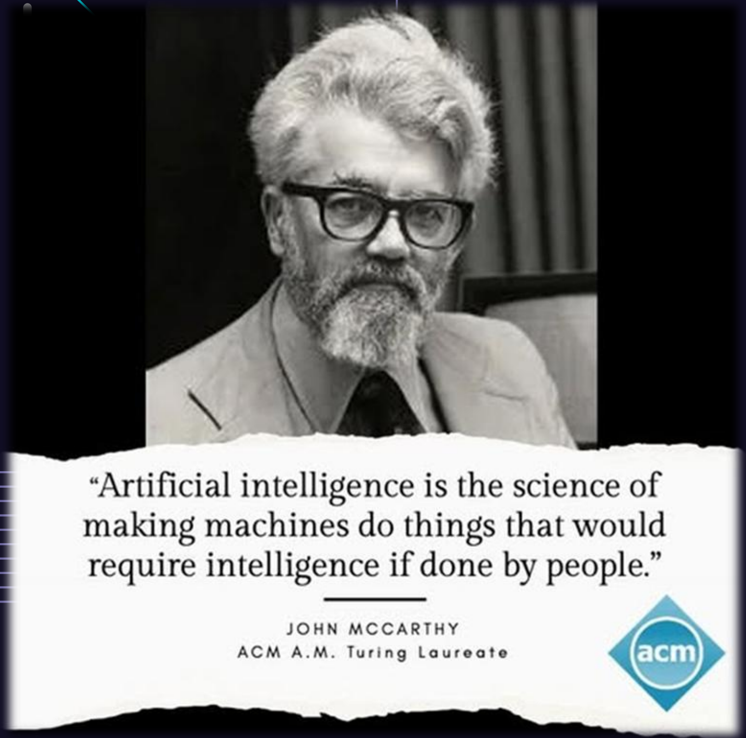
AI στη Νεφρολογία. Τι νεότερο;

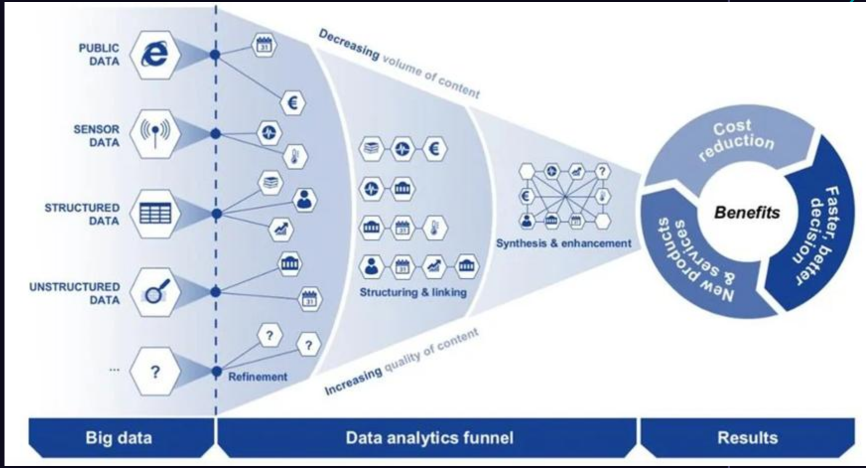
Οικονομάκη Δώρα
Νεφρολόγος, Επιμ.Β’
ΓΝΑ «ο Ευαγγελισμός»

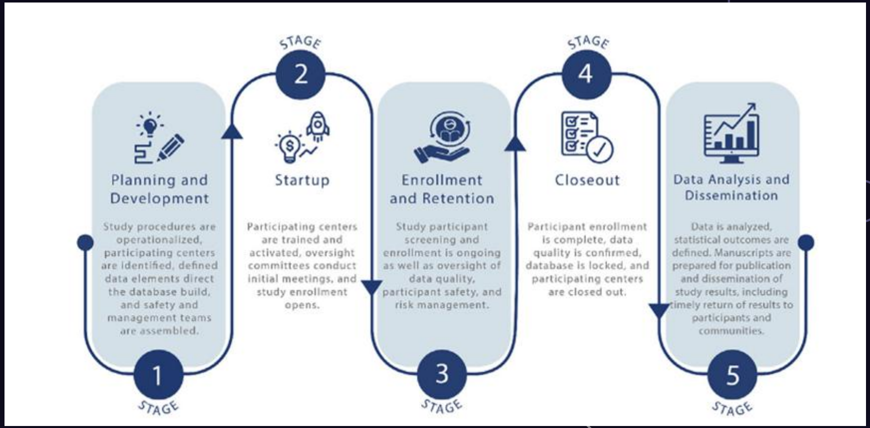
DEFINITION AND CONCEPTS

WHAT IS AI ?

01

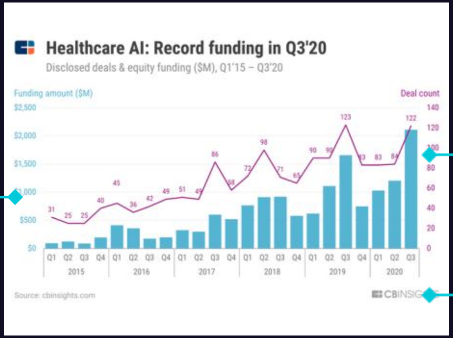

"Artificial intelligence is the science of making machines do things that would require intelligence if done by people."
JOHN MCCARTHY
ACM A.M. Turing Laureate
acm


PUBLIC DATA
SENSOR DATA
STRUCTURED DATA
UNSTRUCTURED DATA
...
Refinement
Decreasing volume of content
Structuring & linking
Synthesis & enhancement
Increasing quality of content
Cost reduction
Faster, better decision
New products & services
Benefits
Big data
Data analytics funnel
Results


STAGE 1
Planning and Development
Study procedures are operationalized, participating centers are identified, defined data elements direct the database build, and safety and management teams are assembled.
STAGE 2
Startup
Participating centers are trained and activated, oversight committees conduct initial meetings, and study enrollment opens.
STAGE 3
Enrollment and Retention
Study participant screening and enrollment is ongoing as well as oversight of data quality, participant safety, and risk management.
STAGE 4
Closeout
Participant enrollment is complete, data quality is confirmed, database is locked, and participating centers are closed out.
STAGE 5
Data Analysis and Dissemination
Data is analyzed, statistical outcomes are defined. Manuscripts are prepared for publication and dissemination of study results, including timely return of results to participants and communities.

ADVANCES IN AI TECHNOLOGY

NEPHROLOGICAL ASPECTS (AKI, TMA in ICUs)



COVID era

THE PRESSURE TO CONDUCT RESEARCH UNDER LIMITED CONDITIONS AND RESOURCES

GLOBAL MORTALITY RISK MANAGEMENT

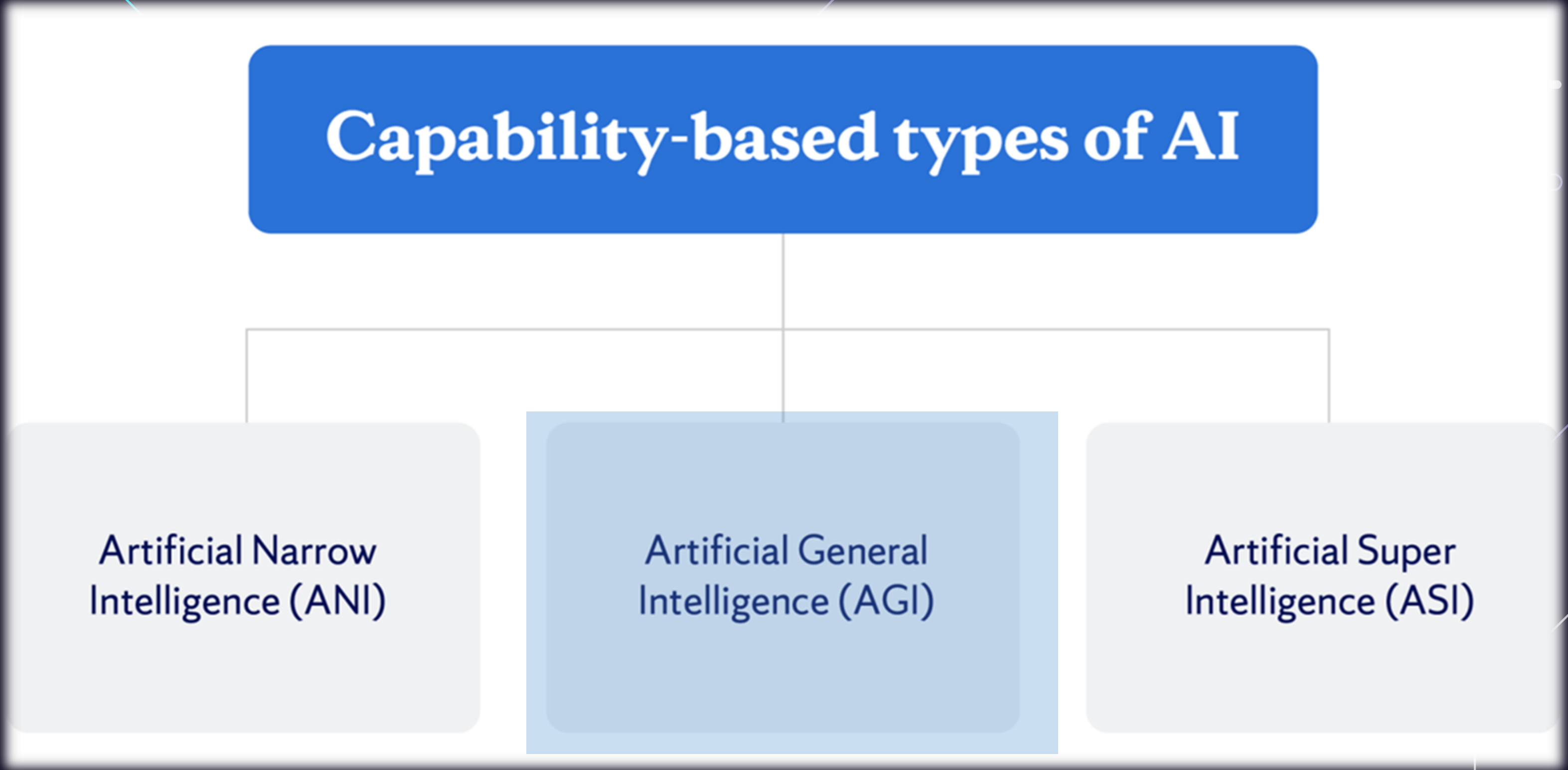
ISOLATION

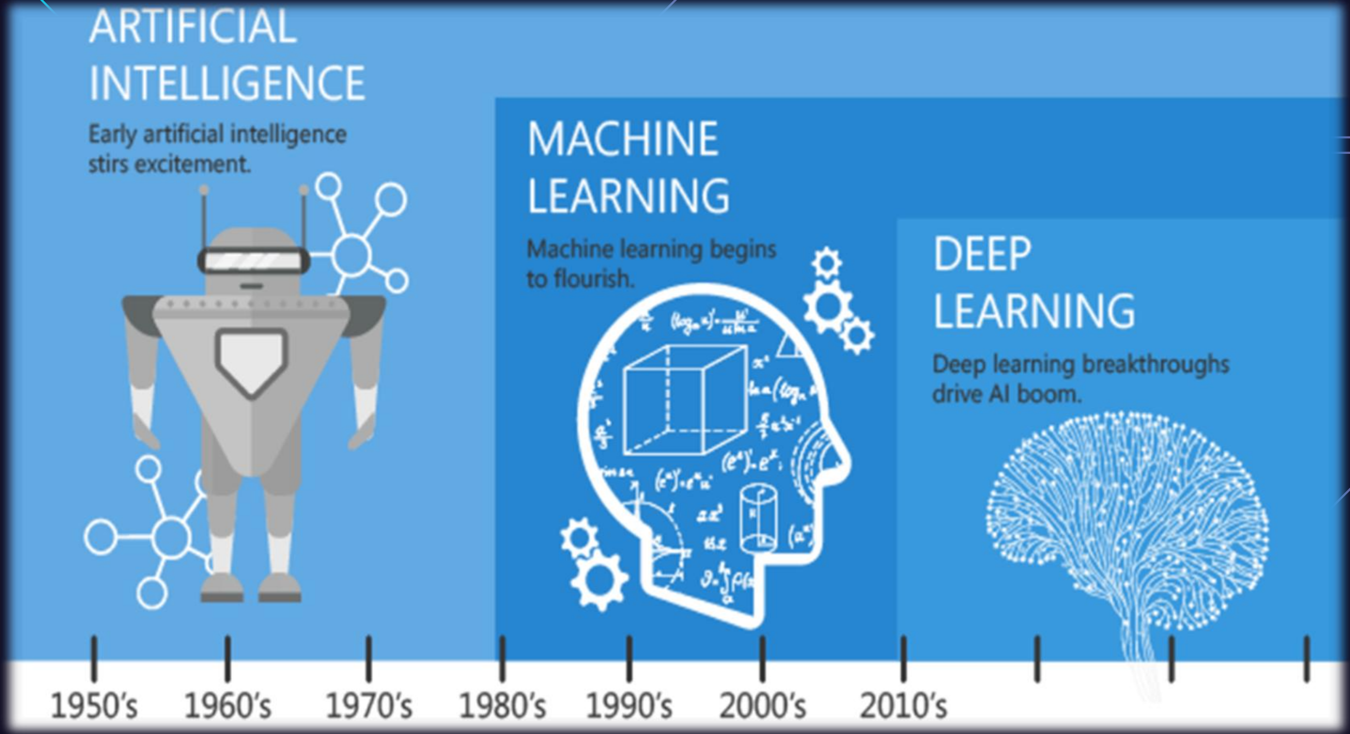
PERCEPTION


Artificial Intelligence for Qualitative Analysis
Natural Language Processing
Sentiment Analysis
Topic Extraction
Speech
Speech to text – automated transcription.
Translation
Vision
Image recognition. Facial emotion recognition.
Admin Assistants
Help with scheduling. Smart replies. Real time summaries of analysis.

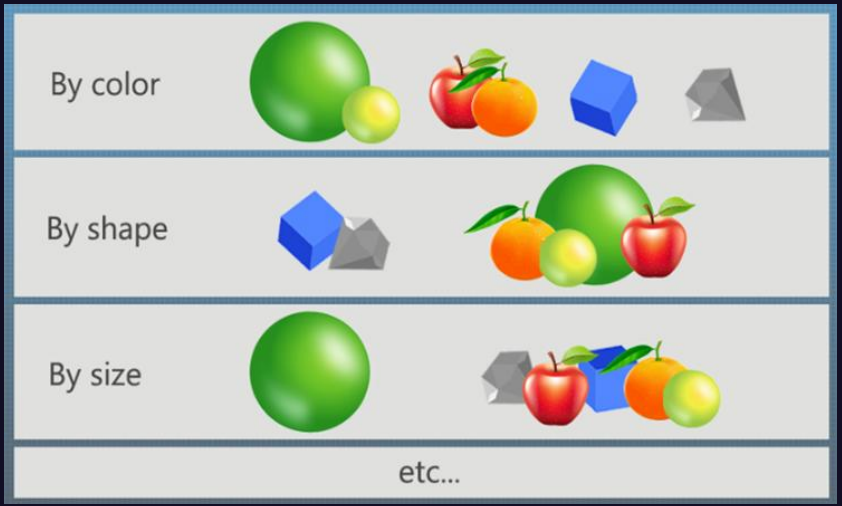
AI CLASSIFICATION

02


Capability-based types of AI
Artificial Narrow Intelligence (ANI)
Artificial General Intelligence (AGI)
Artificial Super Intelligence (ASI)


ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.
MACHINE LEARNING
Machine learning begins to flourish.
DEEP LEARNING
Deep learning breakthroughs drive AI boom.
1950's
1960's
1970's
1980's
1990's
2000's
2010's

MACHINE LEARNING



MACHINE LEARNING

UNSUPERVISED LEARNING

CLUSTERING

ASSOCIATION

- IMAGING
- BIOPSIES

REINFORCEMENT LEARNING

- **RECLASSIFICATION of CKD**

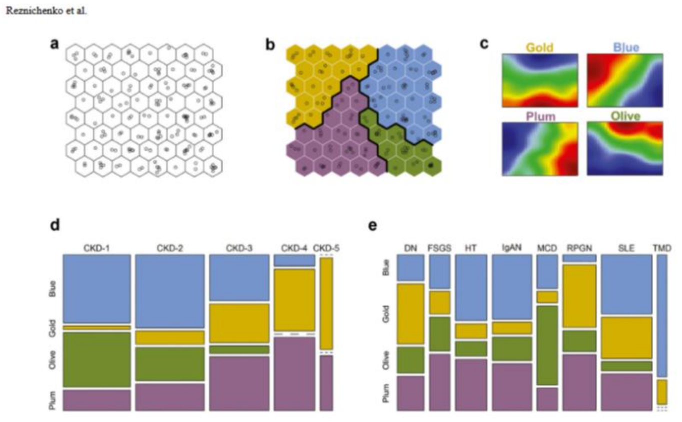
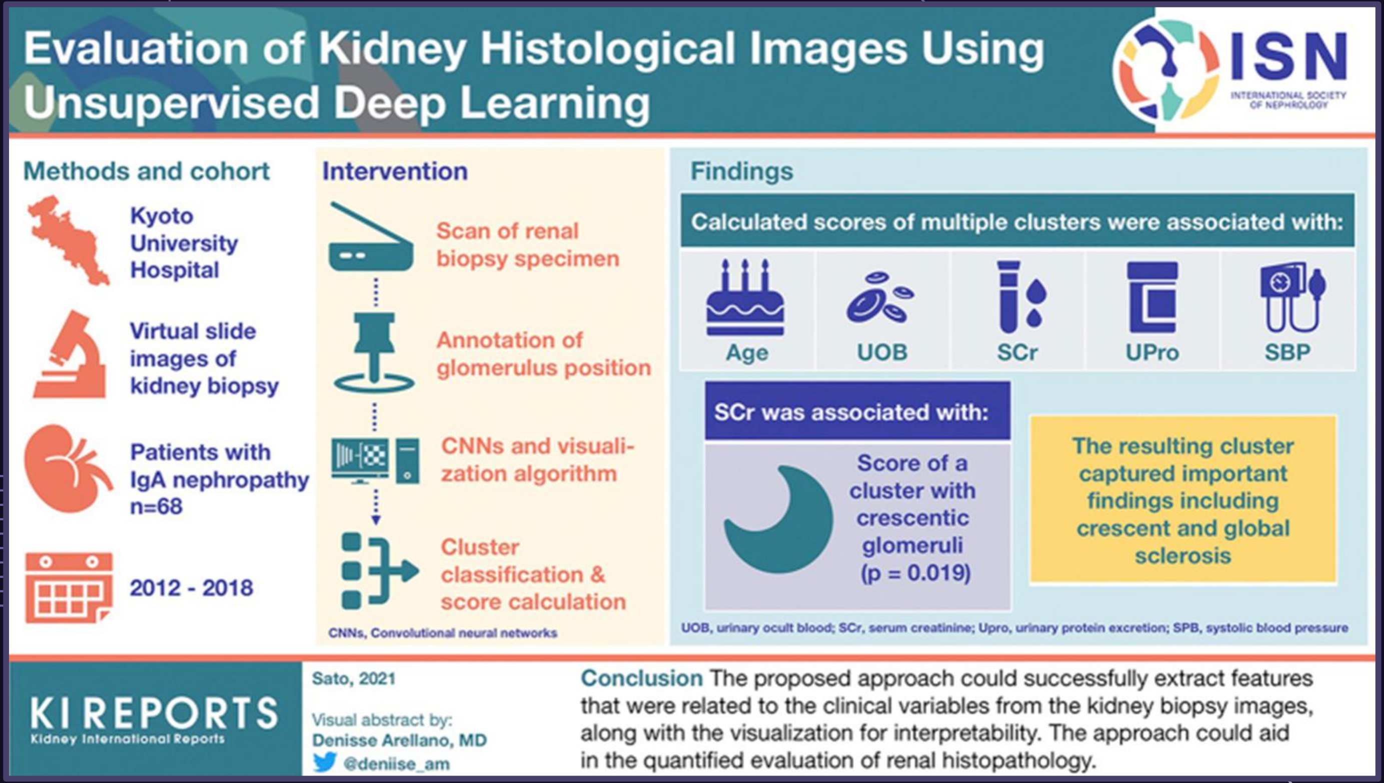


Figure 1 |. Unbiased kidney transcriptomics stratification identified 4 inherent subgroups of patients ("molecular categories") within a chronic kidney disease (CKD) cohort.

Unbiased kidney-centric molecular categorization of chronic kidney disease as a step towards precision medicine. Kidney Int. 2024


Evaluation of Kidney Histological Images Using Unsupervised Deep Learning
ISN
INTERNATIONAL SOCIETY OF NEPHROLOGY
Methods and cohort
Kyoto University Hospital
Virtual slide images of kidney biopsy
Patients with IgA nephropathy n=68
2012 - 2018
Intervention
Scan of renal biopsy specimen
Annotation of glomerulus position
CNNs and visualization algorithm
Cluster classification & score calculation
CNNs, Convolutional neural networks
Findings
Calculated scores of multiple clusters were associated with:
Age
UOB
SCr
UPro
SBP
SCr was associated with:
Score of a cluster with crescentic glomeruli (p = 0.019)
The resulting cluster captured important findings including crescent and global sclerosis
UOB, urinary ocult blood; SCr, serum creatinine; Upro, urinary protein excretion; SPB, systolic blood pressure
KI REPORTS
Kidney International Reports
Sato, 2021
Visual abstract by:
Denisse Arellano, MD
@deniise_am
Conclusion The proposed approach could successfully extract features that were related to the clinical variables from the kidney biopsy images, along with the visualization for interpretability. The approach could aid in the quantified evaluation of renal histopathology.

Differential risk assessment in persons at risk of type 2 diabetes using urinary peptidomics

Anja Schork, Andreas Fritsche, Erwin D. Schleicher, Andreas Peter, Martin Heni, Norbert Stefan, Reiner Jumpertz von Schwartzenberg, Martina Guthoff, Harald Mischak, Justyna Siwy, Andreas L. Birkenfeld, Robert Wagner

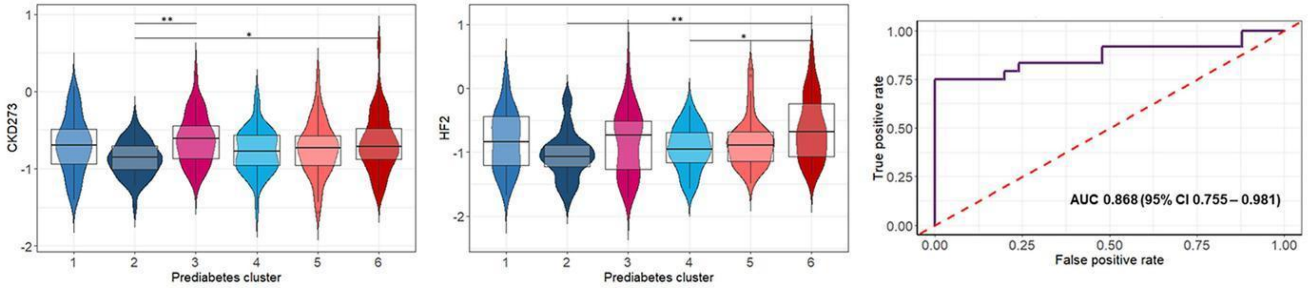
Subphenotypes of persons at risk of type 2 diabetes with classification into 6 prediabetes clusters

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Low risk	Very low risk	High Risk Beta-cell failure High genetic risk	Low risk obese	High risk Insulin resistance High liver fat	High risk High visceral fat High renal sinus fat

Measurement of urine peptidome (CE-MS) + calculation of predifined urinary peptide classifiers

Predefined urinary peptidome classifiers for chronic kidney disease (CKD273) and cardiovascular diseases (HF2, heart failure; CAD283, coronary artery disease) were significantly different across prediabetes clusters.

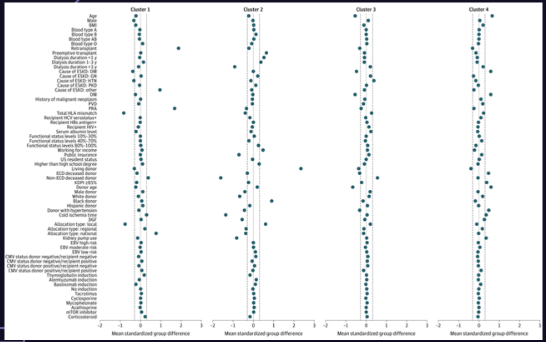
Lasso regression identified a combination of 112 urinary peptides differentiating low-risk and high-risk prediabetes clusters.

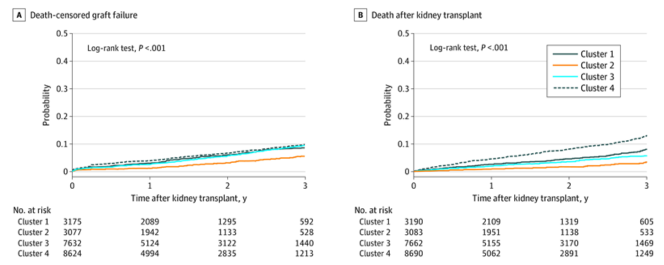


Conclusions: Urinary peptidome classifiers support the increased risk of CKD and suggest an elevated risk of heart failure and coronary artery disease in the high-risk prediabetes cluster 6. Urine peptidomics could be a valuable tool in identifying high-risk prediabetes individuals and guiding early preventive interventions.

Use of Machine Learning Consensus Clustering to Identify Distinct Subtypes of Black Kidney Transplant Recipients and Associated Outcomes

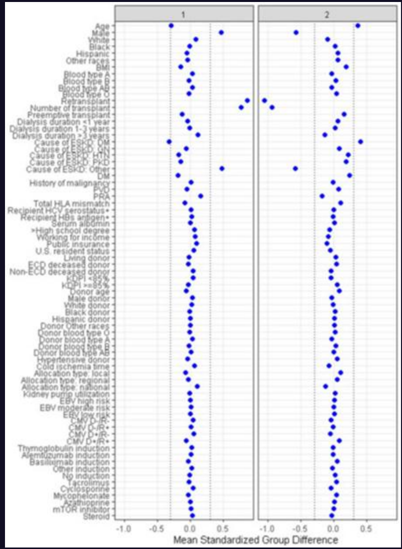
Charat Thongprayoon, MD[1]; Pradeep Vaitla, MD[2]; Caroline C. Jadlowiec, MD[3]; et al

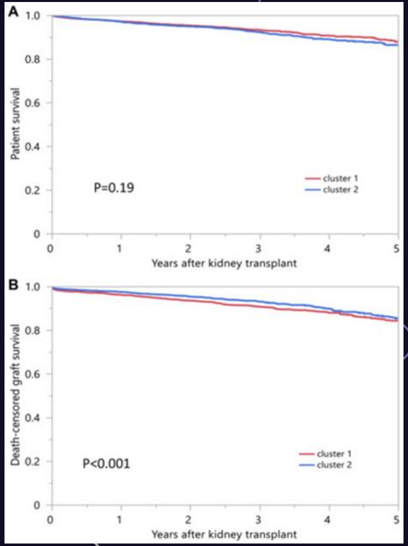




Differences between Very Highly Sensitized Kidney Transplant Recipients as Identified by Machine Learning Consensus Clustering

by Charat Thongprayoon [1,†], Jing Miao [1,†], Caroline C. Jadlowiec [2], Shennen A. Mao [3], Michael A. Mao [4], Pradeep Vaitla [5], Napat Leeaphorn [4], Wisit Kaewput [6], Pattharawin Pattharanitima [7], Supawit Tangpanithandee [1], Pajaree Krisanapan [1,7], Pitchaphon Nissaisorakarn [8], Matthew Cooper [9] and Wisit Cheungpasitporn [1,*]





MACHINE LEARNING

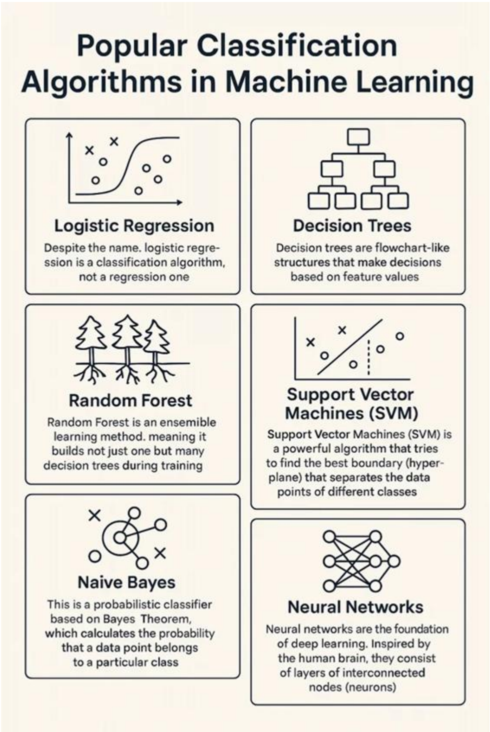
SUPERVISED LEARNING

CLASSIFCATION FOR CATEGORICAL OUTCOME

- K-Nearest Neighbors
- Decision Trees
- Logistic Regression
- Navies Bayes
- Neural Networks
- Random Forest
- Ensembles
- Discriminant Analysis

REGRESSION FOR CONTINUOUS NUMERIC OUTCOME

- K-Nearest Neighbors
- Regression Trees
- Linear Regression
- Ensembles
- Neural Networks

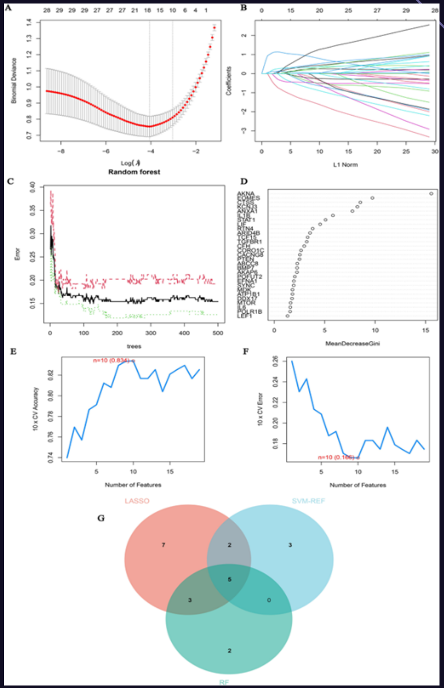


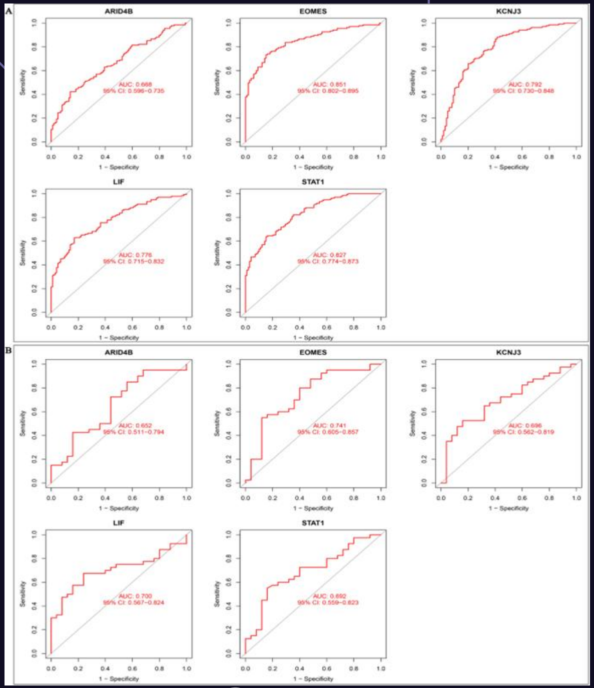
Machine learning selection of basement membrane-associated genes and development of a predictive model for kidney fibrosis

Ziwei Yuan[1,7], Guangjia Lv[2,7], Xinyan Liu[3]✉, Yanyi Xiao[4,5]✉, Yuanfang Tan[1]✉ & Youyou Zhu[6]✉

- Basement membrane-related genes
- Prognostic model for renal fibrosis
- Genetic characteristics that distinguish fibrotic samples from normal samples

Five key genes in a predictive model with very high accuracy, approximately 0.92





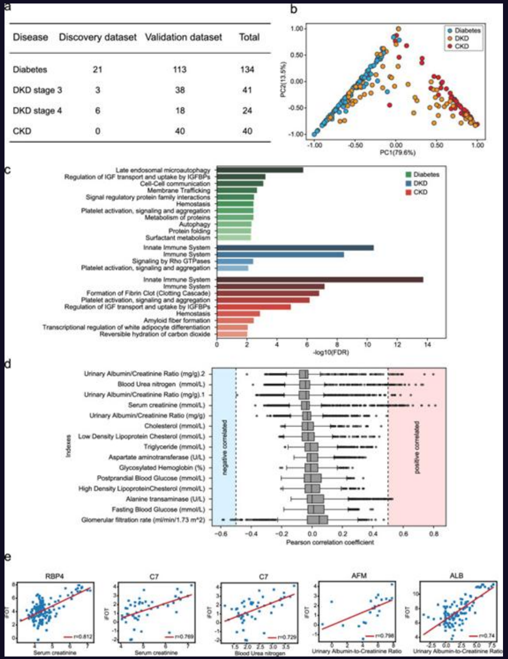
Urine proteomics identifies biomarkers for diabetic kidney disease at different stages

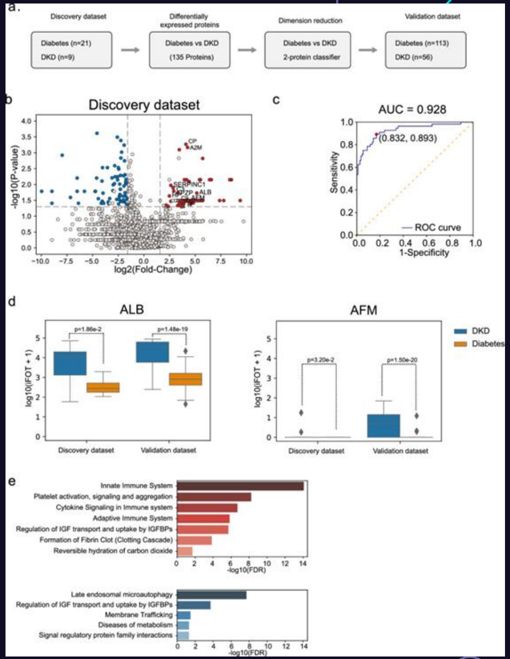
Guanjie Fan[1,2,3,4*†], Tongqing Gong[5†], Yuping Lin[1,2,3,4†], Jianping Wang[6,7†], Lu Sun[1,2,3,4], Hua Wei[1,2,3,4], Xing Yang[5], Zhenjie Liu[1,2,3,4], Xinliang Li[5], Ling Zhao[1,2,3,4], Lan Song[6], Jiali He[1,2,3,4], Haibo Liu[5], Xiuming Li[1,2,3,4], Lifeng Liu[5], Anxiang Li[1,2,3,4], Qiyun Lu[1,2,3,4], Dongyin Zou[1,2,3,4], Jianxuan Wen[1,2,3,4], Yaqing Xia[1,2,3,4], Liyan Wu[1,2,3,4], Haoyue Huang[1,2,3,4], Yuan Zhang[1,2,3,4], Wenwen Xie[1,2,3,4], Jinzhu Huang[1,2,3,4], Lulu Luo[1,2,3,4], Lulu Wu[1,2,3,4], Liu He[1,2,3,4], Qingshun Liang[1,2,3,4], Qubo Chen[1,2,3,4], Guowei Chen[1,2,3,4], Mingze Bai[6,7], Jun Qin[6], Xiaotian Ni[6*], Xianyu Tang[1,2,3,4*] and Yi Wang[6*]

- Urine samples from 239 patients with diabetes, diabetic nephropathy, and non-diabetic nephropathy.
- Nearly 3,000 urinary proteins were identified.
- Logistic regression models were developed that distinguished with very high accuracy (AUC > 0.92):

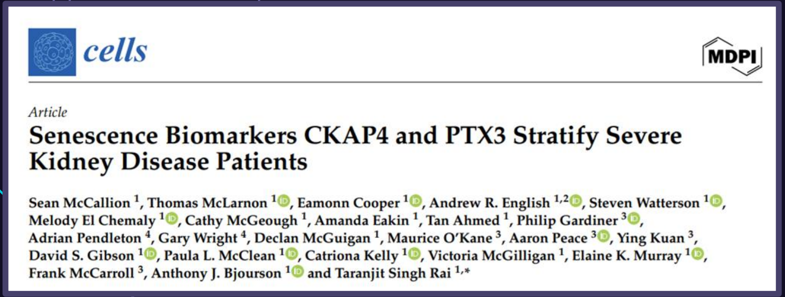
✓ Diabetic nephropathy from uncomplicated diabetes

✓ Stage 3 from stage 4 disease





A four-protein biomarker panel was developed that identified high-risk patients even before clinical signs of the disease appeared.



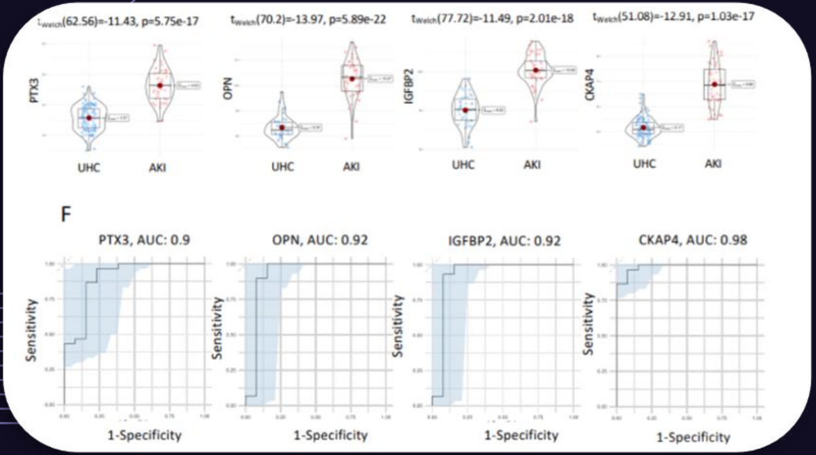
cells

MDPI

Article

Senescence Biomarkers CKAP4 and PTX3 Stratify Severe Kidney Disease Patients

Sean McCallion [1], Thomas McLarnon [1], Eamonn Cooper [1], Andrew R. English [1,2], Steven Watterson [1], Melody El Chemaly [1], Cathy McGeough [1], Amanda Eakin [1], Tan Ahmed [1], Philip Gardiner [3], Adrian Pendleton [4], Gary Wright [4], Declan McGuigan [1], Maurice O'Kane [3], Aaron Peace [3], Ying Kuan [3], David S. Gibson [1], Paula L. McClean [1], Catriona Kelly [1], Victoria McGilligan [1], Elaine K. Murray [1], Frank McCarroll [3], Anthony J. Bjourson [1] and Taranjit Singh Rai [1,*]



CKAP4 and PTX3 may serve as biomarkers for assessing:

- ✓ disease severity
- ✓ disease progression in kidney disorders.

- Two senescence biomarkers, CKAP4 and PTX3, were investigated in patients with severe kidney disease.
- Both biomarkers were elevated in patients with:
- ✓ AKI (Acute Kidney Injury)
- ✓ CKD (Chronic Kidney Disease) compared with healthy controls.

- In AKI, the increase was more pronounced, indicating acute activation of molecular pathways.
- In CKD, the increase was more gradual, reflecting the chronic nature of the disease.

New Diagnostic Model for the Differentiation of Diabetic Nephropathy From Non-Diabetic Nephropathy in Chinese Patients

WeiGuang Zhang[1†], XiaoMin Liu[1†], ZheYi Dong[1], Qian Wang[1], ZhiYong Pei[2], YiZhi Chen[1,3], Ying Zheng[1], Yong Wang[1], Pu Chen[1], Zhe Feng[1], XueFeng Sun[1], Guangyan Cai[1*] and XiangMei Chen[1*]

Supplementary Table 5. Various indicators ranked in order of importance

Importance ranking	Indicator
1	DR
2	Course of DM
3	Hb
4	PP
5	Course of DM <5 years
6	sCr
7	ALB
8	SBP
9	eGFR
10	TC
11	MAP
12	FBG
14	24-h proteinuria
15	Course of hypertension
16	Sudden onset of heavy proteinuria
17	Age
18	BUA
19	Hematuria
20	Family history of DM
21	Systemic disease

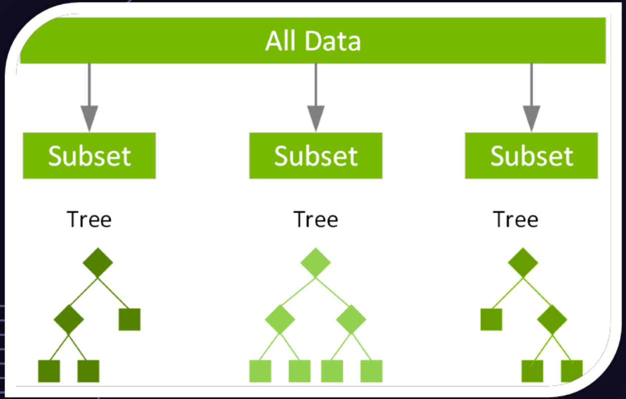
Supplementary Table 2 Two models developed previously in our center

	Model-2008[1]	Model-2014(Liu Moyan)[2]
Models	P_{DN} = exp (−13.5922 + 0.0371Dm+0.0395Bp+0.3224Gh − 4.4552Hu + 2.9613Dr)/[1 + exp(−13.5922 + 0.0371Dm + 0.0395Bp+0.3224Gh − 4.4552Hu + 2.9613Dr)]	P_{DN} = exp (0.846 + 0.022Dm + 0.033 Bp + 2.050 Gh −2.664 Hu–0.078 Hb + 2.942Dr)/[1 + exp (0.846 + 0.022 Dm + 0.033 Bp + 2.050Gh –2.664 Hu–0.078 Hb + 2.942 Dr)]
Variables	Dm, course of diabetes; Bp, SBP; Gh, HbA1C; Hu, hematuria; Hb, hemoglobin; Dr, diabetic retinopathy	Dm, course of diabetes; Bp, systolic blood pressure; Gh, HbA1C (1 HbA1c ≥ 7%, 0 < 7%); Hu, hematuria (1 urine RBC>10/HP, 0 < 10/HP); Hb, Hemoglobin; Dr, diabetic retinopathy

Supplementary Table 6. Best combinations of variables at each number of indices (from 6 to 12)

Number of variables	Random forest	Support vector machine	Variable
6	0.935	0.915	DR, DM course, Hb, PP, sCr, sudden onset of he
7	0.943	0.930	DR, DM course, Hb, PP, sCr, ALB, sudden onse
8	0.948	0.936	DR, DM course, Hb, PP, sCr, ALB, TC, sudden
9	0.949	0.943	DR, DM course, Hb, PP, sCr, ALB, TC, sudden
10	0.953	0.947	DR, DM course, Hb, PP, sCr, ALB, TC, sudden
11	0.956	0.948	DR, DM course, Hb, PP, sCr, ALB, TC, sudden
12	0.955	0.952	DR, DM course, Hb, PP, sCr, ALB, TC, 24hpro.

XGBoost



RESEARCH ARTICLE

Predicting mortality of patients with acute kidney injury in the ICU using XGBoost model

Jialin Liu[1,2], Jinfa Wu[3], Siru Liu[4], Mengdie Li[3], Kunchang Hu[3], Ke Li[3]*

1 Information Center, West China Hospital, Sichuan University, Chengdu, Sichuan Province, China, 2 Department of Medical Informatics, West China Medical School, Chengdu, Sichuan Province, China, 3 School of Life Science & Technology, University of Electronic Science & Technology of China, Chengdu, Sichuan Province, China, 4 Department of Biomedical Informatics, University of Utah, Salt Lake City, UT, United States of America

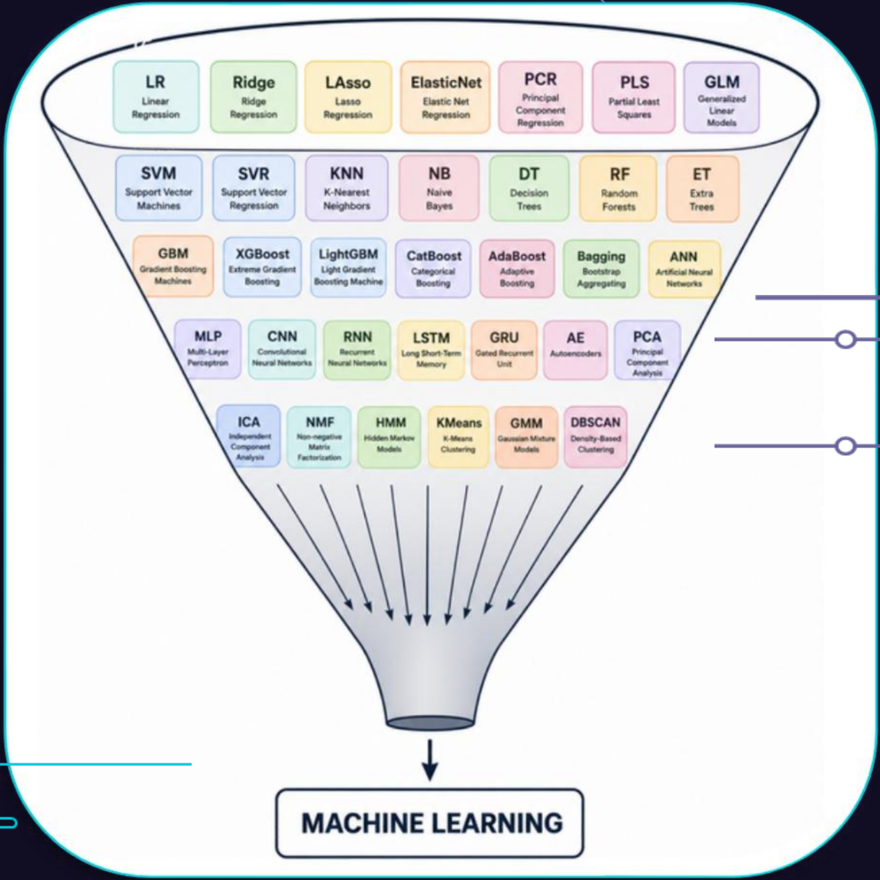
Chang *et al. BMC Nephrology* (2023) 24:169
https://doi.org/10.1186/s12882-023-03227-w

BMC Nephrology

RESEARCH **Open Access**

Predicting hyperkalemia in patients with advanced chronic kidney disease using the XGBoost model

Hsin-Hsiung Chang[1,2], Jung-Hsien Chiang[2*], Chun-Chieh Tsai[3] and Ping-Fang Chiu[3,4,5*]



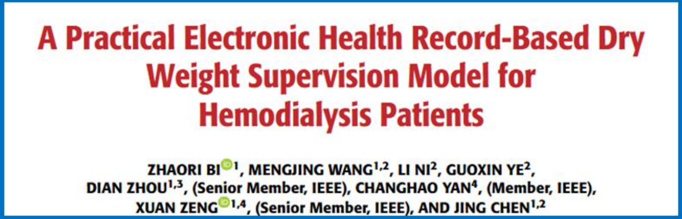
LR
Linear Regression
Ridge
Ridge Regression
LAsso
Lasso Regression
ElasticNet
Elastic Net Regression
PCR
Principal Component Regression
PLS
Partial Least Squares
GLM
Generalized Linear Models
SVM
Support Vector Machines
SVR
Support Vector Regression
KNN
K-Nearest Neighbors
NB
Naive Bayes
DT
Decision Trees
RF
Random Forests
ET
Extra Trees
GBM
Gradient Boosting Machines
XGBoost
Extreme Gradient Boosting
LightGBM
Light Gradient Boosting Machine
CatBoost
Categorical Boosting
AdaBoost
Adaptive Boosting
Bagging
Bootstrap Aggregating
ANN
Artificial Neural Networks
MLP
Multi-Layer Perceptron
CNN
Convolutional Neural Networks
RNN
Recurrent Neural Networks
LSTM
Long Short-Term Memory
GRU
Gated Recurrent Unit
AE
Autoencoders
PCA
Principal Component Analysis
ICA
Independent Component Analysis
NMF
Non-negative Matrix Factorization
HMM
Hidden Markov Models
KMeans
K-Means Clustering
GMM
Gaussian Mixture Models
DBSCAN
Density-Based Clustering
MACHINE LEARNING

REINFORCEMENT LEARNING

Optimization of anemia treatment in hemodialysis patients via reinforcement learning

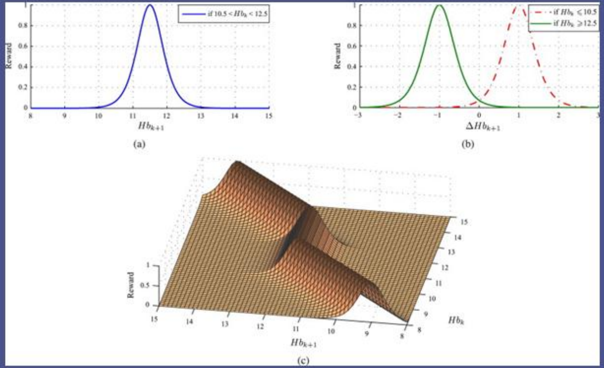
Pablo Escandell-Montero[a,*], Milena Chermisi[b], José M. Martínez-Martínez[a], Juan Gómez-Sanchis[a], Carlo Barbieri[b], Emilio Soria-Olivas[a], Flavio Mari[b], Joan Vila-Francés[a], Andrea Stopper[b], Emanuele Gatti[b,c], José D. Martín-Guerrero[a]

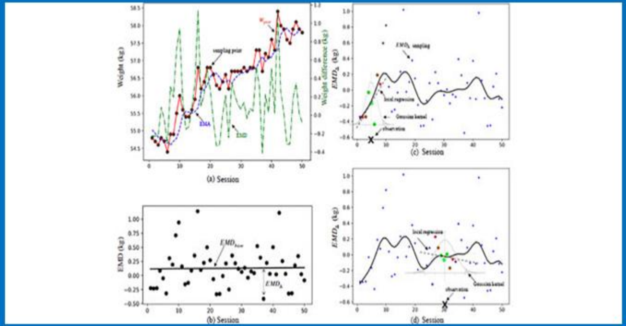
[a] Intelligent Data Analysis Laboratory, University of Valencia, Av. de la Universidad, s/n, 46100 Burjassot (Valencia), Spain
[b] Healthcare and Business Advanced Modeling, Fresenius Medical Care, Else-Kröner-Strasse 1, 61352 Bad Homburg, Germany
[c] Centre for Biomedical Technology at Danube, University of Krems, Dr.-Karl-Dorrek-Strasse 30, 3500 Krems, Austria



A Practical Electronic Health Record-Based Dry Weight Supervision Model for Hemodialysis Patients

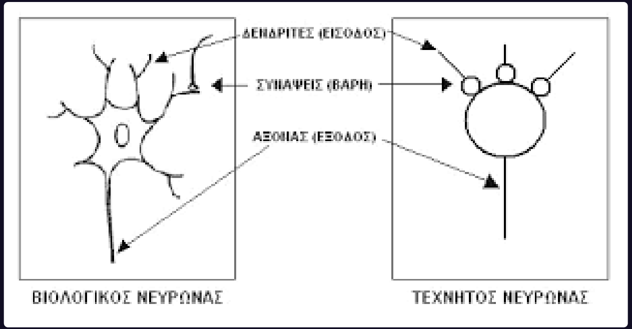
ZHAORI BI[1], MENGJING WANG[1,2], LI NI[2], GUOXIN YE[2], DIAN ZHOU[1,3], (Senior Member, IEEE), CHANGHAO YAN[4], (Member, IEEE), XUAN ZENG[1,4], (Senior Member, IEEE), AND JING CHEN[1,2]

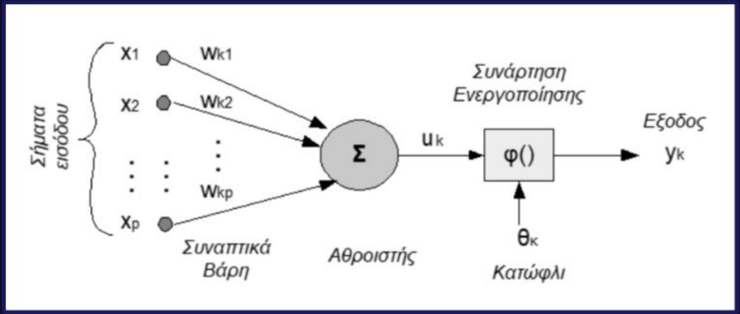


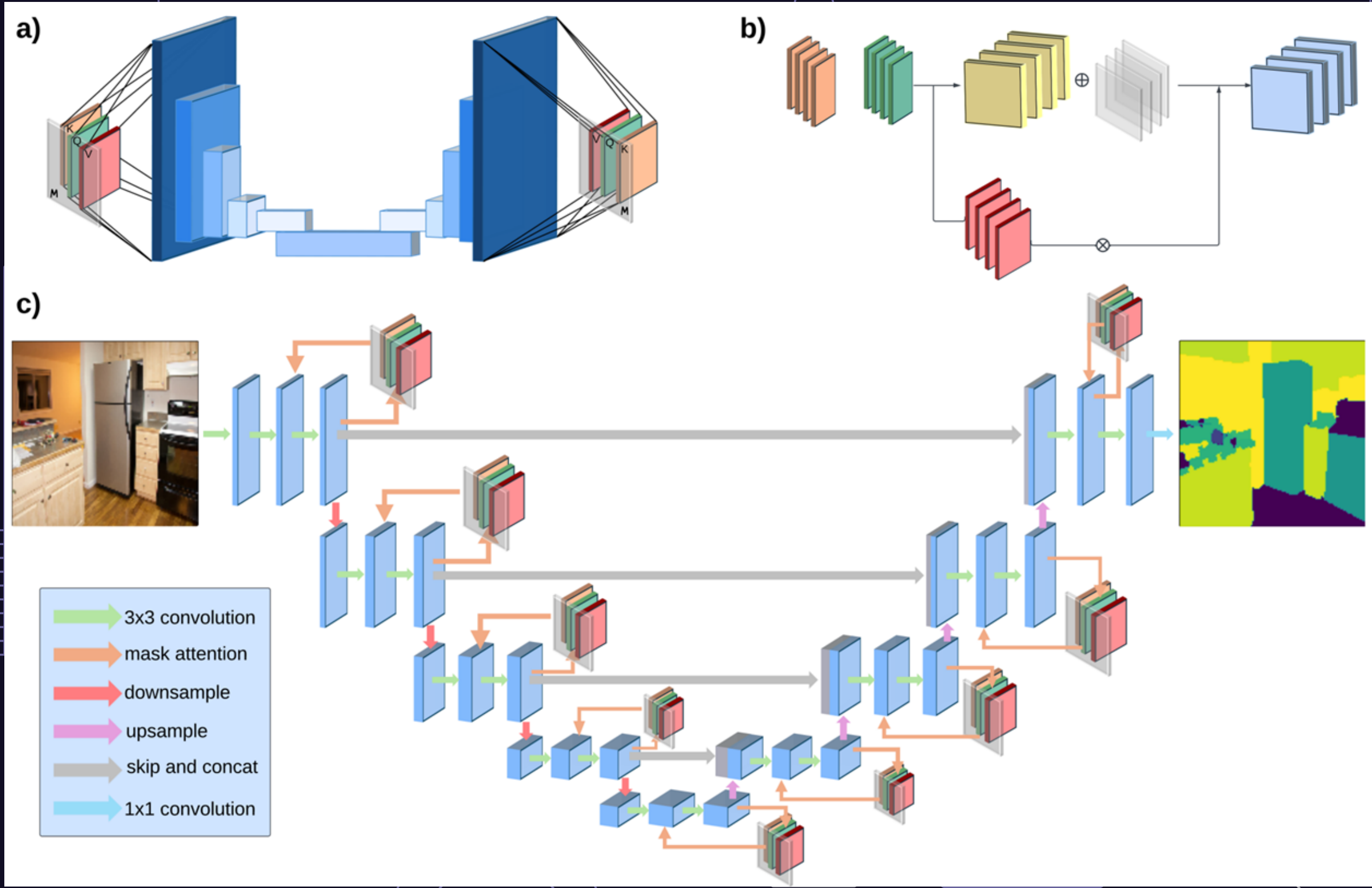


DEEP LEARNING

- Adaptability
- Generalizability
- Time-Evolving/ Training Algorithm

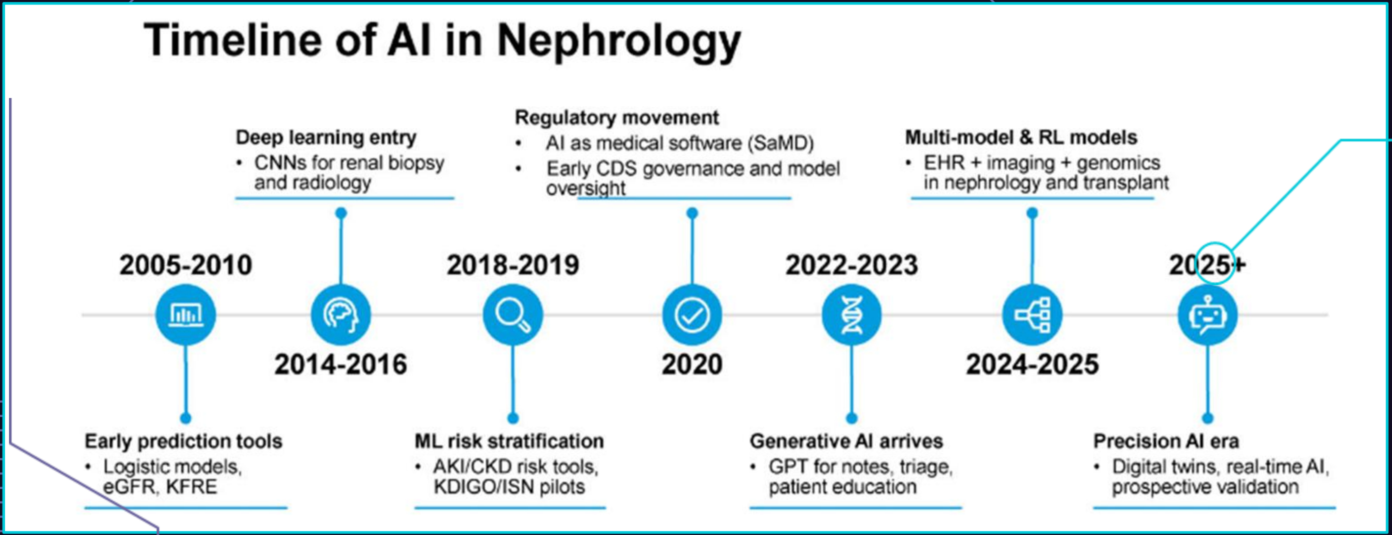





a)
K
Q
V
M
V
Q
K
M
b)
c)
3x3 convolution
mask attention
downsample
upsample
skip and concat
1x1 convolution

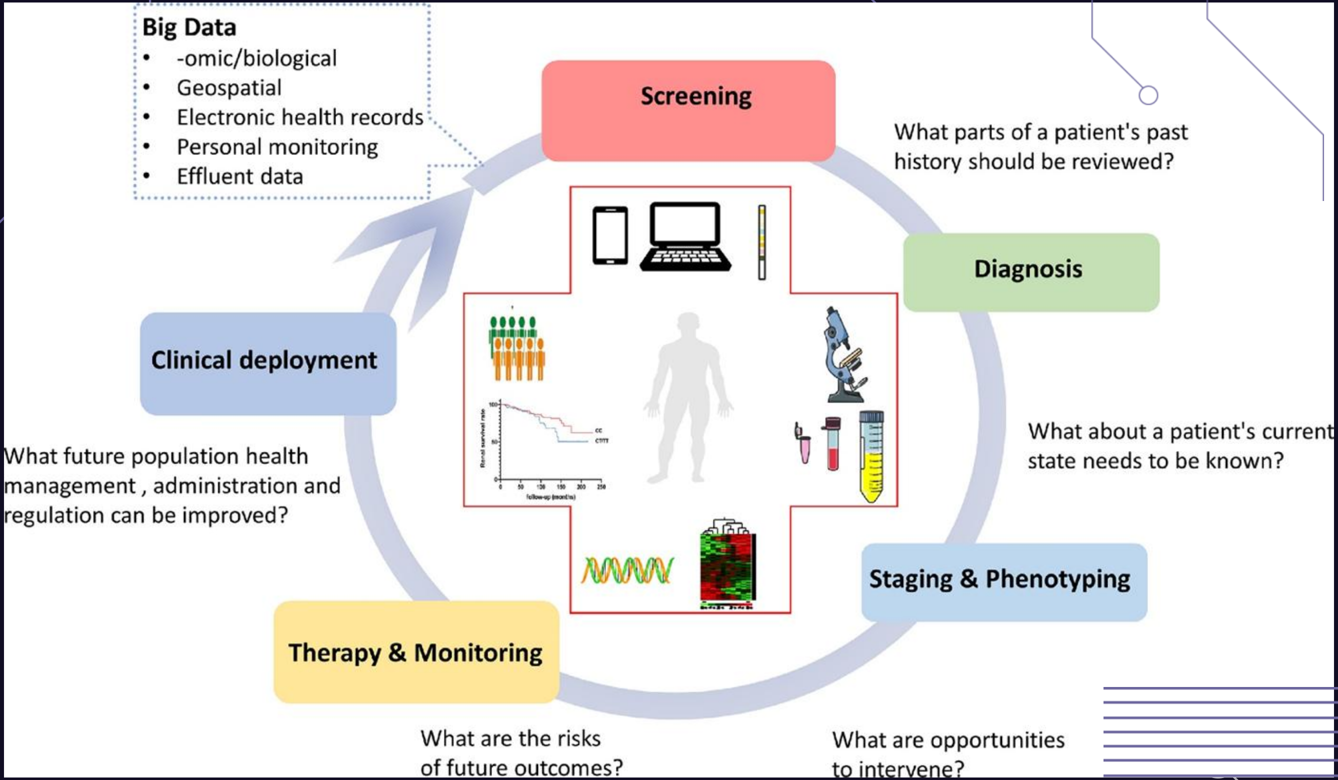
CLINICAL APPLICATIONS in NEPHROLOGY

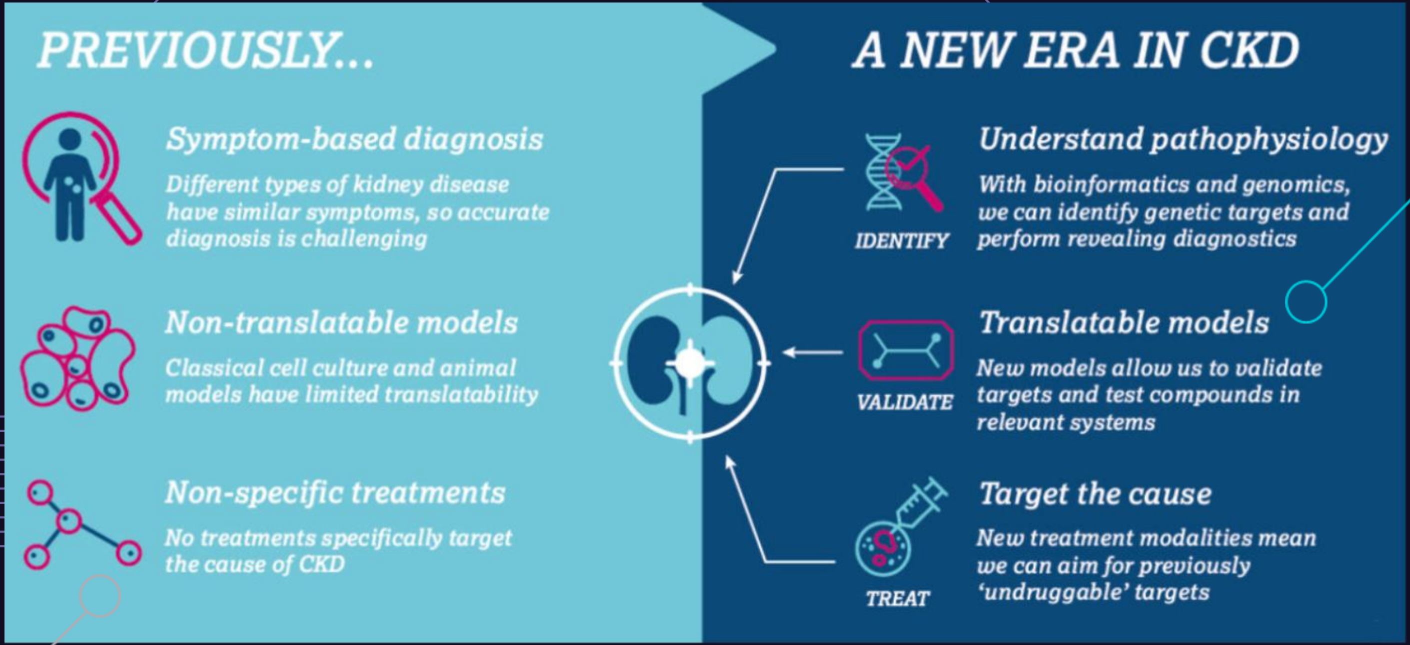
03


Timeline of AI in Nephrology
2005-2010
Early prediction tools
• Logistic models, eGFR, KFRE
2014-2016
Deep learning entry
• CNNs for renal biopsy and radiology
2018-2019
ML risk stratification
• AKI/CKD risk tools, KDIGO/ISN pilots
2020
Regulatory movement
• AI as medical software (SaMD)
• Early CDS governance and model oversight
2022-2023
Generative AI arrives
• GPT for notes, triage, patient education
2024-2025
Multi-model & RL models
• EHR + imaging + genomics in nephrology and transplant
2025+
Precision AI era
• Digital twins, real-time AI, prospective validation

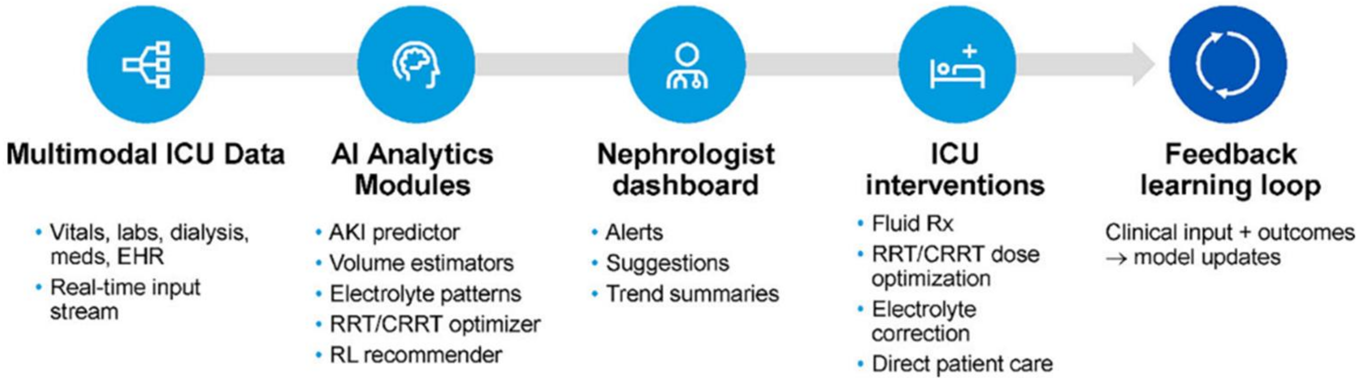
FUTURE PERSPECTIVES

04


Big Data
• -omic/biological
• Geospatial
• Electronic health records
• Personal monitoring
• Effluent data
Screening
What parts of a patient's past history should be reviewed?
Diagnosis
What about a patient's current state needs to be known?
Staging & Phenotyping
What are opportunities to intervene?
Therapy & Monitoring
What are the risks of future outcomes?
Clinical deployment
What future population health management , administration and regulation can be improved?

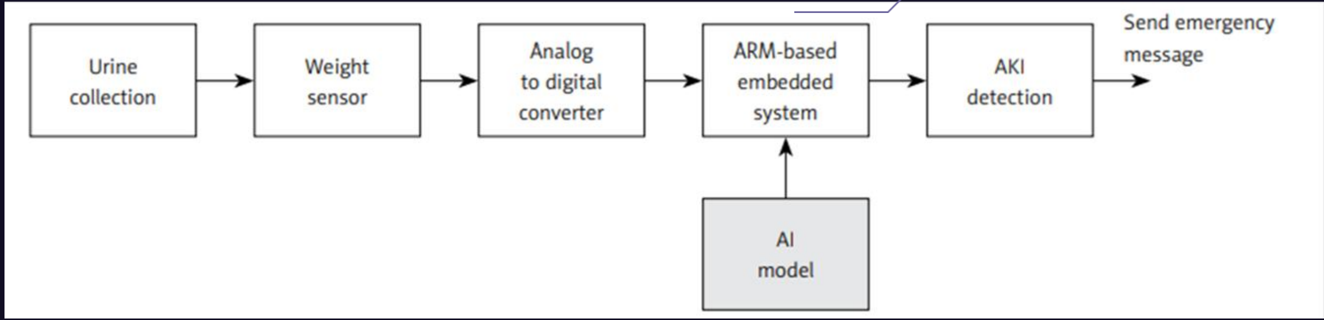

PREVIOUSLY...
Symptom-based diagnosis
Different types of kidney disease have similar symptoms, so accurate diagnosis is challenging
Non-translatable models
Classical cell culture and animal models have limited translatability
Non-specific treatments
No treatments specifically target the cause of CKD
A NEW ERA IN CKD
IDENTIFY
Understand pathophysiology
With bioinformatics and genomics, we can identify genetic targets and perform revealing diagnostics
VALIDATE
Translatable models
New models allow us to validate targets and test compounds in relevant systems
TREAT
Target the cause
New treatment modalities mean we can aim for previously 'undruggable' targets

Real-Time AI Decision Support in ICU Nephrology



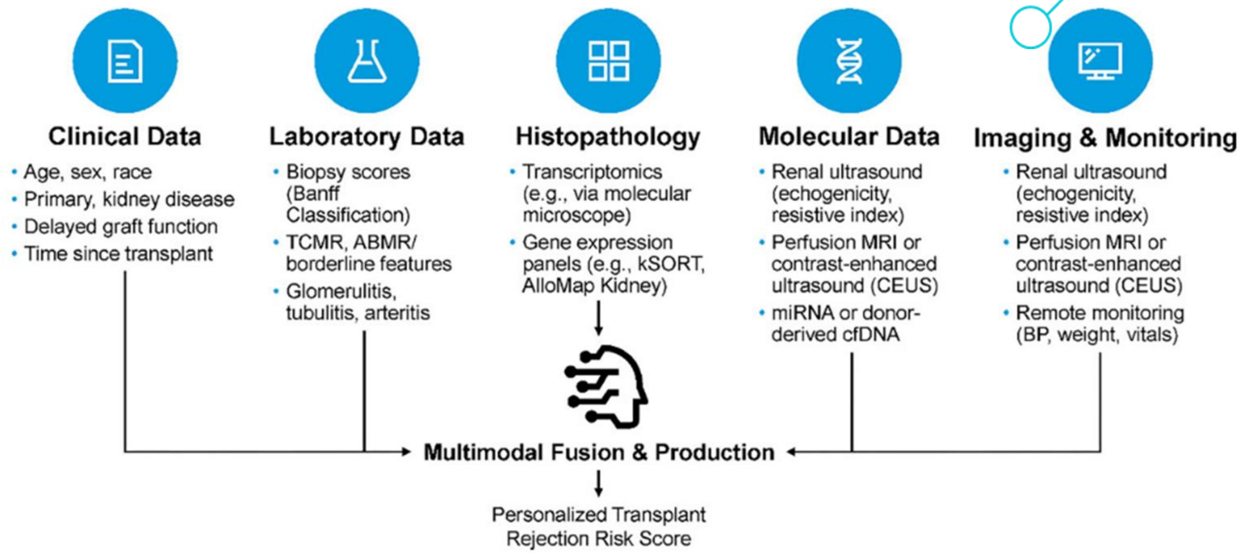
Real-time prediction system for prevention of acute renal failure based on AI model

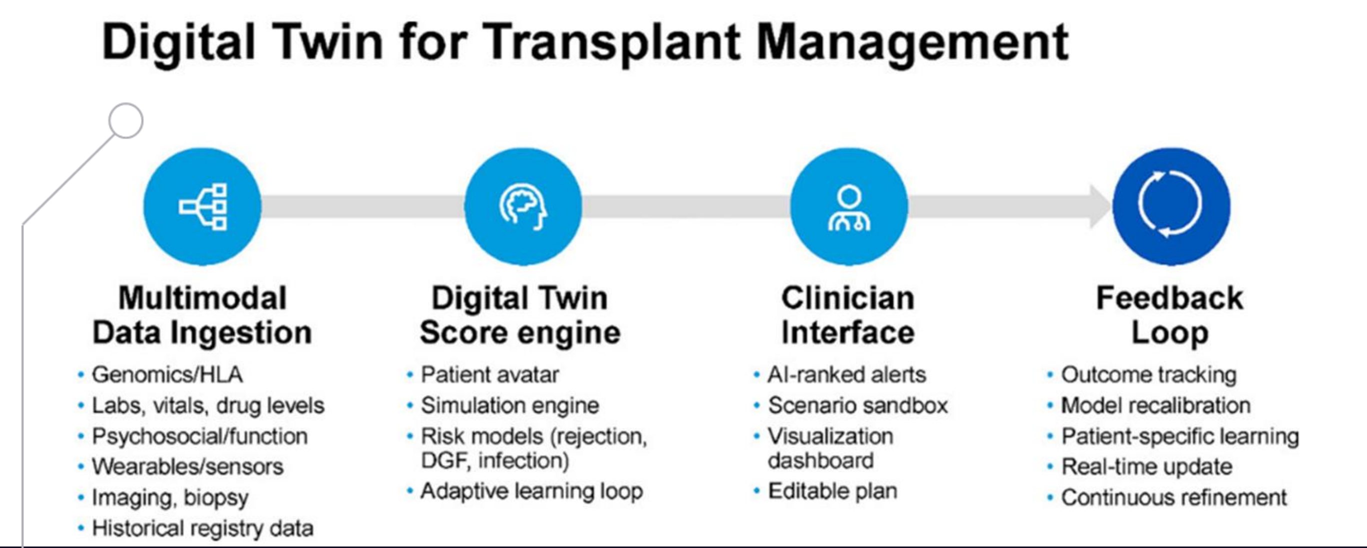
Shih-Chang Hsia*, Szu-Hong Wang, Liang-Fu Chen, Bo-An Ko



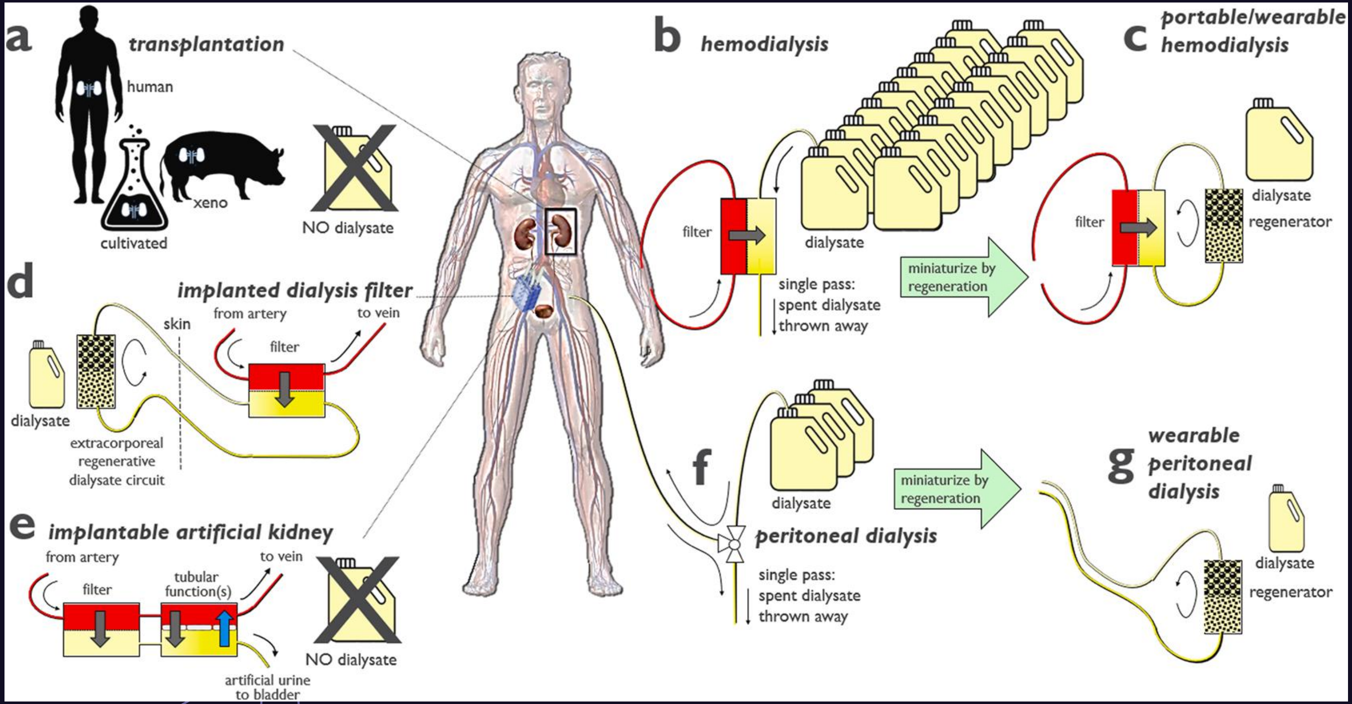
Hsia S, Wang S, Chen L, Ko B. Real-time prediction system for prevention of acute renal failure based on AI model. Archives of Medical Science. 2024

Multimodal Components of an AI-Based Kidney Transplant Rejection Prediction Model

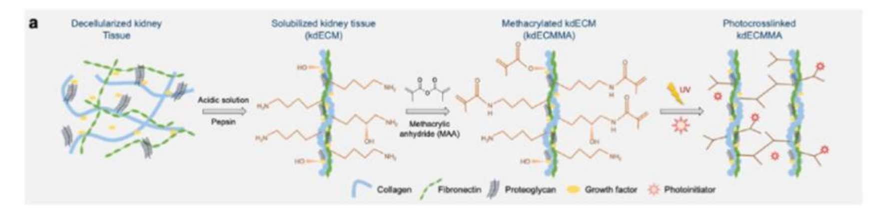


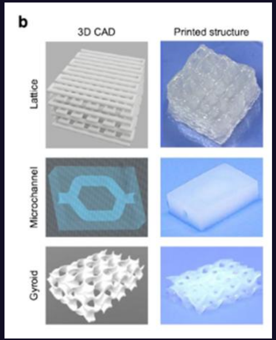

Digital Twin for Transplant Management
Multimodal Data Ingestion
• Genomics/HLA
• Labs, vitals, drug levels
• Psychosocial/function
• Wearables/sensors
• Imaging, biopsy
• Historical registry data
Digital Twin Score engine
• Patient avatar
• Simulation engine
• Risk models (rejection, DGF, infection)
• Adaptive learning loop
Clinician Interface
• AI-ranked alerts
• Scenario sandbox
• Visualization dashboard
• Editable plan
Feedback Loop
• Outcome tracking
• Model recalibration
• Patient-specific learning
• Real-time update
• Continuous refinement

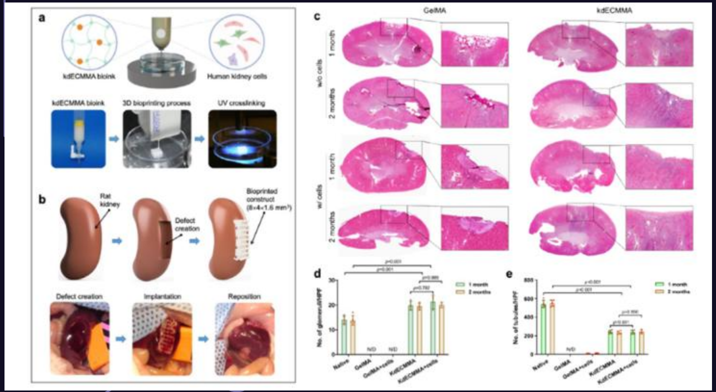
TECHNOLOGICAL ACHIEVEMENTS



TECHNOLOGICAL ACHIEVEMENTS







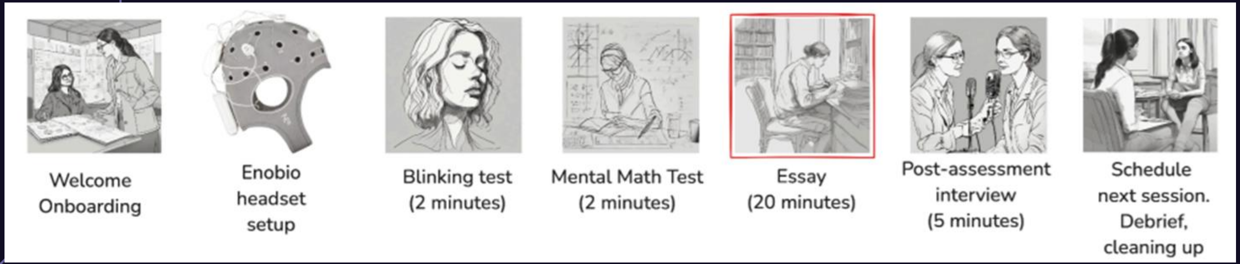
Bioprinted Renal Constructs Using Kidney-Specific ECM Bioink System on Kidney Regeneration. Adv Healthc Mater. 2025

CHALLENGES

- Loss of important features
- Poor-quality or incomplete data
- Changing environment (data drift)
- Poor evaluation

- Technical Limitations
- Delay in updating the model
- Selection of an inappropriate model
- Lack of interpretability (black-box models)

- Data Privacy Concerns
- Overreliance on technology



In a period of four months, LLM users consistently showed lower performance at the neural, linguistic, and behavioral levels

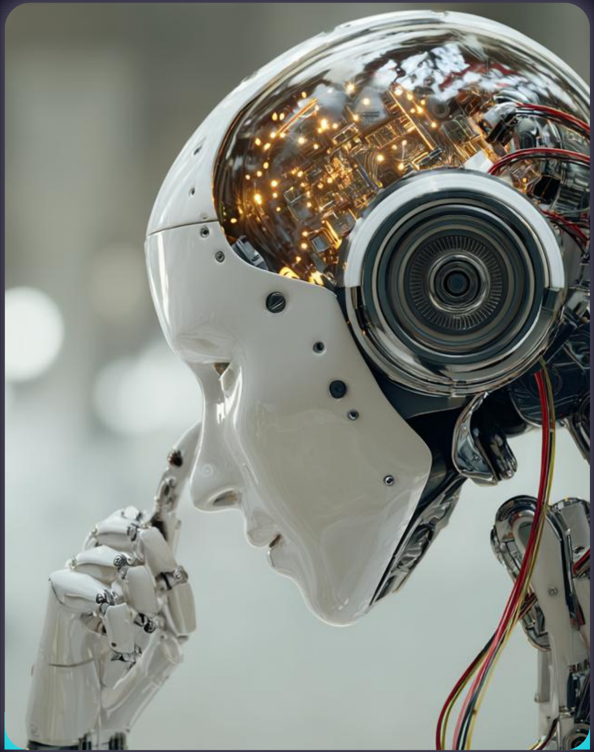
Neural activity

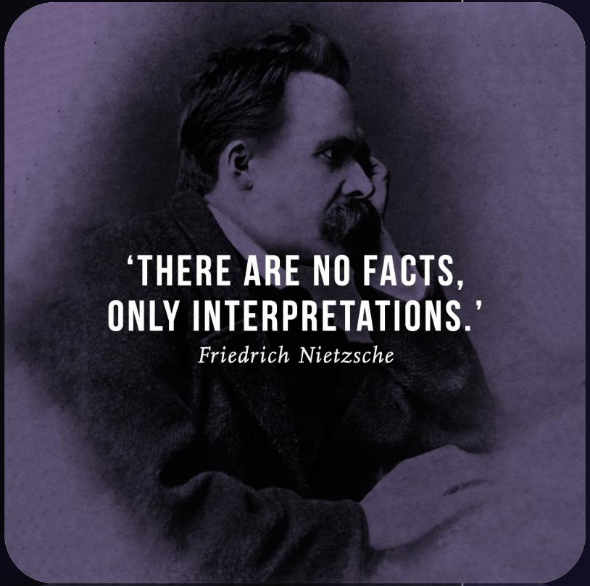
Cognitive activity

Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task. Kosmyna, N et al. arXiv. 2025

CONCERNS

- Disconnection from human sensitivity
- Dehumanization of the human factor
- Balance between machine autonomy and the need for human responsibility and supervision




'THERE ARE NO FACTS,
ONLY INTERPRETATIONS.'
Friedrich Nietzsche

ΕΥΧΑΡΙΣΤΩ