
JOURNAL OF THE AMERICAN SOCIETY OF NEPHROLOGY
METHODS
2696 subjects with mild to moderate CKD in the CRIC study
72 clinical baseline parameters (No outcome)
AI algorithm Consensus Clustering
Examine potential number of clusters: 2, 3, ..., 8 (K-mean)
RESULTS
Optimal number of clusters = 3
OUTCOME
Cluster 1 low risk
Cluster 2 medium risk
Cluster 3 high risk
6 Survival Outcomes
Two CKD progression endpoints
Three CVD endpoints
Death
Kidney failure requiring RRT
CHF, MI, stoke or PAD
Death
CONCLUSION
The three clusters showed distinct profiles at baseline and provided complementary classification information compared to the current KDIGO criteria. Further, the cluster membership was strongly associated with future risks of CKD progression cardiovascular events, and death.
doi: 10.1681/ASN.2020030239

The Cardiovascular Literature-Based Risk Algorithm (CALIBRA): Predicting Cardiovascular Events in Patients With Non-Dialysis Dependent Chronic Kidney Disease

Luca Neri[1*] Caterina Lonati[2] Jasmine Ion Titapiccolo[1] Jennifer Nadal[3] Heike Meiselbach[4] Matthias Schmid[3] Barbara Baerthlein[5] Ulrich Tschulena[6] Markus P. Schneider[4] Ulla T. Schultheiss[7,8] Carlo Barbieri[6] Christoph Moore[6] Sonia Steppan[6] Kai-Uwe Eckardt[4,9] Stefano Stuard[6] Francesco Bellocchio[1]



Group	Variable
Demographics	
	Age, year
	Gender
Traditional CVD risk factors	
	HDL Cholesterol, mg/dl
	LDL Cholesterol, mg/dl
	BMI, kg/cm2
	Triglyceride, mg/dl
	Diabetes
	Hypertension
	Smoking status
	Cerebrovascular disease
	Coronary artery disease
	Congestive heart failure
	Peripheral vascular disease
	Atrial Fibrillation
Nontraditional risk factors	
	Glucose, mg/dl
	hsTNT, ng/l*
	IL-6, ng/l*
	PTH, ng/l
	Anemia
	Alcohol
	Cancer
	COPD
	Connective tissue disorder
	Liver Disease
	Psychiatric Disease
	Albumin, g/dl
	ACR or Urin protein, g/24h
	CRP, mg/l
	eGFR, (ml/min/1·73 m^2)
	Phosphate, mg/dl
	Uric Acid, mg/dl

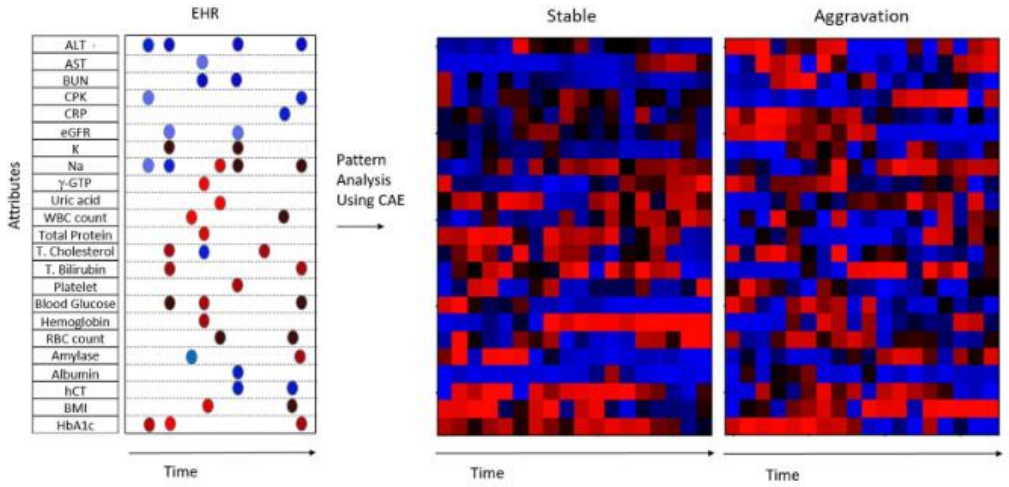
Variables always missing in both datasets.

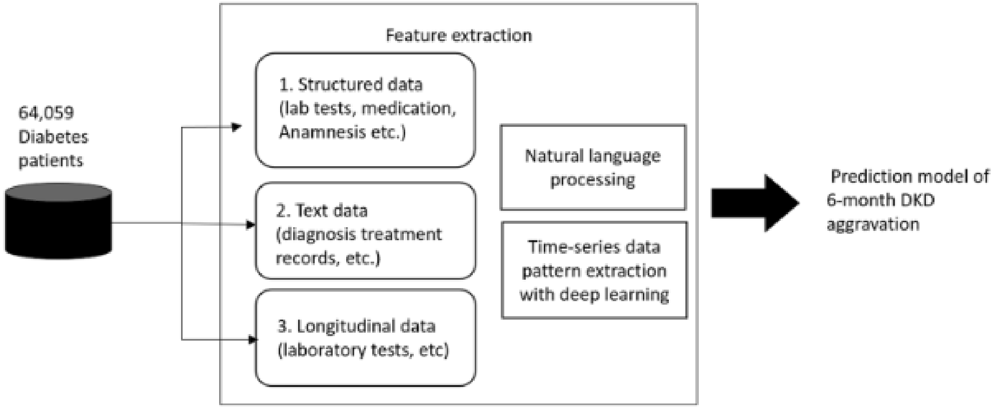
Cohort	Contrast	Effective Sample Size	AUC CALIBRA	AUC benchmark	Delta AUCs	P-value
FMC Nephrocare						
	CALIBRA	14,880	0.79	-	-	-
	ASCVD - CALIBRA	3,960	0.76	0.59	**-0.17**	<0.001
	FHS - CALIBRA	3,960	0.76	0.54	**-0.22**	<0.001
	INDANA - CALIBRA	3,960	0.77	0.63	**-0.14**	<0.001
G-CKD						
	CALIBRA	4,822	0.73	-	-	-
	ASCVD - CALIBRA	4,792	0.73	0.61	**-0.12**	<0.001
	FHS - CALIBRA	4,792	0.73	0.57	**-0.16**	<0.001
	INDANA - CALIBRA	4,792	0.73	0.69	-0.04	<0.001

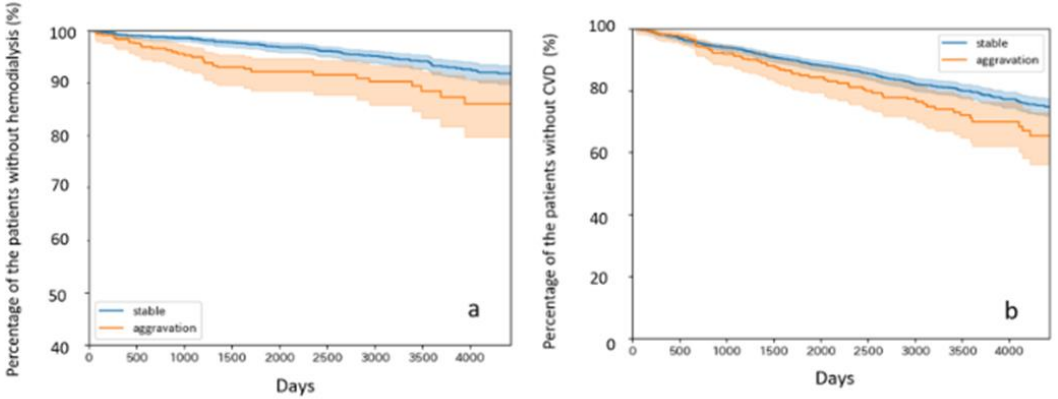
CALIBRA performance was assessed either including all cases or excluding patients with missing information. The benchmark model scores were computed considering only complete cases. The column "Effective sample size" reports the number of patients included in each analysis. Imputation method: Listwise. Non-inferiority was defined as ΔAUC<0.05, while superiority was set at ΔAUC >=0.05.

Artificial intelligence predicts the progression of diabetic kidney disease using big data machine learning

Masaki Makino [1], Ryo Yoshimoto [1], Masaki Ono [2], Toshinari Itoko [2], Takayuki Katsuki [2], Akira Koseki [2], Michiharu Kudo [2], Kyoichi Haida [3], Jun Kuroda [4], Ryosuke Yanagiya [5], Eiichi Saitoh [6], Kiyotaka Hoshinaga [7], Yukio Yuzawa [8], Atsushi Suzuki [9]







Hierarchical clustering analysis for predicting 1-year mortality after starting hemodialysis

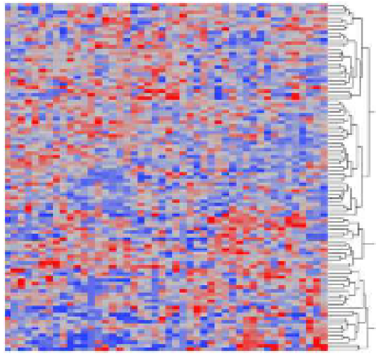
PATIENTS & DESIGN

101 patients
- started hemodialysis
- Used baseline demographics and laboratory data

Prospective observational study
- followed for 1 year
- Death and length of hospital stay

METHODS & CLUSTERING

Agglomerative hierarchical clustering
- Included 46 variables
- Classified into **3 clusters:**



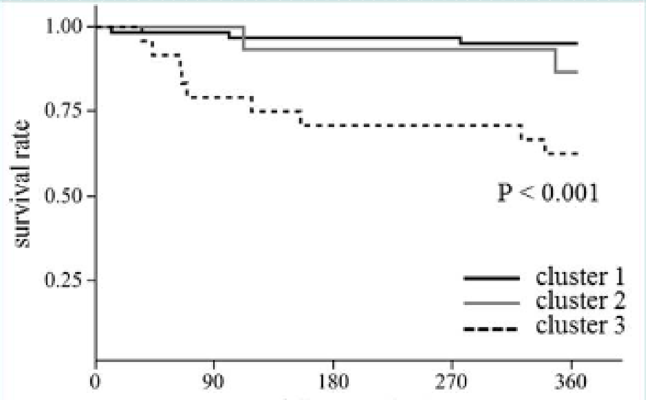
cluster 1:
- The largest cohort
- Low WBC & CRP

cluster 2:
- High BNP & serum K

cluster 3:
- Not hypertensive
- Low serum creatinine
- Low urinary L-FABP

RESULTS

1-year Mortality:
Cluster 1 (4.8%) < Cluster 3 (37.5%)
Hospital stay (days): Cluster 1 < Clusters 2, 3



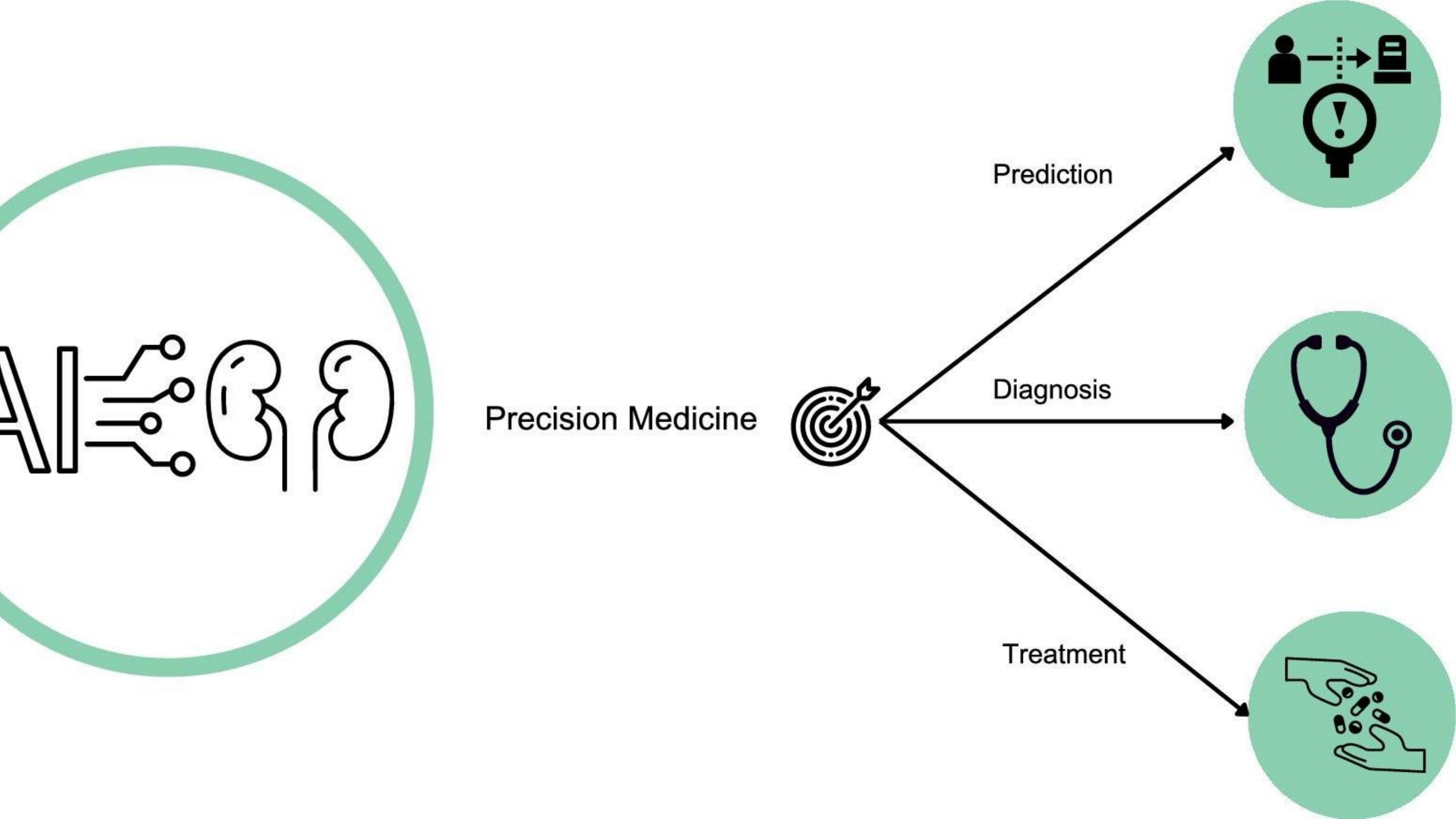
CONCLUSION:

Agglomerative hierarchical clustering was applied to patients newly starting maintenance HD. The resulting clusters were associated with 1-year mortality and length of hospital stay.

Abbreviations: BNP, B-type natriuretic peptide; CRP, C-reactive protein; L-FABP, liver-type fatty acid-binding protein; WBC, white blood cell

KI REPORTS
KIReports.org

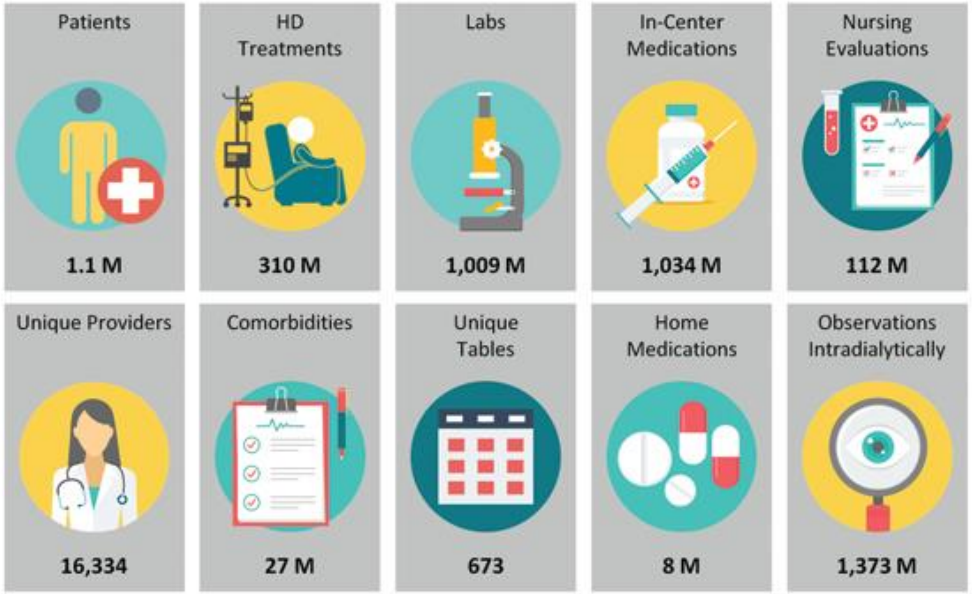
Komaru & Yoshida et al, 2020



AI
Precision Medicine
Prediction
Diagnosis
Treatment

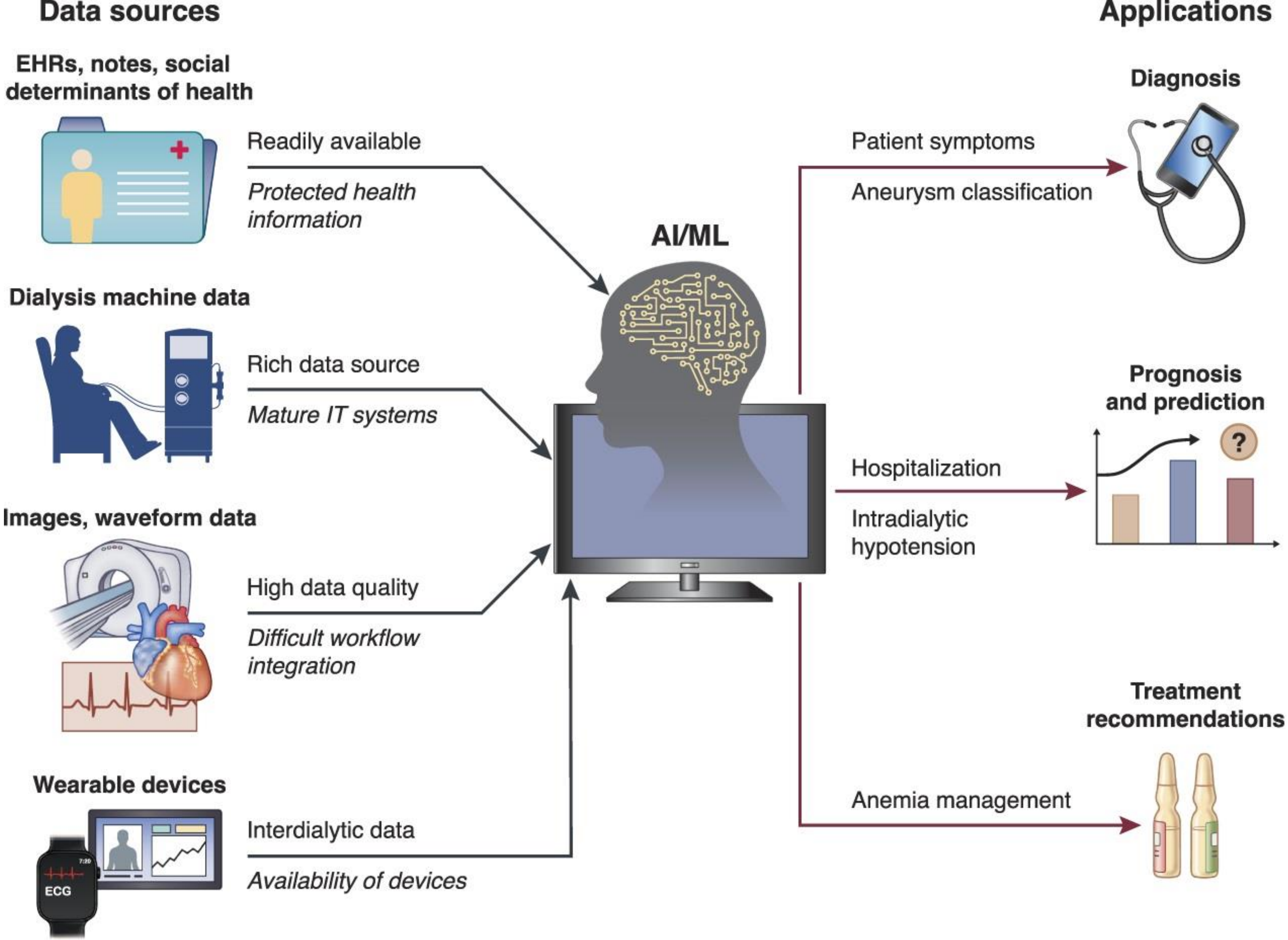
γιατί AI στην αιμοκάθαρση;

- η αιμοκάθαρση είναι μια τυποποιημένη διαδικασία που προσφέρει μεγάλο όγκο δεδομένων
- η συνταγογράφηση της ΑΚ (διάρκεια, όγκος υπερδιήθησης, ροή αίματος) καθώς και η φαρμακευτική αγωγή της ΑΚ καταγράφονται τακτικά και συστηματικά
- υπάρχουν διαθέσιμες πληροφορίες για τα δημογραφικά χαρακτηριστικά των ασθενών, τις συννοσηρότητες και τα εργαστηριακά τους αποτέλεσματα
- υπάρχει συνεχής καταγραφή των ζωτικών σημείων των ασθενών (αρτηριακή πίεση, καρδιακός ρυθμός κ.α) ενώ η χρήση βιομετρικών συσκευών δίνει τη δυνατότητα καταγραφής αυτών των σημείων και εκτός αιμοκάθαρσης



Artificial kidney

Artificial intelligence


Data sources
EHRs, notes, social determinants of health
Readily available
Protected health information
Dialysis machine data
Rich data source
Mature IT systems
Images, waveform data
High data quality
Difficult workflow integration
Wearable devices
ECG
Interdialytic data
Availability of devices
AI/ML
Applications
Diagnosis
Patient symptoms
Aneurysm classification
Prognosis and prediction
Hospitalization
Intradialytic hypotension
Treatment recommendations
Anemia management

Dialysis	Barbieri et al. (2016) [34]	Treatment: hemodialysis patients (n = 752) in three different NephroCare centers (Fresenius Medical Care network) across the EU	Anemia control model to recommend suitable erythropoietic-stimulating agent doses based on patient profiles	DL: ANN	Hb SD decreased (0.97 ± 0.41 g/dL to 0.8 ± 0.29 g/dL) Hb within target 84.1% vs 64.5%	Not a randomized or blinded controlled trial Short follow-up period to assess outcomes No external validation
	Zhang et al. (2022) [44]	Diagnosis: digital images of AV accesses before cannulation (1425 AV access images) Cohort of hemodialysis patients from 20 dialysis clinics across six US states	Classification of vascular access aneurysm as “non-advanced” or “advanced”	DL: CNN	AUROC 0.96	Real world testing in a demographically diverse population remains to be published Clinical parameters not included
	Lee et al. (2021) [45]	Prediction: analysis of 261 647 hemodialysis sessions (N = 9292) One center (Seoul National University Hospital)	DL model to predict the risk of intradialytic hypotension using a timestamp-bearing dataset	DL: RNN	AUC 0.94 for prediction of intradialytic hypotension 1 (defined as nadir systolic BP <90 mmHg)	Retrospective cohort. One center Other factors not included (cardiac monitoring, dialysis vintage and medical records)

Development of an Artificial Intelligence Model to Guide the Management of Blood Pressure, Fluid Volume, and Dialysis Dose in End-Stage Kidney Disease Patients: Proof of Concept and First Clinical Assessment Free

Subject Area: Nephrology

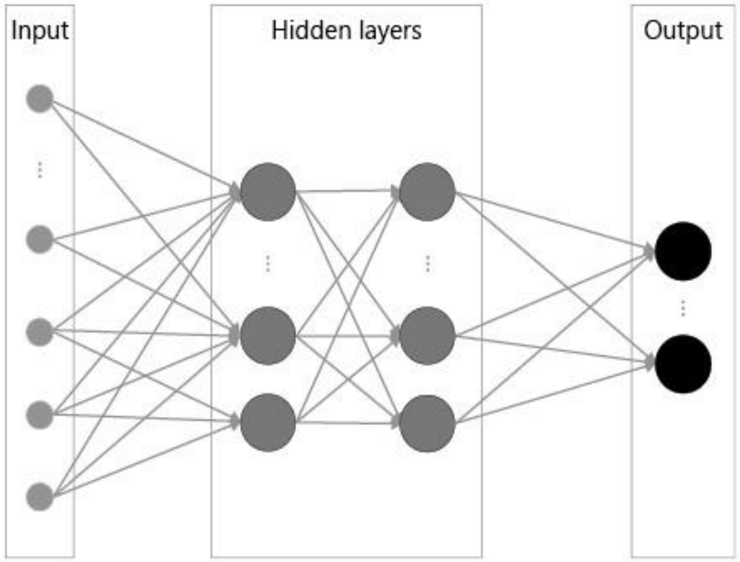
Carlo Barbieri; Isabella Cattinelli; Luca Neri; Flavio Mari; Rosa Ramos; Diego Brancaccio; Bernard Canaud; Stefano Stuard

Kidney Dis (2019) 5 (1): 28–33.

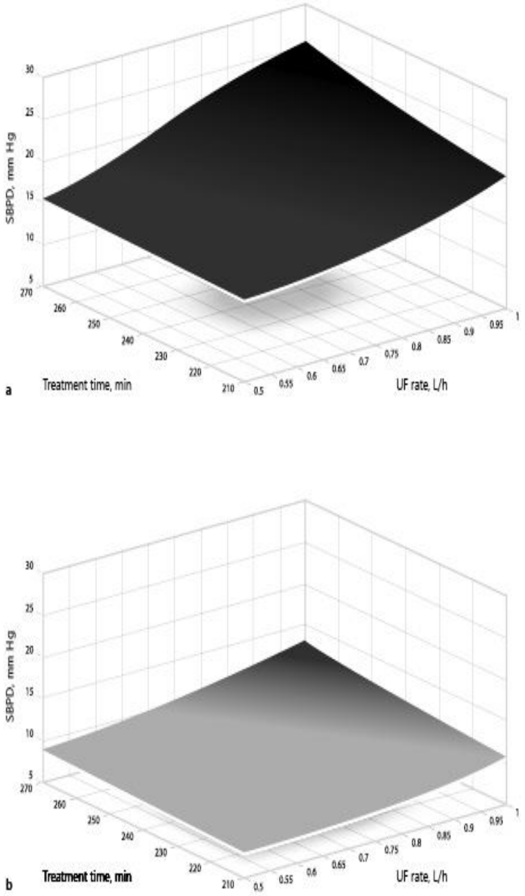
Despite significant progresses in technical aspects, fluid volume and BP control are still a challenging situation for clinicians in hemodialysis patients. On the one hand, fluid volume removal, osmolality changes, and electrolyte imbalance are well-known interacting key players of hemodynamic instability and maltolerance of hemodialysis session [3, 4]. On the other hand, inadequate control of fluid overload and high BP may favor the occurrence of cardiovascular events and mortality. It is now established, that both chronic fluid overload and hypertension and intradialytic hemodynamic stress due to hypovolemia are associated with poor long-term patient outcomes including cardiovascular morbidity (hospitalization), altered quality of life, and mortality [5].

Artificial intelligence can be used to predict the individualized, session-specific patient reaction to dialysis-related prescriptions on multiple relevant hemodynamic parameters (e.g., intradialytic heart rate and BP changes and trends) and dialysis adequacy parameters (e.g., Kt/V and fluid removal) so that the best strategy can be chosen based on clinical judgment or formal utility functions.

- Χαρακτηριστικά ασθενούς
- Εκβάσεις προηγούμενων συνεδριών
- Δεδομένα προ αιμοκάθαρσης
- Συνταγογράφηση αιμοκάθαρσης



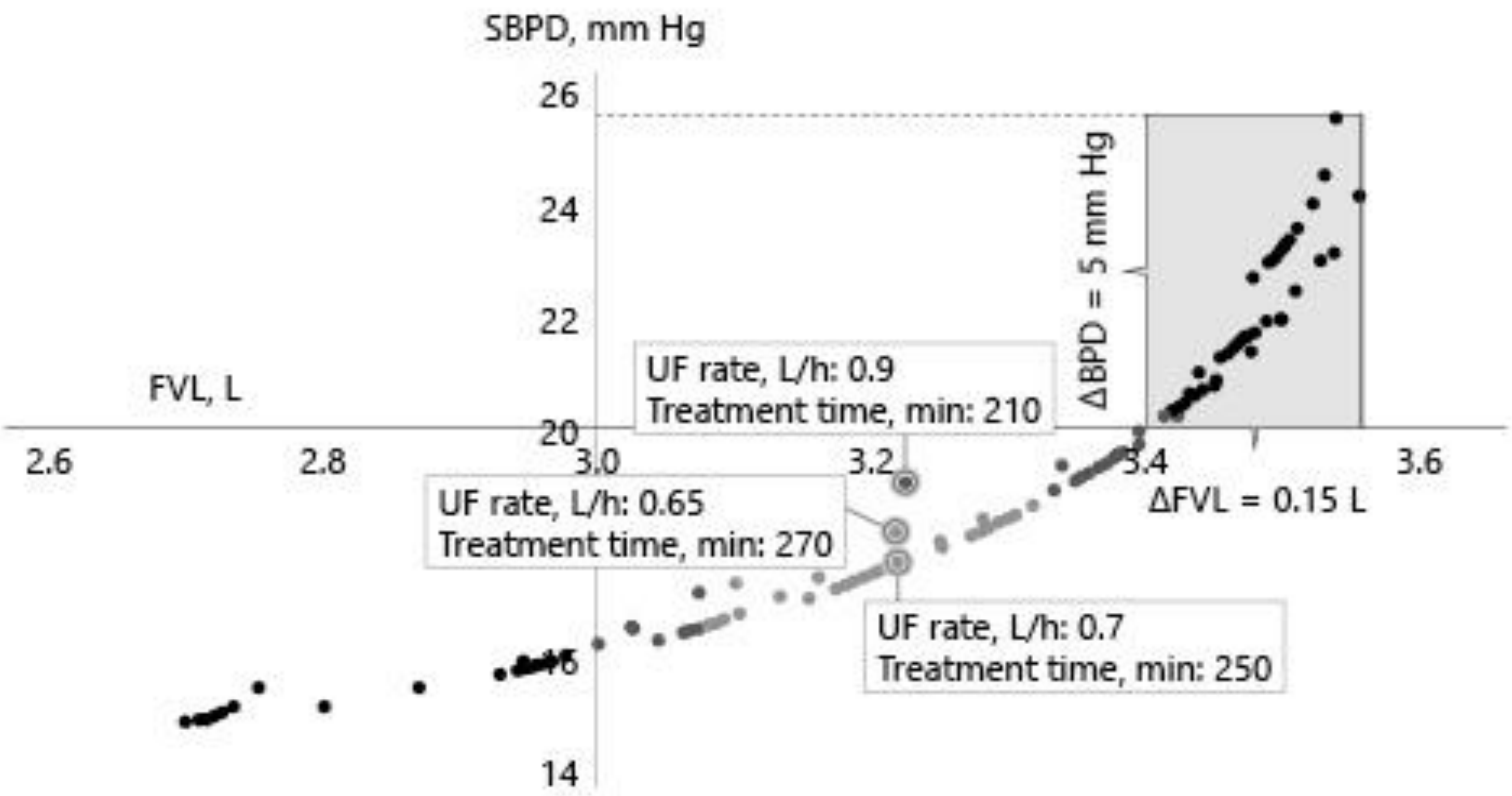
- Ελάχιστη ΑΠ της συνεδρίας
- Καρδιακός ρυθμός μετά την συνεδρία
- Βάρος ασθενούς μετά την συνεδρία
- Kt/V



	Patient A	Patient B
Weight, kg	80	98
Heart rate, bpm	76	68
DBP, mm Hg	82	60
Body fat mass, kg	40	57
Age, years	80	56
Diabetes vintage, years	10	30
HTN vintage, years	12	30
D-sodium, mEq/L	140	138
S-sodium, mEq/L	137	140
Ferritin	362	40
Hemoglobin	10	13
Glucose	225	97
Phosphate	5	8

DBP, diastolic BP; HTN, hypertension.

Both Patients A and B were obese (BMI = 32), had multiple comorbidities including a long history of diabetes and hypertension, had similar predialysis SBP levels (110 vs. 115 mm Hg, respectively), estimated overhydration (> 4 L for both), and received the same UF prescription (UF rate: 1 L/h; dialysis time: 240 min). However, only Patient A experienced a major hypotensive event during the index session



A closer look at Patient A's simulated reaction allows to detect a safer UF prescription while maximizing fluid removal

Deep Learning Model for Real-Time Prediction of Intradialytic Hypotension

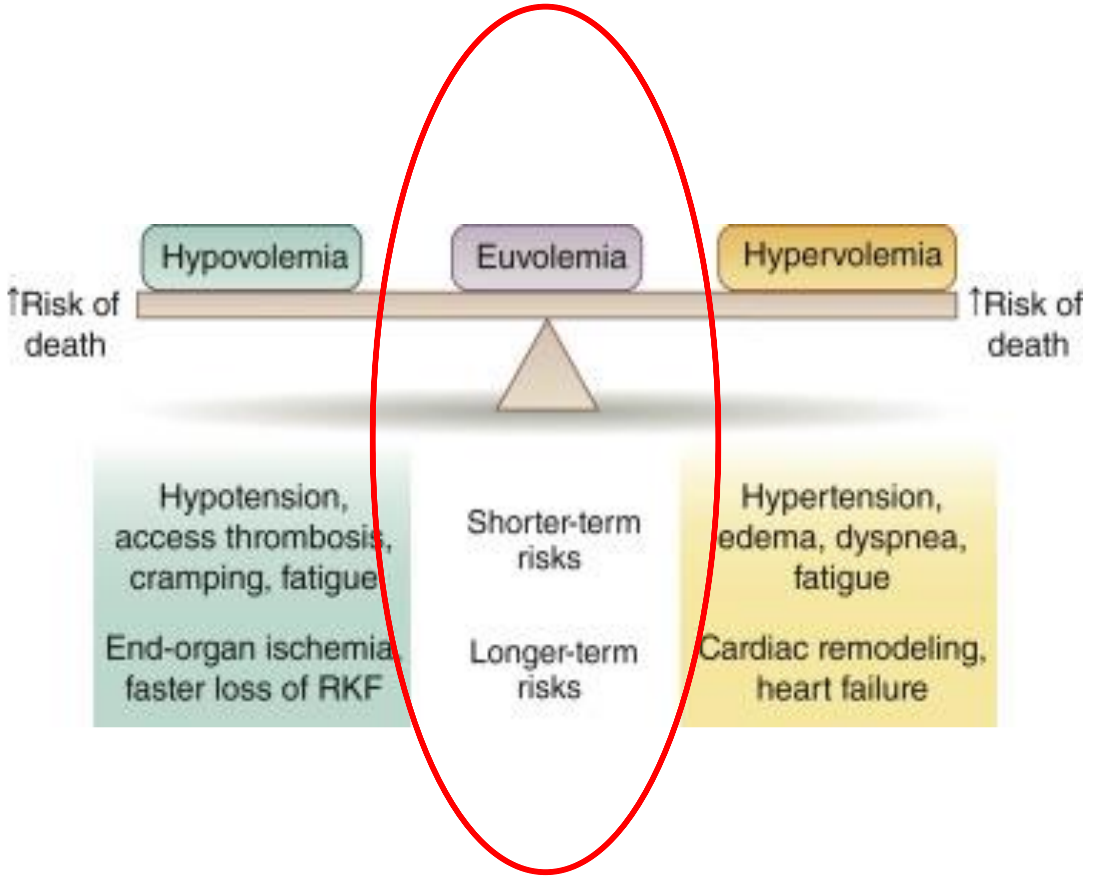
Hojun Lee [1], Donghwan Yun [2] [3], Jayeon Yoo [1], Kiyoon Yoo [1], Yong Chul Kim [3], Dong Ki Kim [3], Kook-Hwan Oh [3], Kwon Wook Joo [3], Yon Su Kim [2] [3], Nojun Kwak [1], Seung Seok Han [2] [3]

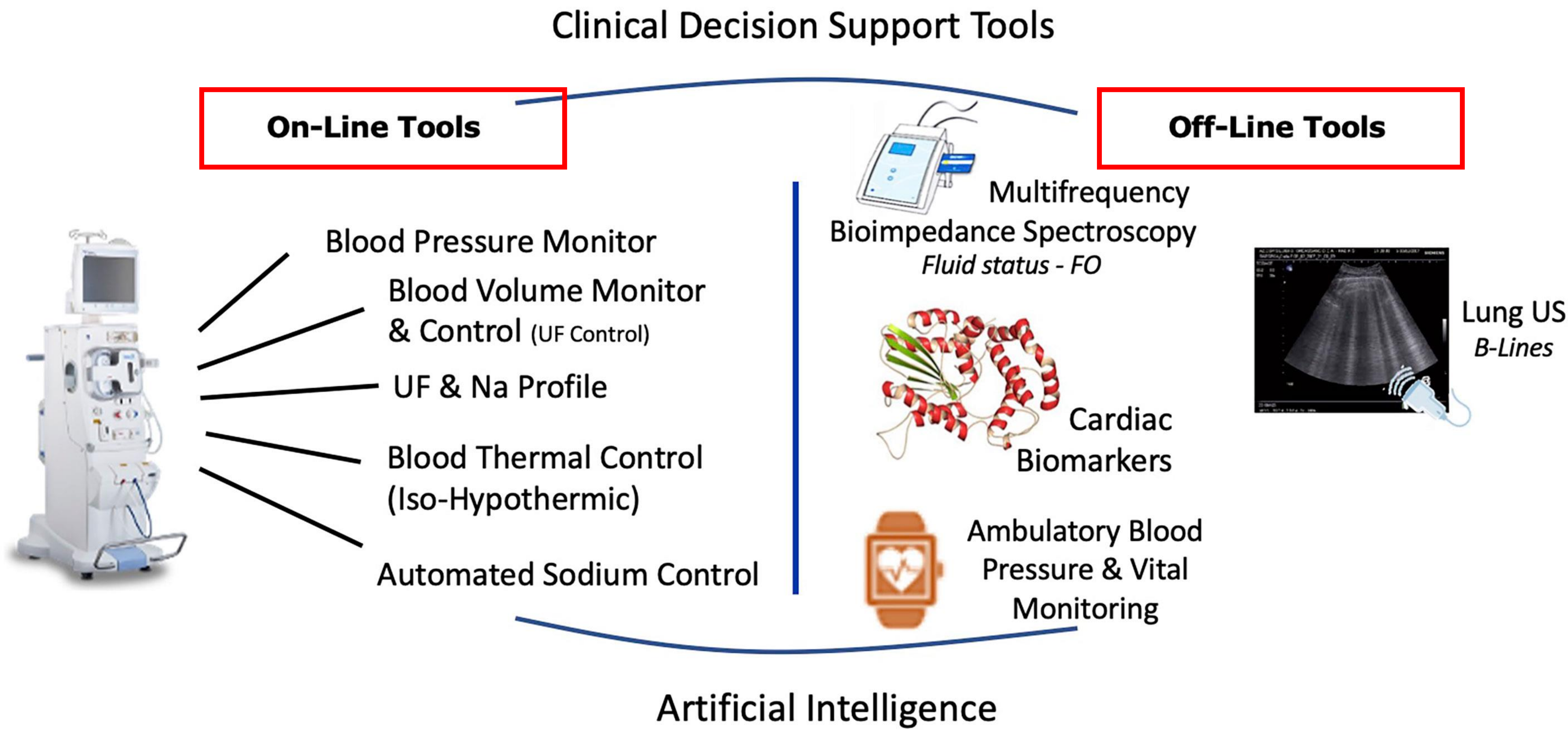
Each hemodialysis session was automatically saved to the database. Along with the initial hemodialysis settings, measured values, including arterial line pressure (AP), venous line pressure (VP), blood flow rate, dialysate flow rate, ultrafiltration rate, total ultrafiltration volume, temperature, and dialysate sodium level were collected from the hemodialysis machine every minute. Vital signs, including systolic blood pressure (SBP), diastolic blood pressure (DBP), mean arterial pressure (MAP), and pulse rate, were recorded every 1 h by default, and all additional measurements were also recorded at any time-point during hemodialysis session. Blood pressure was additionally measured when patient complained of any symptoms associated abnormal blood pressure.

The developed models use 30 min information to predict an IDH event in the following 10 min window

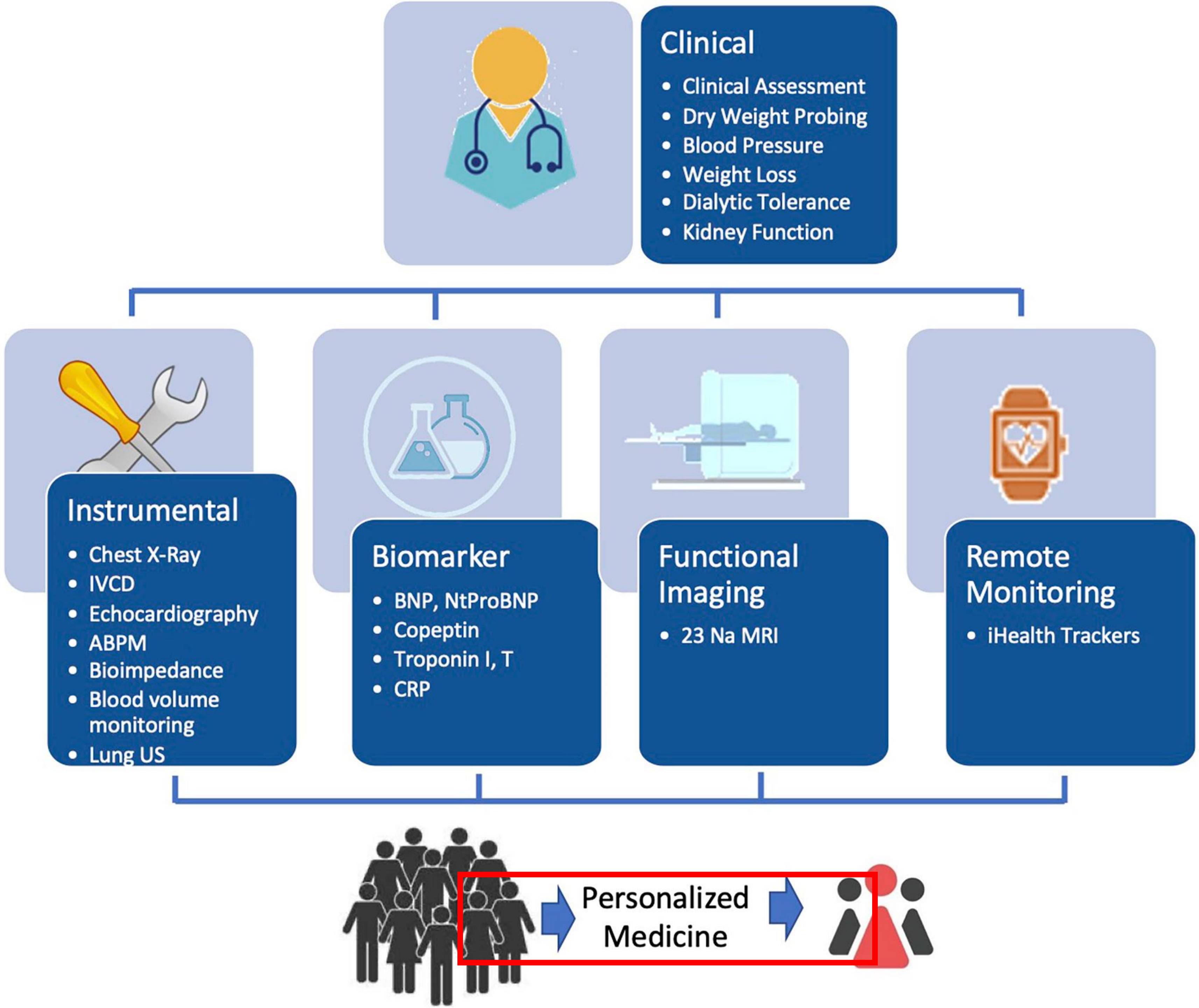
Conclusions: The deep learning model performed well only using monitoring measurement of hemodialysis machine in predicting IDH without any personal information that could risk privacy infringement.

ποιος είναι ο στόχος;



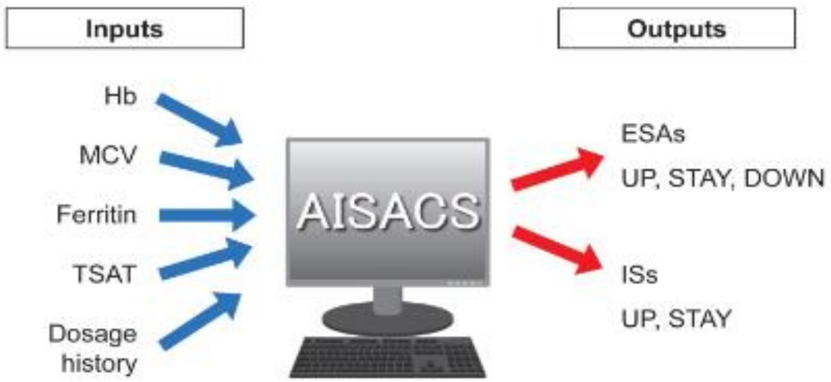


Clinical Decision Support Tools
On-Line Tools
Off-Line Tools
Blood Pressure Monitor
Blood Volume Monitor
& Control (UF Control)
UF & Na Profile
Blood Thermal Control
(Iso-Hypothermic)
Automated Sodium Control
Multifrequency
Bioimpedance Spectroscopy
Fluid status - FO
Lung US
B-Lines
Cardiac
Biomarkers
Ambulatory Blood
Pressure & Vital
Monitoring
Artificial Intelligence


Clinical
Clinical Assessment
Dry Weight Probing
Blood Pressure
Weight Loss
Dialytic Tolerance
Kidney Function
Instrumental
Chest X-Ray
IVCD
Echocardiography
ABPM
Bioimpedance
Blood volume monitoring
Lung US
Biomarker
BNP, NtProBNP
Copeptin
Troponin I, T
CRP
Functional Imaging
23 Na MRI
Remote Monitoring
iHealth Trackers
Personalized Medicine

An international observational study suggests that artificial intelligence for clinical decision support optimizes anemia management in hemodialysis patients

Carlo Barbieri [1], Manuel Molina [2], Pedro Ponce [3], Monika Tothova [4], Isabella Cattinelli [5], Jasmine Ion Titapiccolo [5], Flavio Mari [5], Claudia Amato [5], Frank Leipold [5], Wolfgang Wehmeyer [5], Stefano Stuard [5], Andrea Stopper [5], Bernard Canaud [6]



The purpose of this study was to determine how ACM support can affect outcomes of anemia management in daily clinical practice, with the aims of maintaining Hb targets and reducing Hb variability and ESA consumption in ESKD patients.

	Control phase	Observation phase	*P*-value
All patients (*N* = 383)			
Anemia outcomes			
Hb SD, g/dl, mean ± SD	0.95 ± 0.41	0.83 ± 0.33	<0.001[a]
Patients with >66.6% Hb within target range, no. (%)	247 (64.5)	322 (84.1)	<0.001[b]
Median darbepoetin doses, μg, median (IQR)	40.00 (68.75)	30.00 (70.00)	<0.001[c]
Median absolute delta darbepoetin doses,[e] μg, median (IQR)	10.00 (25.00)	20.00 (40.00)	0.03[c]
Adverse events			
Patients with cardiovascular events, no. (%)	82 (21.5)	54 (14.1)	0.01[b]
Cardiovascular events (incidence/ 1000 patient-years)	296.73	248.91	0.11[d]
Hospitalization days (incidence/ 1000 patient-years)	3488.63	3768.45	0.006[d]
Patients with transfusion events, no. (%)	9 (2.3)	3 (0.8)	0.14[b]
Transfusion events (incidence/ 1000 patient-years)	55.46	8.68	<0.001[d]
ACM-compliant patients (*n* = 313)			
Anemia outcomes			
Hb SD, g/dl, mean ± SD	0.97 ± 0.41	0.80 ± 0.29	<0.001[a]
Patients with >66.6% Hb within target range, no. (%)	204 (65.2)	280 (89.5)	<0.001[b]
Median darbepoetin dose, μg, median (IQR)	40.00 (80.00)	20.00 (70.00)	0.001[c]
Median absolute delta darbepoetin dose, μg, median (IQR)	10.00 (25.00)	10.00 (40.00)	0.24[c]
Adverse events			
Patients with cardiovascular events, no. (%)	64 (20.4)	39 (12.5)	0.009[b]
Cardiovascular events (incidence/ 1000 patient-years)	276.36	191.15	0.002[d]
Hospitalization days (incidence/ 1000 patient-years)	3319.69	3348.67	0.42[d]
Patients with transfusion events, no. (%)	7 (2.2)	0 (0)	0.02[b]
Transfusion events (incidence/ 1000 patient-years)	54.59	0	<0.001[d]

Deep learning to classify arteriovenous access aneurysms in hemodialysis patients

Hanjie Zhang [1], Dean Preddie [2], Warren Krackov [2], Murat Sor [2], Peter Waguespack [3], Zuwen Kuang [3], Xiaoling Ye [1], Peter Kotanko [1]

Affiliations + expand

PMID: 35371451 PMCID: PMC8967675 DOI: 10.1093/ckj/sfab278

Not-advanced AVF

Advanced AVF

καταληκτικά σημεία

- τα πεδία εφαρμογής της AI θα επεκταθούν τα επόμενα χρόνια
- οι νεφρολόγοι θα πρέπει να μάθουν να αλληλεπιδρούν με τα συστήματα αυτά προκειμένου να λαμβάνουν ορθές αποφάσεις
- η κλινική πράξη, η διαθέσιμη βιοτεχνολογία και οι ερευνητικές μελέτες παράγουν έναν τεράστιο όγκο δεδομένων που δεν είναι δυνατόν να τον διαχειριστεί ο ανθρώπινος εγκέφαλος
- απαιτείται λοιπόν η εξοικείωση του ανθρώπου-νεφρολόγου με αυτές τις τεχνολογίες προκειμένου να τις θέσει στην υπηρεσία των ανθρώπων- ασθενών του


LOOKING
FOR A
JOB


THANK
YOU