Brigham and Women's Hospital
Founding Member, Mass General Brigham

Applications of Artificial Intelligence in Kidney Disease

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Champion – ASN Committee for Responsible AI in Kidney Care
Clinical Focus

- CKD Prevention/Screening/Treatment
- Risk Based Care

Disclosures

Consultant

- Roche
- AZ
- Vera
- Bayer
- BI-Lilly
- Otsuka
- Pulsedata
- Prokidney
- Novo Nordisk
- Panoramic

Equity

- Prokidney
- Pulsedata
- Mesentech
- Klinrisk
- Quanta
- Marizyme

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ASN Guiding Principles for Responsible AI in Kidney Care

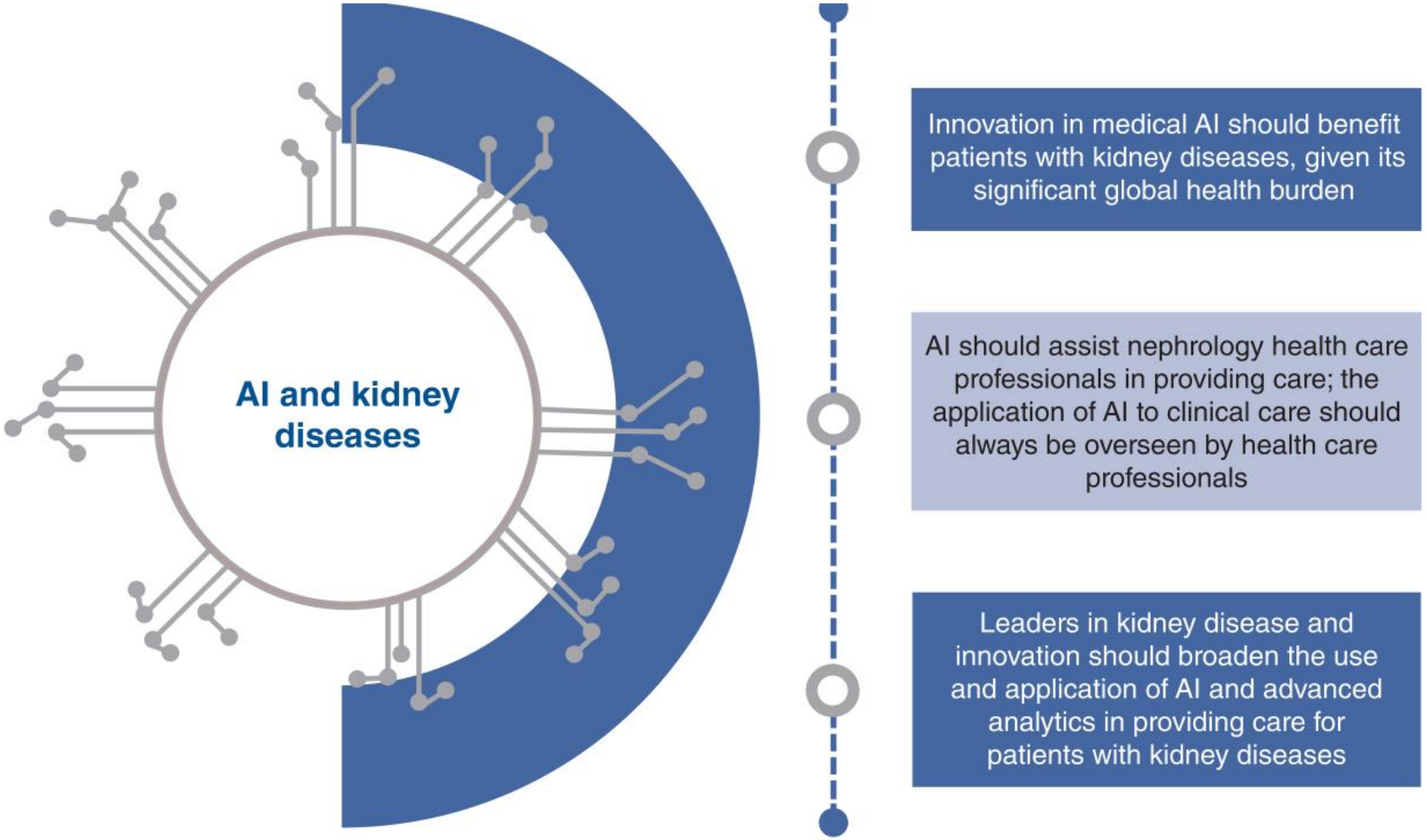


Figure 1. Guiding principles of the American Society of Nephrology Workgroup on responsible AI and kidney diseases. AI, artificial intelligence.

Phase 1: Early Detection (CKD)

Image-based Deep Learning analyzing non-traditional markers (e.g., retinal fundus).

Phase 2: Acute Care (AKI)

Continuous prediction via physiological data lakes.

Phase 3: Chronic Management (Dialysis)

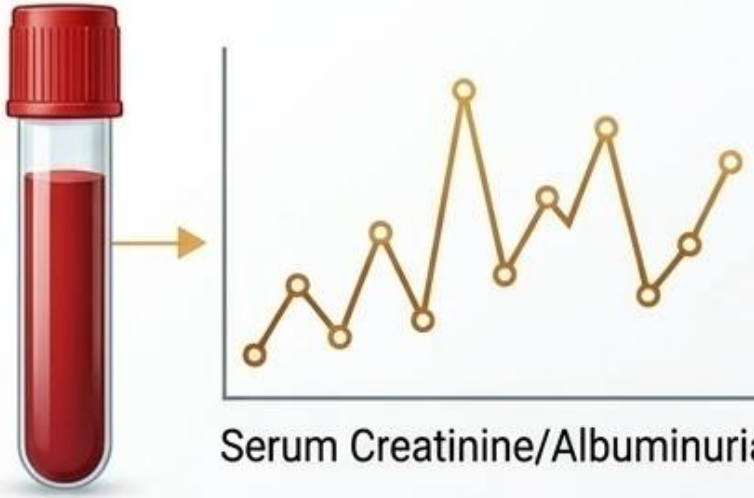
Supervised learning for real-time treatment recommendations & IDH prediction.

Phase 4: End-Stage (Transplantation)

Machine Learning for deceased donor matching and waitlist prediction.

Key Takeaway: AI is a suite of specialized tools mapped to specific clinical workflows, not a monolith.

The Traditional Hurdle

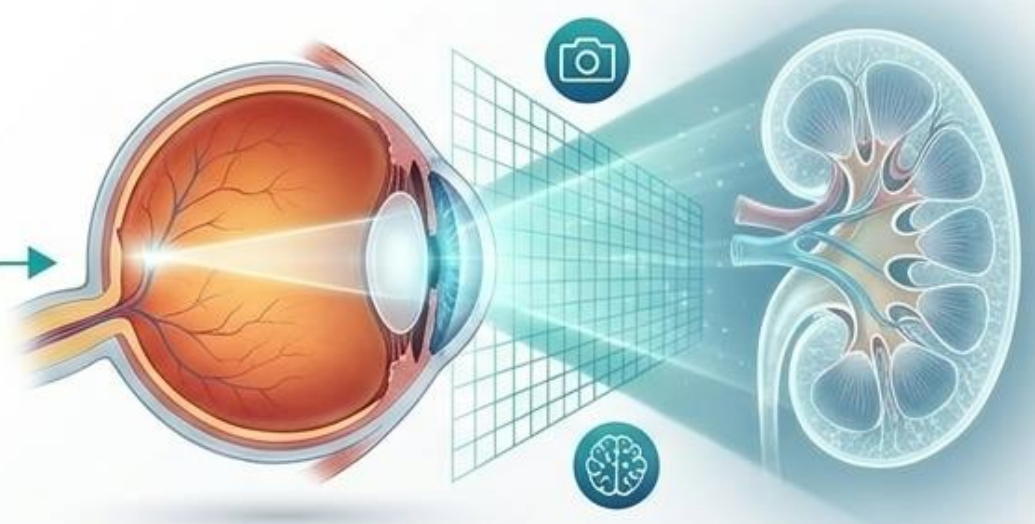


Serum Creatinine/Albuminuria

Screening rates for CKD remain low despite guidelines.

Serum creatinine and albuminuria exhibit up to 50% intra-individual variability and require clinical lab visits.

The AI Alternative: RetiKid



Technology: Deep Learning utilizing retinal fundus images to bypass blood tests entirely.

Performance: 91% internal accuracy in detecting eGFR <60, matching traditional risk-factor models.

Impact: Accessible, non-invasive, point-of-care screening for low-resource or needle-phobic populations.

Rethinking CKD Screening Through a Non-Invasive Clinical Lens

The Barrier

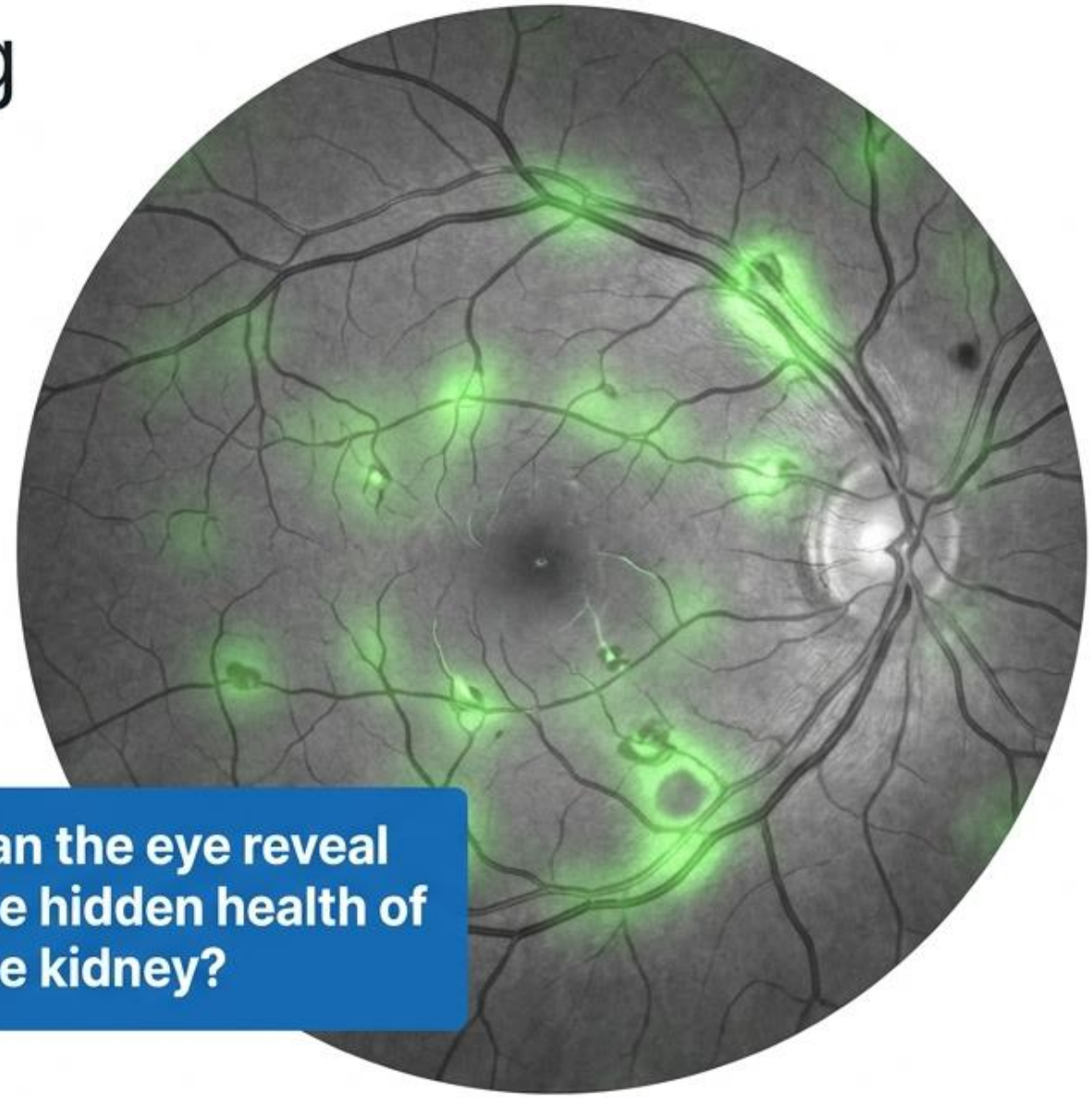
Chronic Kidney Disease (CKD) screening currently relies entirely on invasive blood draws or highly variable urine tests.

The Fallout

Nearly 50% of high-risk patients with diabetes remain unscreened over an 18-month period due to inconvenience and needle avoidance.

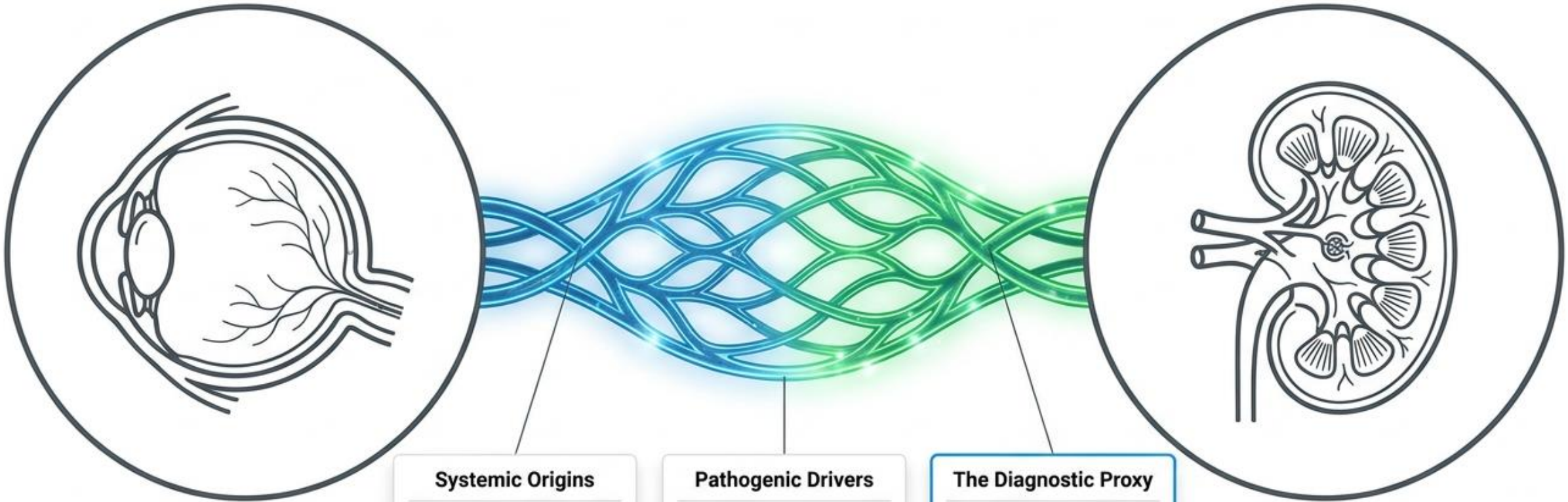
The Proposition

A Deep Learning Algorithm (DLA) designed to opportunistically detect CKD using standard, non-invasive digital retinal photographs.



Can the eye reveal the hidden health of the kidney?

The Biological Bridge: Shared Microvascular Pathways



Systemic Origins

Both organs share identical developmental, physiological, and renin-angiotensin-aldosterone cascade pathways.

Pathogenic Drivers

Inflammation, Oxidative Stress, Endothelial Dysfunction, and Microangiopathy.

The Diagnostic Proxy

Clinically visible retinal microvascular signs (retinopathy, arteriolar narrowing) serve as direct, visible proxies for occult systemic microvascular damage in the kidneys.

Global Validation Datasets and Deep Learning Architecture

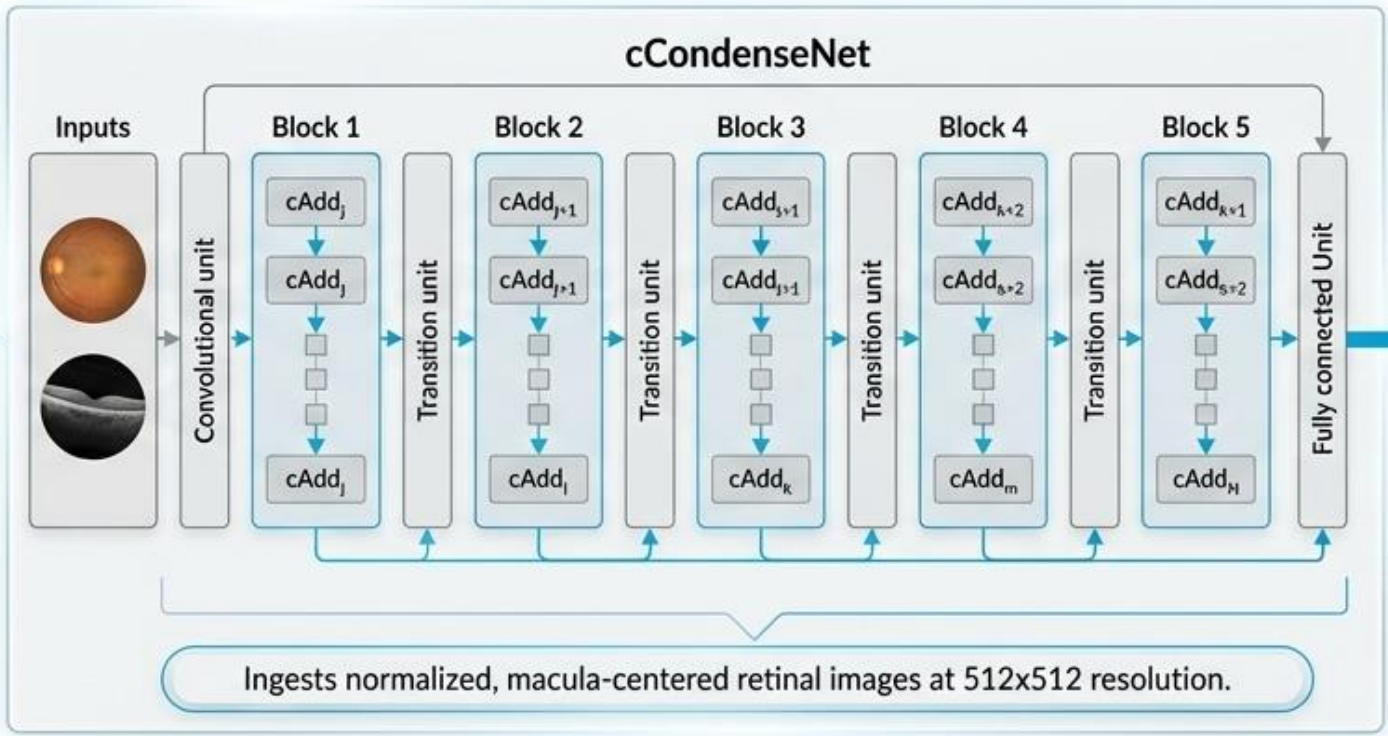
Phase 1: Global Multi-ethnic Datasets

SEED (Singapore)
N=6,485
Development & Internal Validation

SP2 (Singapore)
N=3,735
Independent External Testing

BES (Beijing)
N=1,538
Independent External Testing

Phase 2: The Deep Learning Algorithm (DLA)



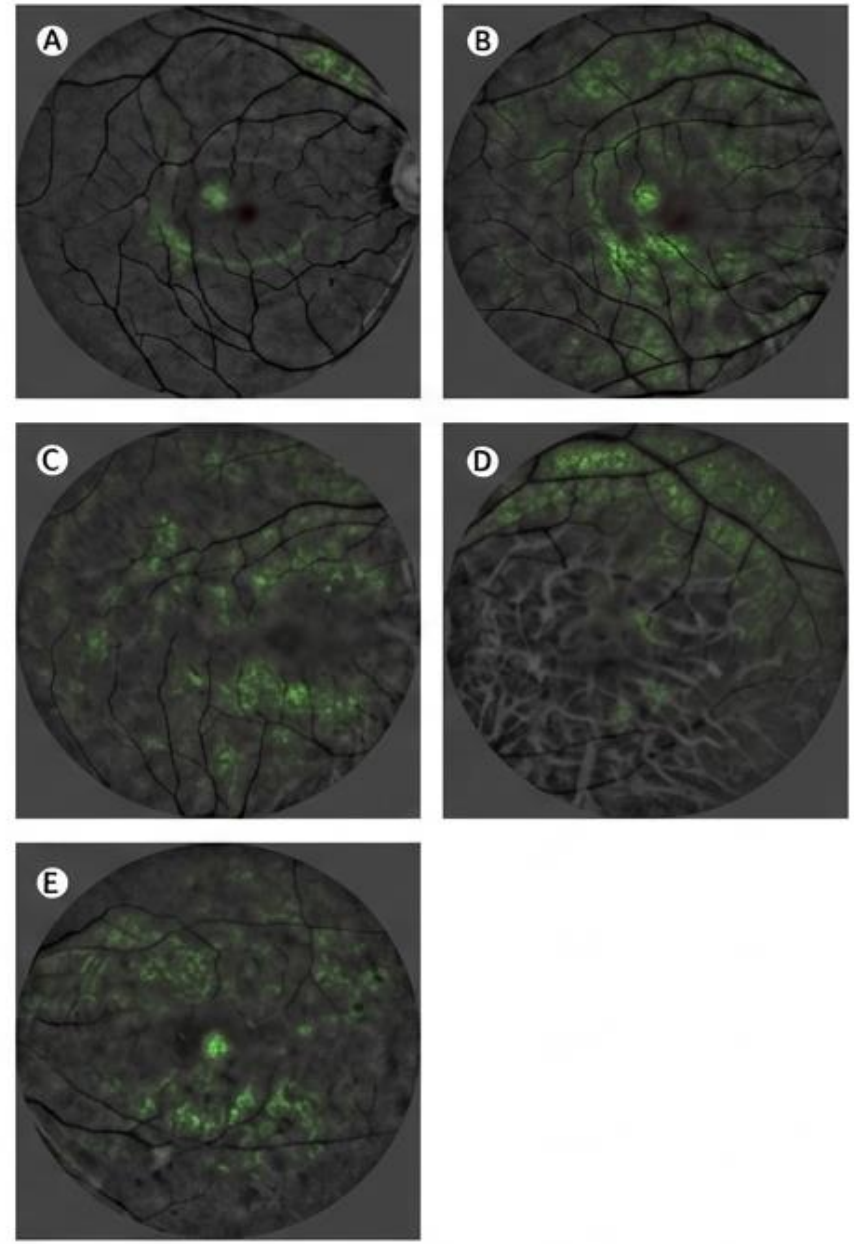
Phase 3: Diagnostic Output

Binary Classification: Presence or Absence of CKD (eGFR <60 mL/min per 1.73m²)

Performance Metrics: The Image-Only Model vs. Clinical Risk Factors

Model	SEED (Validation)	SP2 (Testing)	BES (Testing)
Image-Only DLA	0.911	0.733	0.835
Risk Factor (RF) Model	0.916	0.829	0.887
Hybrid (Image + RF)	0.938	0.810	0.858

Key Insight: The Image-only DLA performs remarkably close to classic clinical risk factor models. Adding clinical data (Hybrid) only modestly improves prediction, proving the retinal image alone is a highly viable screening proxy.



The DLA accurately detects predictive signals distributed throughout the retina without requiring manual clinical inputs.

Transforming Point-of-Care Screening in the Community

The Current Paradigm

Methodology: Heavy reliance on blood draws and variable urine samples.

Friction Points: Requires specialized labs, causes delayed results, and faces a 10% population barrier due to needle phobia.

Result: Missed cases and low adherence, particularly in high-risk diabetic and hypertensive populations.

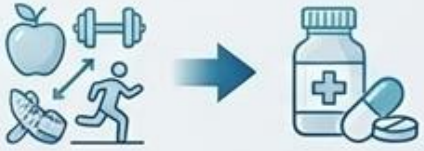
The DLA Paradigm

Methodology: Opportunistic, completely non-invasive screening.

Implementation: Software integration directly into existing primary care retinal cameras (already widely used for diabetic retinopathy).

The Triage Impact: Acts as a rapid first-stage triage tool. Only positive screens are recalled for confirmatory serum creatinine testing, drastically reducing healthcare friction.

A non-invasive window into systemic health.

	Inputs	Outputs	Clinical Integration
KidneyIntelX (Supervised ML)	 3 proprietary blood biomarkers + clinical EHR data.	 Categorizes diabetic kidney disease into low/intermediate/high risk of progression.	 FDA-authorized; high-risk patients 2.5x more likely to be referred to specialty care.
Klinrisk (Random Forest)	 Routine labs (Complete Blood Count, Metabolic Panel, UACR).	 Predicts CKD progression up to 5 years.	 Top 30% of high-risk patients account for 87% of progression events over 2 years.
Digital Twins (Unsupervised Clustering)	 Generalized Metabolic Fluxes (GMF) and multi-omics.	 Virtual patient replicas predicting CKD onset within 3 years (75-86% accuracy).	 Simulates lifestyle/medication changes on individual disease trajectories.

How it works

Routine Blood & Urine Samples

Standard Lab Results

Klinrisk Analysis

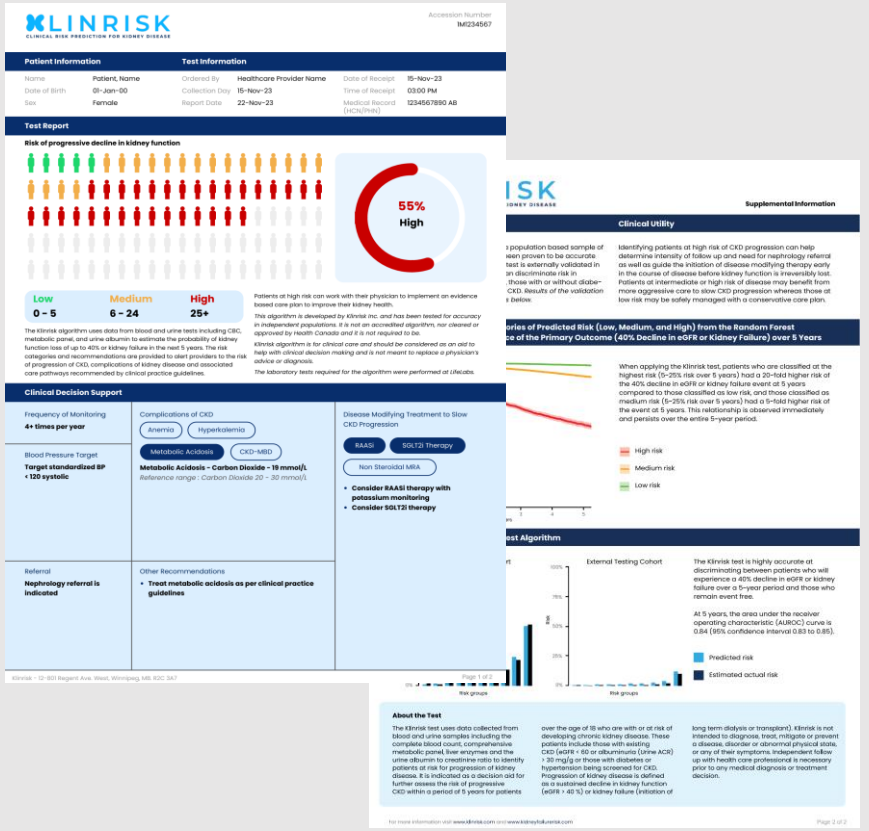
KLINRISK

Personalized Risk & Guideline-Directed Care Plan

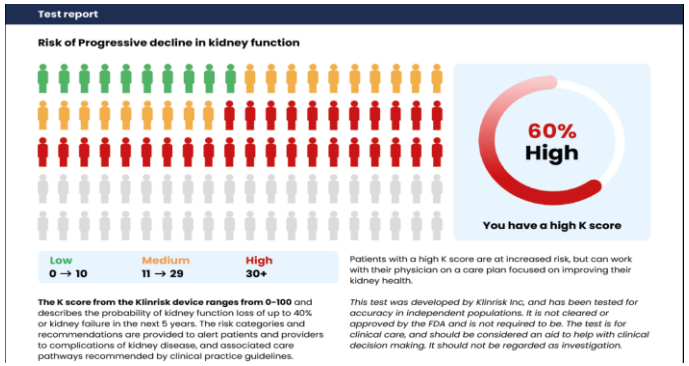
Identifies risk in time for effective intervention:
Finds high risk of CKD progression & related utilization before kidney function is lost

No extra steps:
Uses lab data collected at routine visits

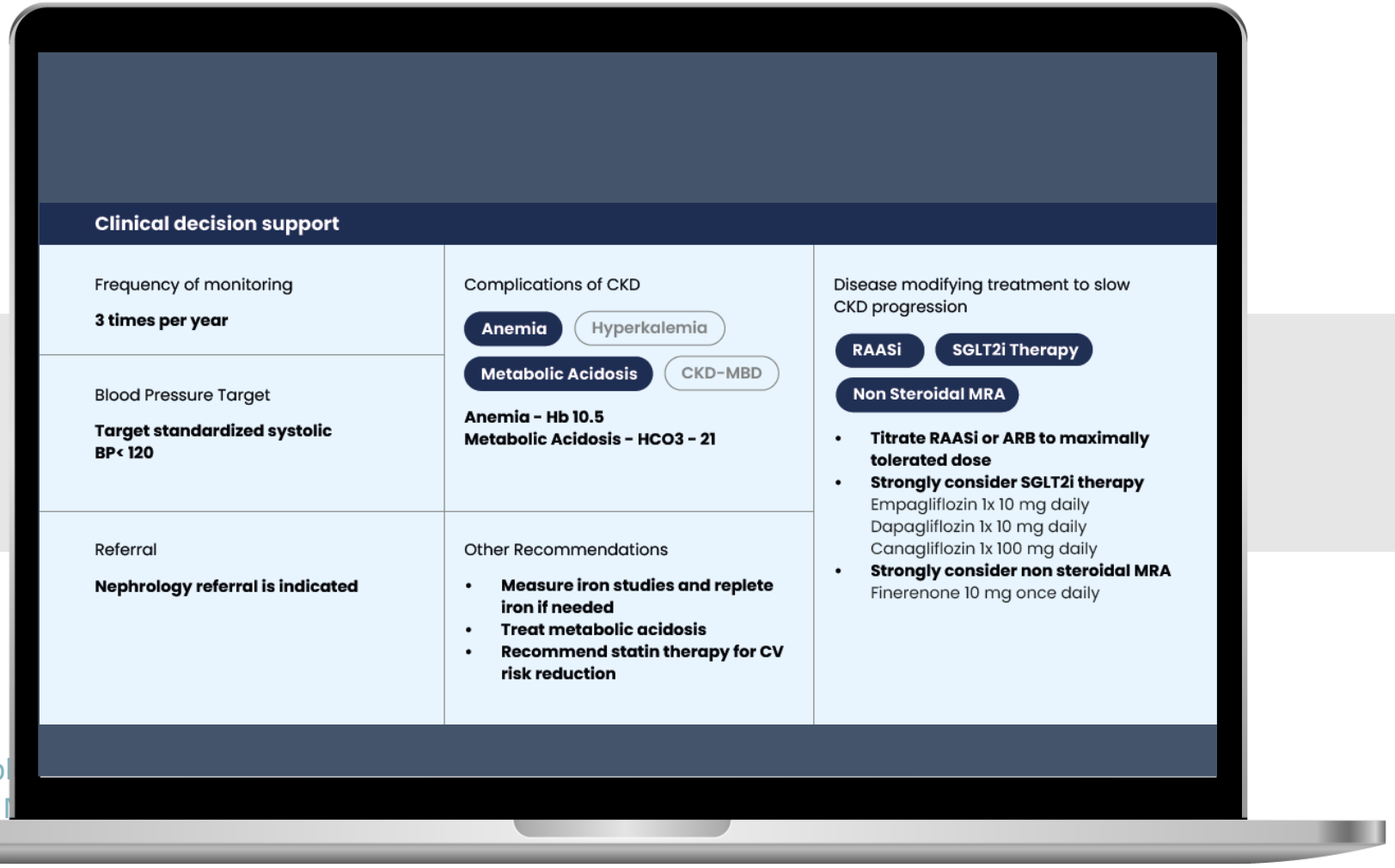
Simulating a virtual nephrology consult:
Personalized medication management and care plan provided at the point of care



Enabling risk-based care by connecting risk to clinical decision support



Physicians need to make the link between risk and clinical decisions



ARB, angiotensin receptor bl
mineral and bone disorder; M
aldosterone system

Reference: 1. Klinrisk. Clinical risk prediction for kidney disease. Lifelabs. Accessed Jan 17, 2024. https://go.lifelabs.com/Klinrisk-Sample-Report.

Patient Report — Plain-Language Risk Summary & Lab Results

- **Medical Record Number:** [2000012848]
- **Report Date:** [June 25, 2025]

Your Kidney Health at a Glance

You are in the **LOW RISK** category.

Your report shows that your risk of a big change in your kidney function (like a decline of more than 40% or needing kidney failure treatment) over the next 5 years is 5%.

This test uses information from your blood and urine sample to help your doctor understand your kidney health and plan the best personalised care for you.

Key Numbers from Your Test

Test Name	Results	What it Means for You
eGFR (Kidney Function)	**80.0** mL/min/1.73m²	This number tells us how well your kidneys are cleaning your blood. A healthy number is usually 60 or higher. Your result is good!
Albumin/Creatinine Ratio, Urine	**3.0** mg/mmol	This checks for a protein called albumin in your urine, which can be a sign of kidney damage. Your result is at the upper limit of the normal range (≤3.0), which your doctor will discuss.
Potassium	**4.0** mmol/L	This is an important mineral in your blood. Your result is in the healthy range (3.5-5.2).

Risk in plain English

"You are in the LOW RISK category" — no jargon, no numbers without context. The 5% 5-year risk is stated explicitly so patients can understand their result.

Three key labs explained clearly

eGFR, ACR, and Potassium each have a plain-language interpretation — "your result is good!" or "your doctor will discuss" for borderline values.

Borderline ACR flagged — not dismissed

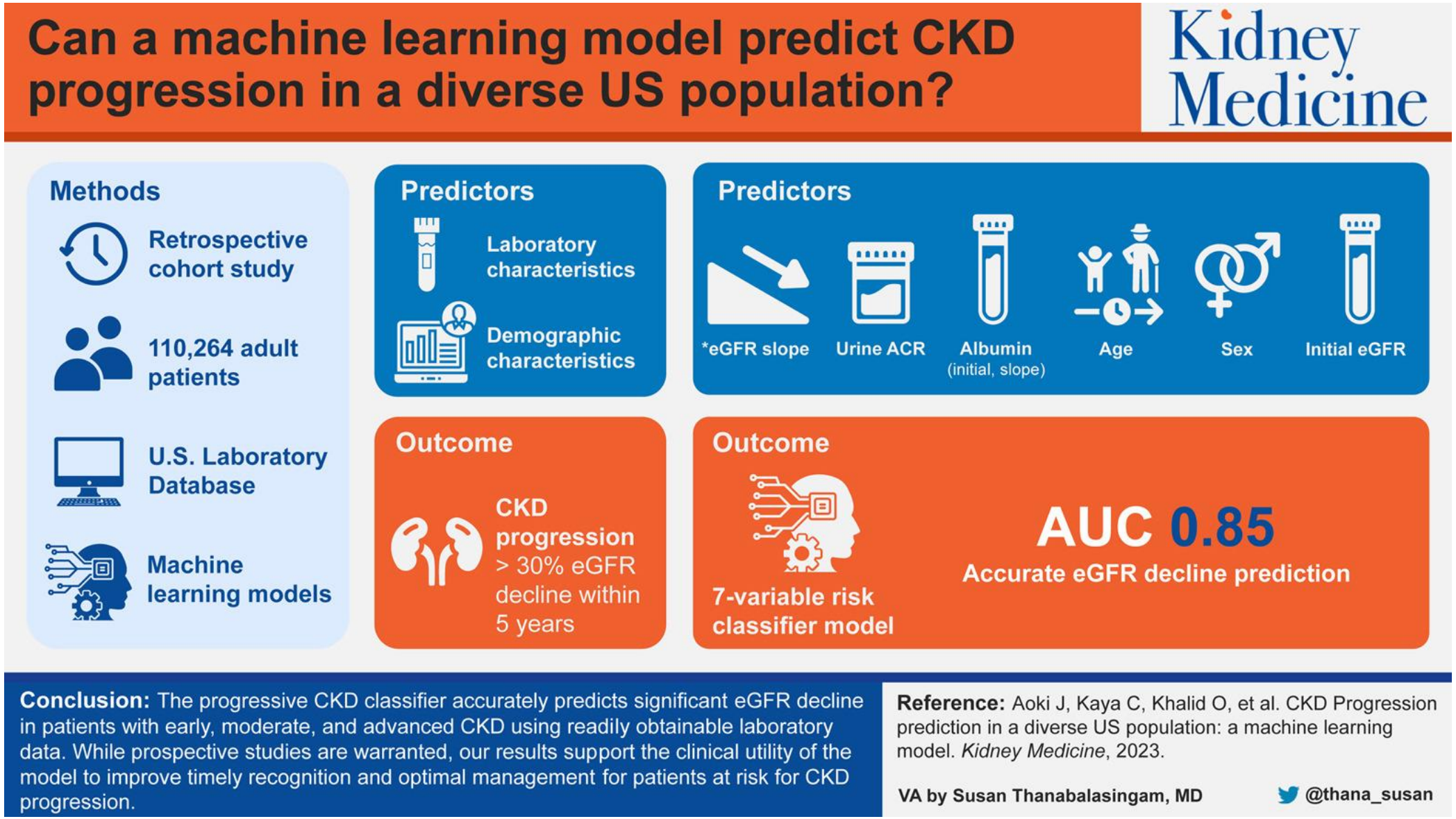
ACR 3.0 mg/mmol is at the upper limit and is specifically noted for physician discussion. Builds early awareness without causing alarm.

Potassium context provided

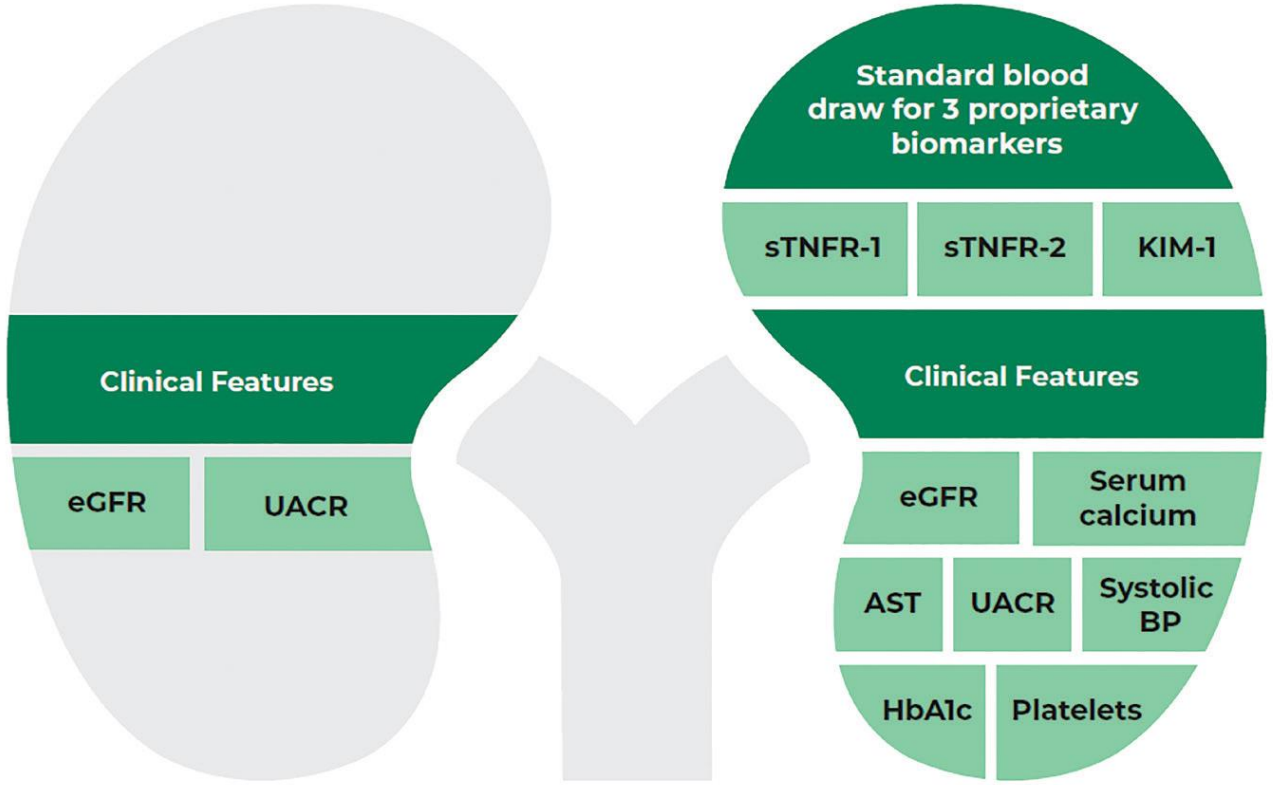
K^+ 4.0 mmol/L confirmed healthy with the normal range shown — directly relevant given hyperkalemia monitoring emphasis in the physician report.

Source: Klinrisk Patient Report 2026, Page 1. Report language aligned with health literacy best practices. klinrisk.com

SONIC model – Relies on eGFR slope, predicts 30 % decline



Combining AI and Biomarkers for Chronic Kidney Disease - KidneyIntelx



Diagnosis

Assesses level of kidney function and damage

Bioprognosis

Predicts risk of rapid progressive kidney function decline

KidneyIntelX™

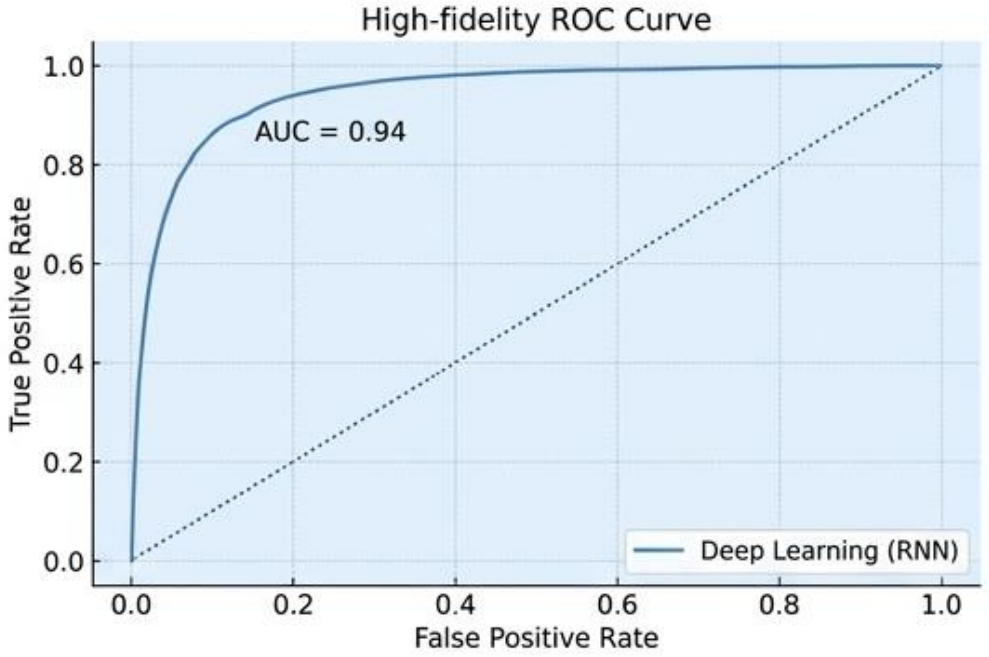
AUC 0.74-0.77

Validated in 2 US populations (n~1,100) and CANVAS/CREDENCE trials – FDA Cleared

The Dialysis Data-Rich Environment

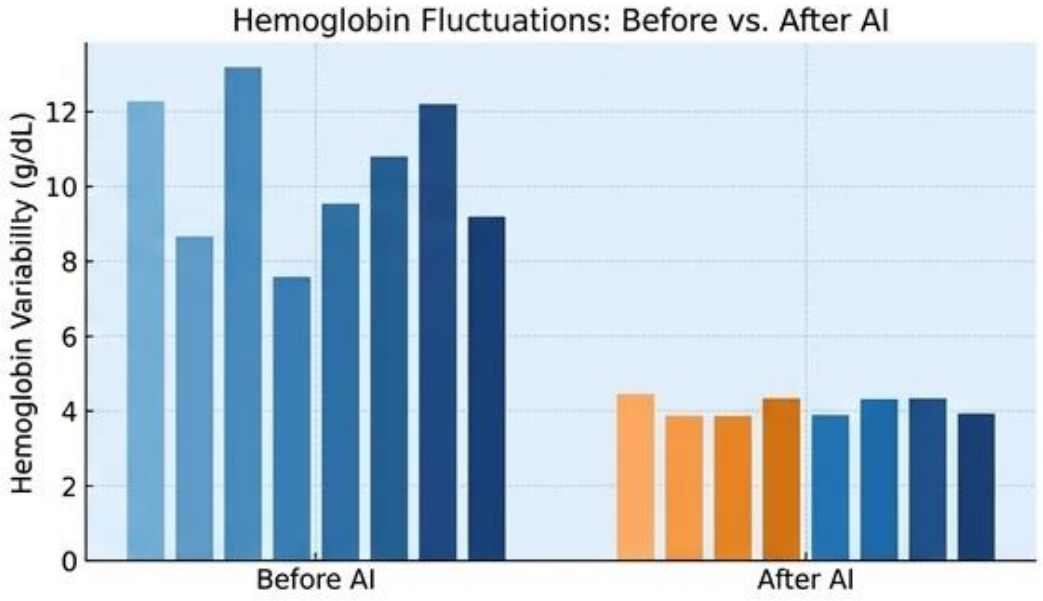
Highly standardized, longitudinal data (ultrafiltration volumes, flow rates, biosignals) makes chronic care the prime candidate for Machine Learning optimization.

Widget 1: Predicting Complications



Deep Learning (RNN) analyzes over 260,000 hemodialysis sessions to predict intradialytic hypotension in real-time.

Widget 2: Treatment Optimization



Anemia Control Model (ANN) trained on 170,000 records suggests exact ESA and iron doses, reducing overall use and hospitalization risks.

Precision AI in Home Dialysis: Clinical Applications and Future Directions

From Population Evidence to Precision Medicine

Data Lakes

Data Thread

Vital Signs

Demographics

Labs

Genomics

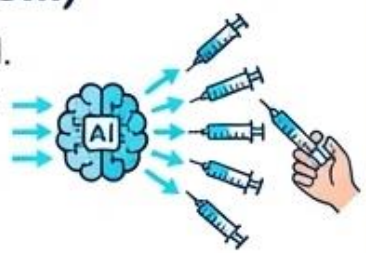
Artificial Neural Network (ANN) / Machine Learning

Predictive Modeling for IDH

Real-time Intradialytic Hypotension forecasting using time-varying vital signs. Achieves an AUROC of 0.94.

Anemia Control Model (ACM)

Personalized ESA dosing via ANN. Demonstrates a 25% reduction in darbepoetin consumption while achieving 83.2% of Hemoglobin values on target.

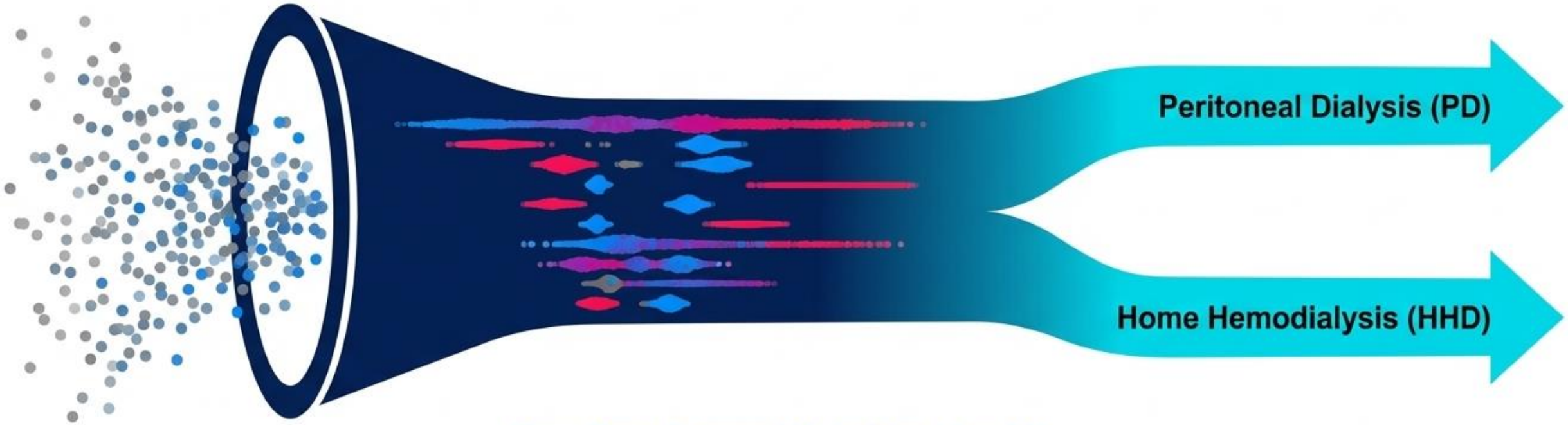


AI-Assisted Dry Weight

Dynamic adjustments utilizing bioimpedance and continuous blood volume monitoring. Outperforms experienced nephrologists (mean difference 0.497 kg) and allows reduction in antihypertensives.

Kotanko et al. CJASN 2023

Machine Learning for Modality Stratification



Key Predictors Weighted by ML

Age
(Younger predicts HHD; older predicts in-center)

Comorbidities
(Pre/post-KRT acuity markers managed safely at home)

Pre-Dialysis Care
(Early nephrologist exposure drives home modality success)

Dialysis Vintage
(Shorter vintage is the strongest predictor for PD)

Applying ML-driven practices from top-performing HRRs can increase nationwide home dialysis penetration from 17.3% to >27%.

Monaghan et al. Kidney Medicine 2025

The Evolution of Bidirectional Cloud Connectivity

Legacy Care

Technology: Paper logs and manual memory cards

Process: Delayed intervention (monthly reviews), high risk of human data entry error, falsified blood pressure/weight logs.

Visibility: Blind spots between monthly clinical visits.

The eHealth Paradigm Shift

Precision Care

Technology: Bidirectional, cloud-connected platforms

Capabilities: Automated, accurate data collection (fill/drain volumes, ultrafiltration, alarms).

Intervention: Real-time therapy oversight allowing remote prescription adjustments without an in-clinic visit.

Evidence-Based Impact of Remote Monitoring

Clinical Outcomes (Medical Impact)

Superior BP Control

Improved adherence leads to reduced reliance on antihypertensive medications.

Clinical Outcomes (Medical Impact)

Enhanced Quality of Life

Greater autonomy, less commute time, and more PD-free time.

Operational Outcomes (Systemic Impact)

Healthcare Utilization

Significant reduction in ED visits and shortened hospital lengths of stay.

Operational Outcomes (Systemic Impact)

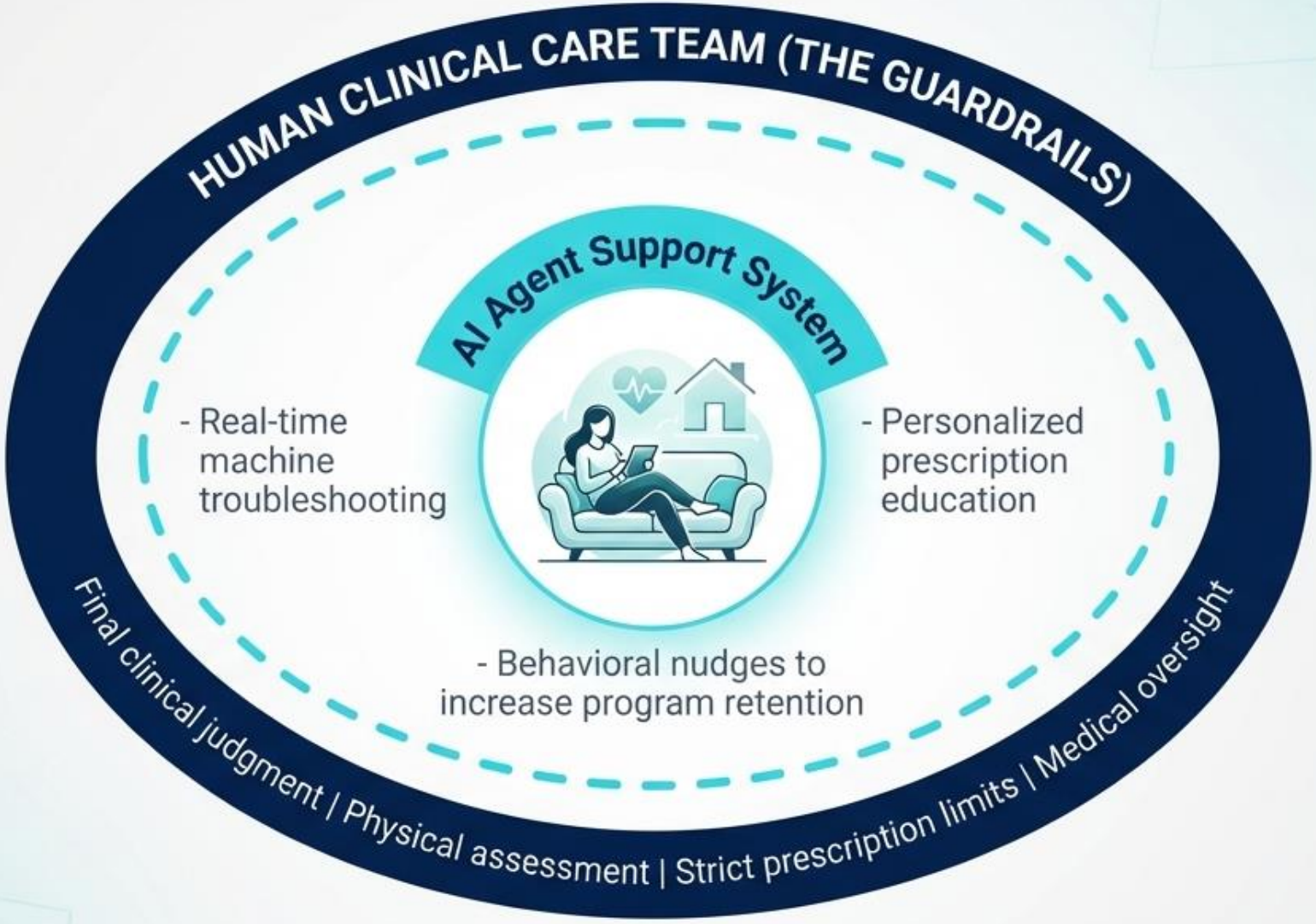
Program Retention

Decreased technique failure rates and improved overall treatment adherence.

Continuous data flow shifts care from reactive emergency management to proactive therapy optimization.

Nygard et al. BMJ Open 2022

AI as an Extension of the Clinical Care Team



AI agents operate strictly within the boundaries set by the care team—managing technical and educational friction so physicians can focus on practicing high-level medicine.

Premium Clinical Editorial

Shifting paradigms: The clinical power of narrow, predictive algorithms

While open-ended search engines struggle with complex reasoning, tightly constrained AI excels at predictive math. The ACM tackles a highly specific, mathematically complex challenge: managing the non-linear dose-response relationship of anemia medications over time.

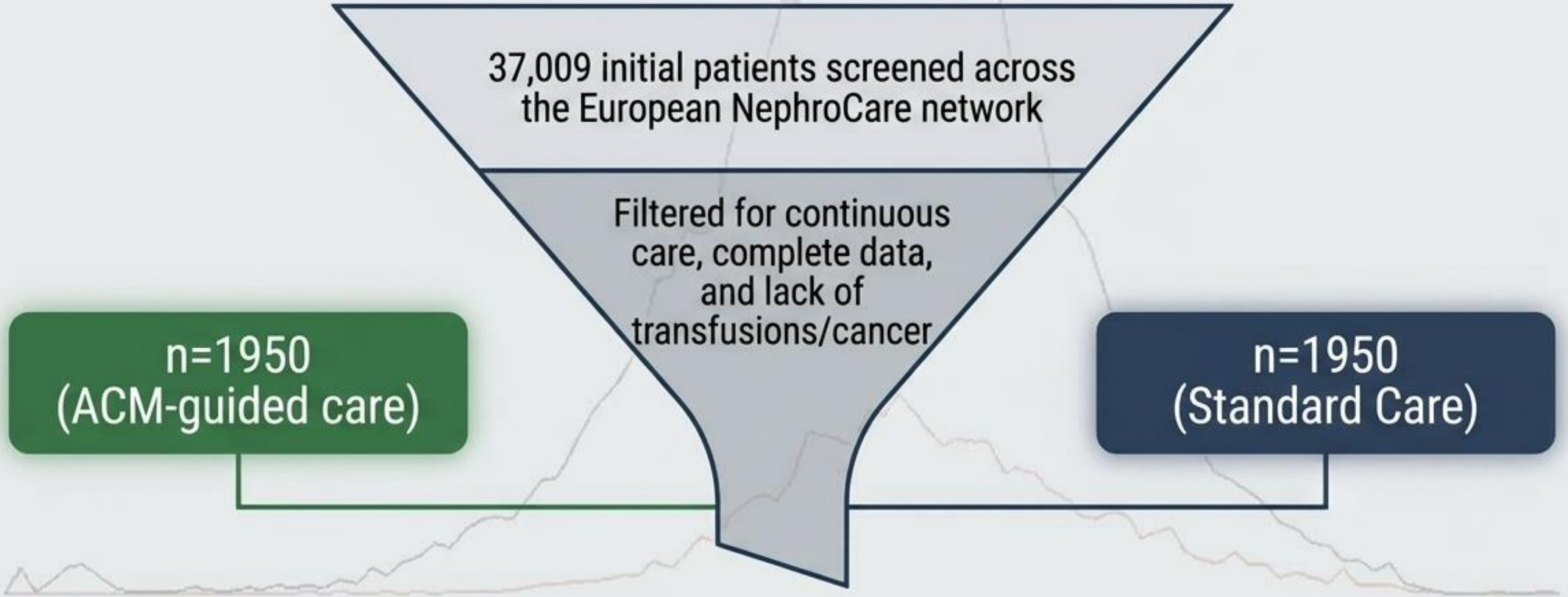
Anemia Control Model (ACM)

The Context:	Chronic Kidney Disease Anemia (CKD-An) in hemodialysis patients.
The Challenge:	Balancing Erythropoietin-Stimulating Agents (ESAs) to correct anemia without causing hemoglobin cycling or cardiovascular toxicity.
The Solution:	An Artificial Intelligence decision-support system certified as a medical device in the EU, designed exclusively to personalize ESA and iron dosages.

Premium Clinical Editorial

Simulating a clinical trial through rigorous propensity matching

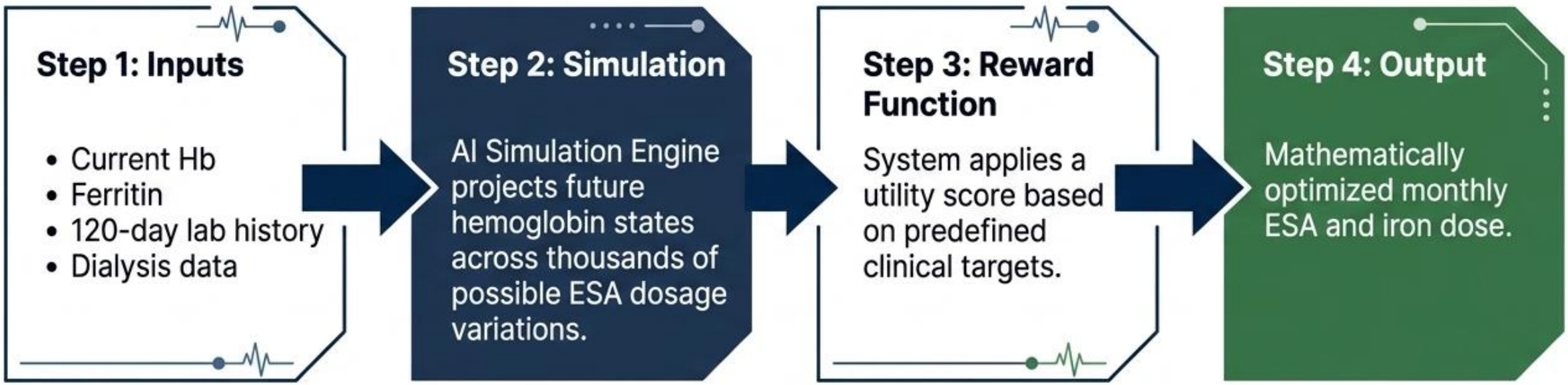
To eliminate indication bias and simulate the conditions of a randomized controlled trial, the study utilized optimal 1:1 propensity score matching. The resulting cohorts exhibited negligible differences in baseline demographic, comorbidity, and dialysis treatment characteristics.



Premium Clinical Editorial

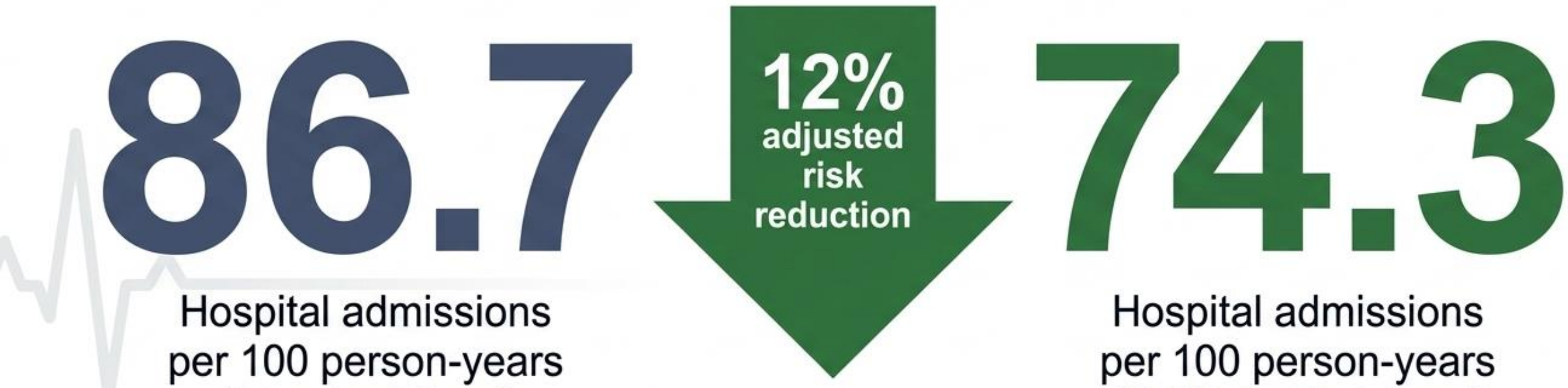
Inside the neural reward loop of the Anemia Control Model

Unlike generative language models, the ACM does not reason; it simulates. By evaluating a comprehensive dataset of patient history and applying a strict reward function anchored to clinical targets, it minimizes drug utilization while maximizing target achievement.



Algorithmic anemia control significantly reduces patient hospitalizations

When physicians accepted the ACM's personalized dosage recommendations, patient outcomes improved. Even after adjusting for residual imbalances in dialysis adequacy (Kt/V), ACM-guided care was associated with a statistically significant reduction in all-cause hospitalizations. However, no corresponding survival benefit was observed during the one-year follow-up.



The gold standard for AI utility is specialized clinical decision support

The Verdict on Predictive Medical AI:

The Anemia Control Model proves that artificial intelligence can directly improve patient outcomes when properly constrained.

Overcomes human limitations in tracking non-linear, temporal drug responses.

Achieves large savings in **medication usage** while improving **clinical targets**.

Demonstrates that the **highest-value medical AI systems are tightly scoped, rigorously validated,** and **built to solve specific, mathematical clinical challenges.**

Problem: Unplanned Hospitalizations

Unplanned hospitalizations drive cost and lost revenue

40%
of Medicare
ESRD **Costs**

Lower
Transplant Rates

34%
30-day
Readmission Rate

Up to 2%
QIP Penalty
(Revenue at Risk)

Penalties Start **>33%**
Readmission Rate

Outcomes:

Worse Patient
Outcomes → **Higher Costs**
of Care

Lost Revenue
for Centers

Predicting Hospitalization in the Next 90 Days

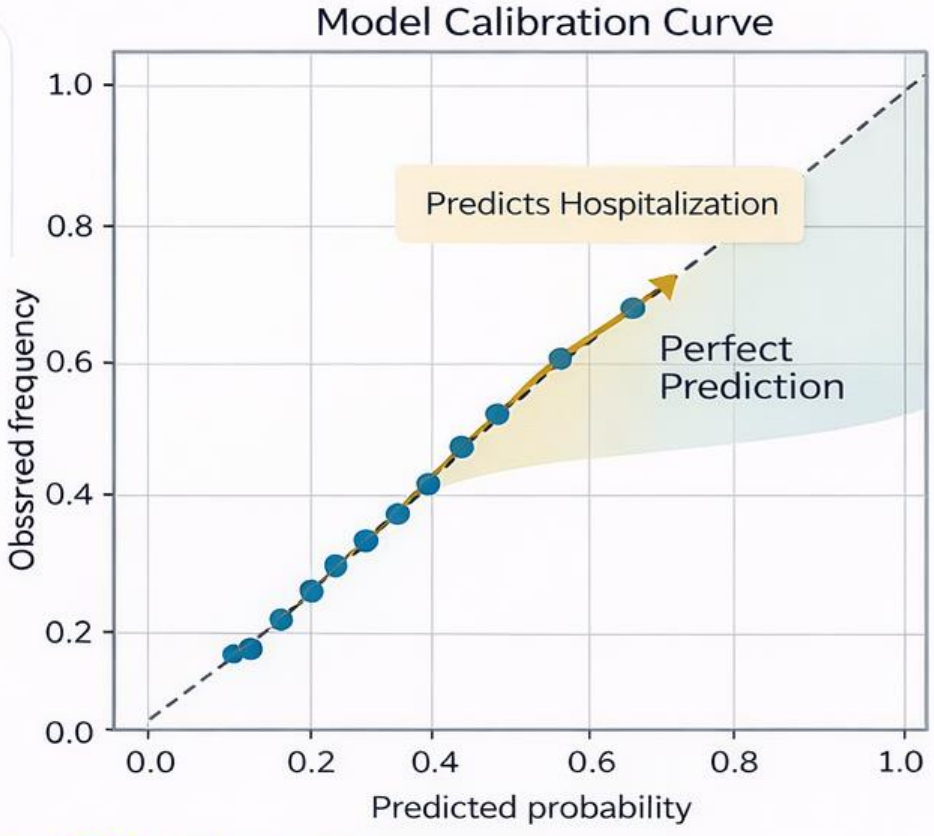
CATBoost model predicts dialysis patient hospitalizations and reduces admissions

Trained on
28,000 Patients
4.5M Dialysis Treatments

Validated on
5,000 Patients Internally validated
785K Dialysis Treatments

100+ Predictors → Final 20 Key Features

Excellent Calibration High discrimination and calibration performance



+34% Fewer Hospitalizations & +40% Clinic Revenue

Prediction Metrics:

High Risk — PPV **51%**
> 1 in 2 chance of hospitalization in 90 days

Low Risk — NPV **14%**
< 1 in 7 chance of hospitalization in i 90 days

Fast access

Search Patient

Patient

Assessment

Labs

Care Plan

In-Center Hemodialysis

Home Hemodialysis

Peritoneal Dialysis

Reports

Miscellaneous

Import/Export

Admin Options

Attachments

Local Application

Predictive AI: Anemia Risk

Facility: All Facility

Search

Name	Age	Gender	MR#	Facility	Nephrologist	Tx Schedule	Modality	ESA Name	Dose	Last Administered Date	Latest HGB	New Suggested Dose	Action	Action History
						M, W, F	Permanent Hemodialysis	Mircera	60 mcg/IV/1st tx every 2 wks (05/03/2022)	05/02/2022	10.1 (01/14/2026)	75	Diet Order	Create View
						M, W, F	Permanent Hemodialysis	Mircera	50 mcg/IV/1st tx every 2 wks (04/19/2022)	05/02/2022	12.3 (01/14/2026)		Notes	Create View
						Tu, Th, Sa	Permanent Hemodialysis	Mircera	30 mcg/IV/1st tx every 2 wks (05/04/2022)	05/03/2022	12.9 (01/14/2026)		Action	
						Tu, Th, Sa	Permanent Hemodialysis	Mircera	100 mcg/IV/1st tx every 2 wks (02/05/2025)	05/03/2022	10.4 (01/14/2026)	75	Diet Order	Create View
						M, W, F	Permanent Hemodialysis	Mircera	50 mcg/IV/1st tx every 2 wks (05/07/2022)	05/02/2022	10.6 (01/14/2026)		Notes	Create View
						Tu, Th, Sa	AKI In-center Hemo	Mircera	30 mcg/IV/1st tx every 2 wks (05/04/2022)	05/03/2022	16 (01/14/2026)	150	Action	
						M, W, F, Sa	Permanent Hemodialysis	Mircera	100 mcg/IV/1st tx every 2 wks (05/03/2022)	05/02/2022	4.8 (01/14/2026)	75	Action	
						M, W, F	Permanent Hemodialysis	Mircera	60 mcg/IV/1st tx every 2 wks (05/07/2022)	05/02/2022	10.8 (01/14/2026)		Action	
						M, Tu, W, Th, F, Sa	Pre ESRD	Mircera	200 mcg/IV/1st tx weekly (04/28/2025)	01/22/2025	10 (01/14/2026)	75	Action	
						Tu, Th, Sa	Permanent Hemodialysis	Mircera	60 mcg/IV/1st tx every 2 wks (05/04/2022)	05/03/2022	10.6 (01/14/2026)	30	Action	
						Tu, Th, Sa	Permanent Hemodialysis	Mircera	30 mcg/IV/1st tx every 2 wks (04/13/2022)	05/03/2022	19 (01/14/2026)		Action	
						M, W, F	Permanent Hemodialysis	Mircera	30 mcg/IV/1st tx every 2 wks (04/19/2022)	05/02/2022	18 (01/14/2026)		Action	
						M, W, F	Permanent Hemodialysis			11/20/2017	9 (01/14/2026)		Action	
						Tu, Th, Sa	Permanent Hemodialysis	Mircera	100 mcg/IV/1st tx every 2 wks (11/20/2021)	05/03/2022	10.8 (01/14/2026)		Action	
						Tu, Th, Sa	Permanent Hemodialysis					30	Action	
						M, W, F	Permanent Hemodialysis			06/13/2011		30	Action	

AI Interventions Across the Transplant Continuum

1. Boosting Living Donation

- ML predicts patients at risk of failing evaluation to reduce disparities.
- NLP assesses digital sentiment to identify barriers and engage living donors.

2. Optimizing Organ Matching

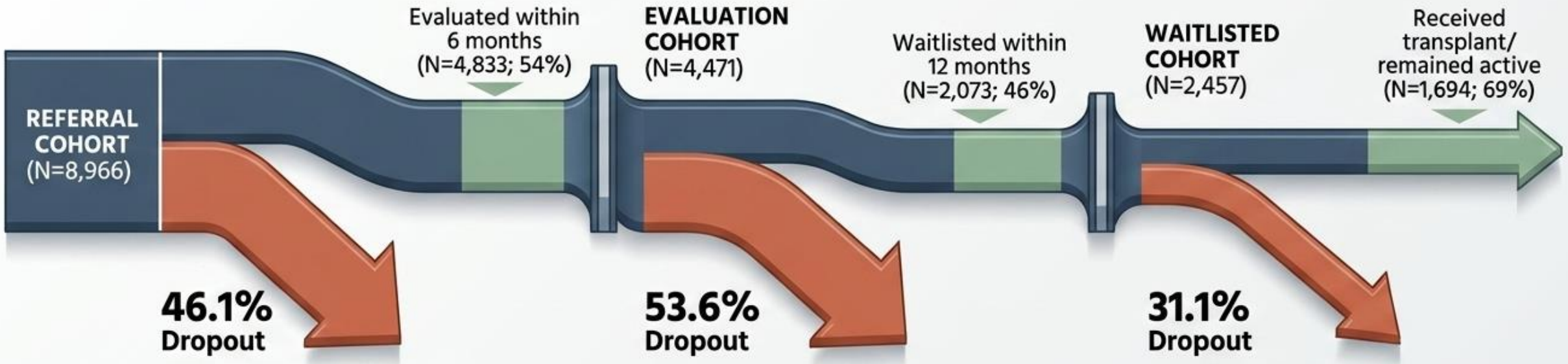
- AI integrates with KDPI and EPTS indices.
- ML uncovers variables beyond tissue compatibility, proving high-KDPI organs improve survival for high-risk patients.

3. Post-Transplant Outcomes

- AI dosing systems integrate genetic polymorphisms.
- Predicts precise tacrolimus bioavailability to minimize toxicity and rejection.

Massive Hidden Attrition Plagues Early Transplant Stages

Up to half of potential candidates drop out at early stages not captured in national transplant registries.



46.1%
Dropout

Referral to Evaluation: 4,133 of 8,966 failed to attend first visit.

53.6%
Dropout

Evaluation to Waitlisting: 2,398 of 4,471 failed to complete.

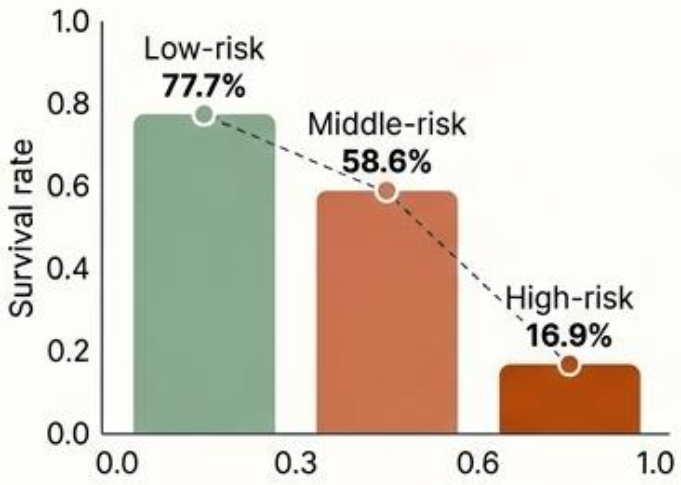
31.1%
Dropout

Waitlisting to Transplant: 763 of 2,457 became inactive or un-transplanted.

Harnessing Machine Learning for Early Risk Identification

ML effectively stratifies patients into actionable risk tiers, enabling targeted interventions before dropout occurs.

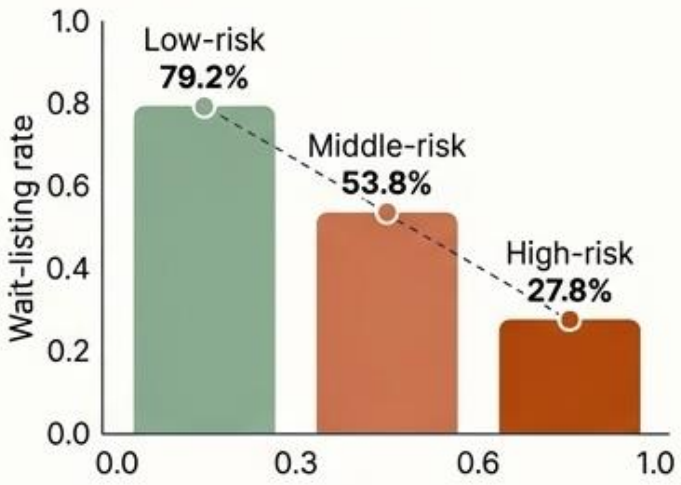
Referral Stage



Machine learning model predicting risk of no evaluation in 6 months

Model: XGBoost
Predictive Power: AUROC 0.79
Function: Predicts evaluation initiation within 6 months.

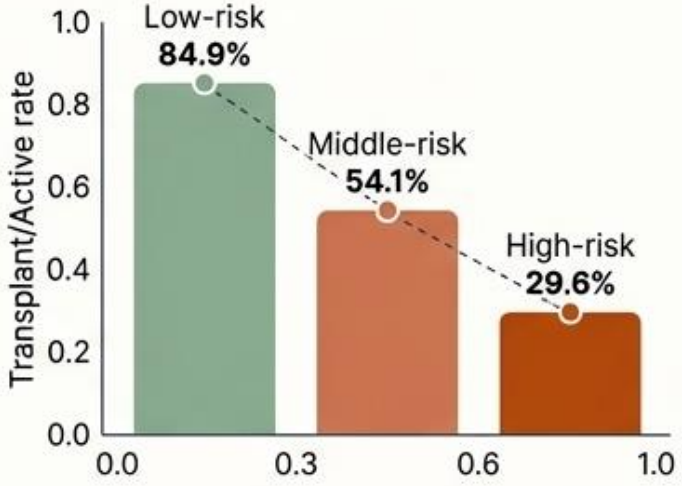
Evaluation Stage



Machine learning model predicting risk of no listing in 12 months

Model: Random Forest
Predictive Power: AUROC 0.71
Function: Predicts successful waitlisting within 12 months.

Waitlist Stage



Machine learning model predicting risk of permanent removal

Model: Random Forest
Predictive Power: AUROC 0.76
Function: Predicts dropout or permanent removal.

How Drivers of Dropout Evolve Across the Pipeline

Social isolation stops patients at the door; severe clinical burden and structural neighborhood barriers stop them on the waitlist.

	Referral Stage	Evaluation Stage	Waitlist Stage
Demographic	**High impact:** African American race, single status	**Pronounced:** African American & Hispanic	**Pronounced:** Hispanic ethnicity
Socioeconomic	**High impact:** Unemployment, lower education	**Growing impact:** Lower income, aging	**Severe impact:** High Area Deprivation Index (ADI), severe digital exclusion
Clinical	Low impact	**Emerging impact:** Hypertension, diabetes	**Dominant impact:** Severe comorbidities (Diabetes up to 95%)

Disproportionate Impact on Underserved Communities

Generic transplant education is failing these populations. Interventions must be culturally, linguistically, and socioeconomically tailored.

African American Candidates

Higher prevalence of obesity.

Lower rates of private insurance (32% vs 44%).

Less likely to have an intended living donor (17% vs 32%).

Hispanic Candidates & Socioeconomic Drivers

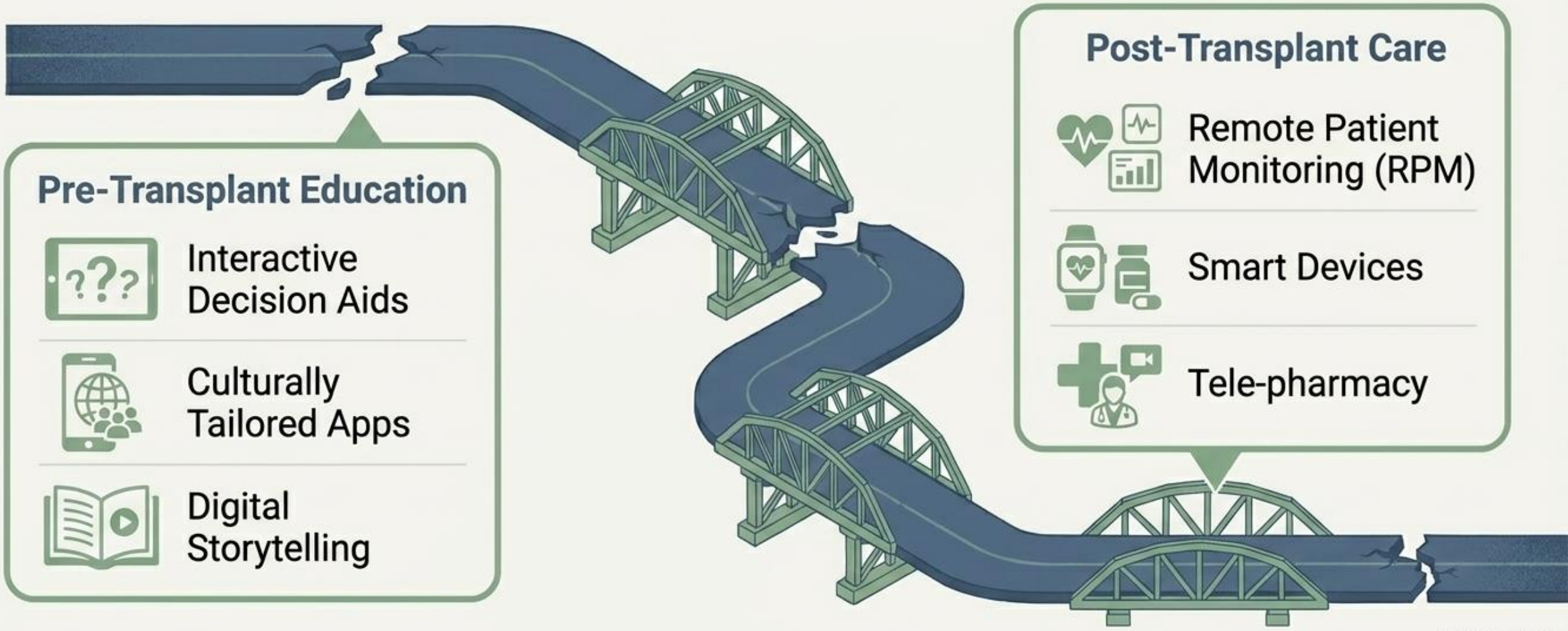
Highest risk representation at evaluation and waitlisting stages.

Higher Area Deprivation Index (ADI).

Digital exclusion heavily skews toward minority patients.

Deploying Digital Solutions for a Fragmented Journey

The Goal: Empower patient self-management, overcome barriers, and maintain long-term graft survival for the highest-risk cohorts.



Pre-Transplant Education

- Interactive Decision Aids
- Culturally Tailored Apps
- Digital Storytelling

Post-Transplant Care

- Remote Patient Monitoring (RPM)
- Smart Devices
- Tele-pharmacy

Culturally and Socioeconomically Tailored Education Platforms

Explore Transplant at Home (ETH)

- **Approach:** Tailored animated videos and modules delivered directly to the home.
- **Result:** Increased knowledge and active pursuit of transplant for disadvantaged and low-income patients.

Infórmate & NM HKTP

- **Approach:** Bilingual, culturally targeted living donor website integrating immigrant issues and cultural myths.
- **Result:** Contributed to a 91% growth in Hispanic waitlisting additions.

iChoose Kidney & My Transplant Coach

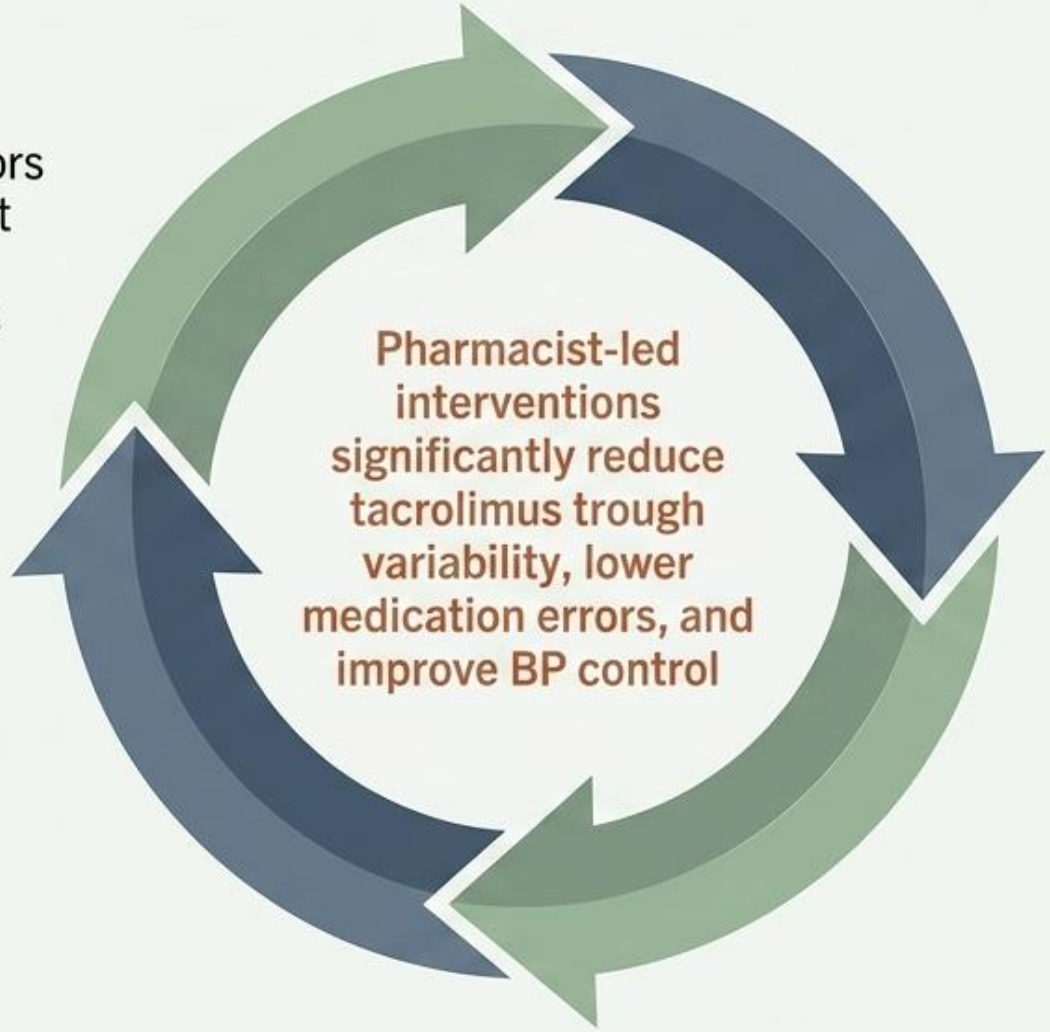
- **Approach:** Mobile risk-adjusted survival estimates based on personal health profiles.
- **Result:** 52% improvement in transplant knowledge across all racial and ethnic groups.

Continuous Care to Sustain the Graft via Remote Monitoring

Challenge: Up to 1/3 of adult recipients suffer from immunosuppressive therapy nonadherence.

Step 1:
Patient self-monitors at home with smart pillboxes and Bluetooth BP cuffs

Step 2:
Data uploads to secure cloud in real-time



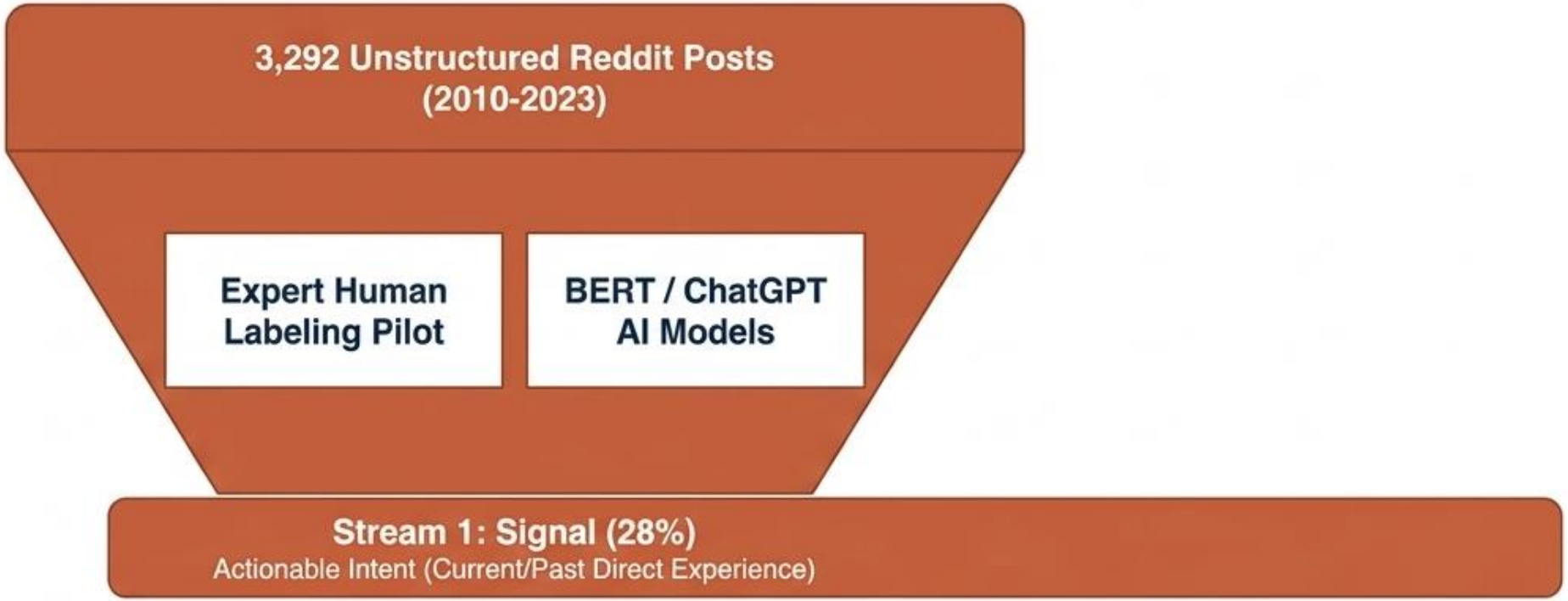
Step 3:
Pharmacist or Provider reviews adherence data

Step 4:
Care alert triggers targeted support and tele-visits

The Synthesis: The Human Technology Co-Care Model

Technology handles data and baseline education, freeing clinicians to provide personalized, empathetic care to high-risk patients.

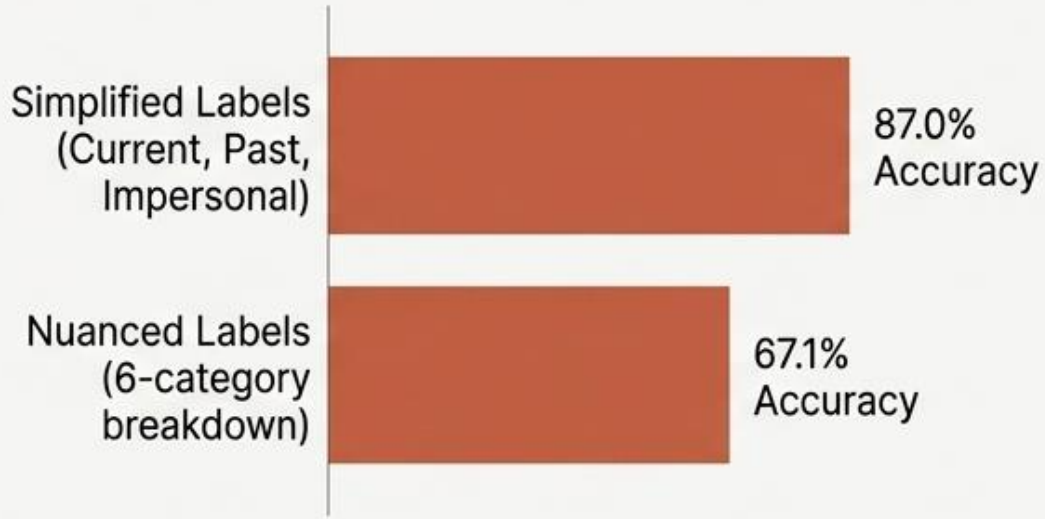
The NLP Digital Sieve



Type of Post	Simplified Type	Number (%)	Example Post
Current Direct – Personally involved with LKD at present	Current	363 (11.0%)	A friend of mine is in need of a kidney. My first instinct is to offer one of mine. I have Googled and read LOTS of info. What would you do? Have you donated a kidney? What am I missing?
Current Indirect – Secondhand experience with LKD at present	Current	177 (5.4%)	I need help finding a kidney for my dad.
Past Direct – Personally involved with LKD in the past	Past	164 (5.0%)	Eight years ago today, I donated a kidney to a friend. Ask me anything.
Past Indirect – Secondhand experience with LKD in the past	Past	58 (1.8%)	[Here's a] picture of my dad and the woman who donated a kidney to save his life.
General Commentary/Hypothetical	Impersonal	159 (4.8%)	If you donate a kidney, then later your only one starts to fail, would you be put on a higher priority?
News/Noise	Impersonal	2371 (72.0%)	Story: A man donated his kidney to his wife of 51 years after finding out he's her perfect

Model Performance: Complexity vs. Accuracy

Label Complexity (BERT Model)



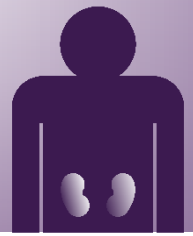
Insight: Precision drops significantly as human intent categories become highly nuanced.

Architecture Showdown

	Simplified Labels	Nuanced Labels
BERT Model	87.0%	67.1%
ChatGPT	69.0%	45.3%

Insight: Specialized NLP architectures (BERT) currently outperform generalized generative models (ChatGPT) for strict intent classification.

Key Take-home Messages



- Artificial Intelligence has already developed and highly relevant applications in every aspect of kidney care
- Our patients and colleagues (allied health/other specialists) are using AI tools – and we should also responsibly use them
- A clinical orientation to a problem followed by a solution (AI/non-AI) is our preferred approach
- Tools available today can augment care
- Tools available today are not autonomous

CKD, chronic kidney disease; eGFR, estimated glomerular filtration rate; ACR, albumin-to-creatinine ratio; CV, cardiovascular

The Path Forward: The Human-in-the-Loop Mandate

Assist, Do Not Substitute: Algorithms are tools for narrowly defined tasks. They cannot replace the holistic, nuanced judgment of a clinician.

The Workflow Imperative: The success of AI depends entirely on seamless integration into the point-of-care workflow, not just predictive accuracy.

The Ultimate Goal: Leverage AI not just for technological novelty, but to advance innovation in high-burden disease areas for the continuous benefit of the patient.

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