POPULATION HEALTH MANAGEMENT
Volume 00, Number 00, 2021

DOI: 10.1089/pop.2021.0112

Redesigning Kidney Disease Care to Improve Value Delivery

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Abstract

This article describes the articulation, development, and deployment of a machine learning (ML) model-driven value solution for chronic kidney disease (CKD) in a health system. The ML model activated an electronic medical record (EMR) trigger that alerted CKD patients to seek primary care. Simultaneously, primary care physicians (PCPs) received an alert that a CKD patient needed an appointment. Using structured checklists, PCPs addressed and controlled comorbid conditions, reconciled drug dosing and choice to CKD stage, and ordered prespecified laboratory and imaging tests pertinent to CKD. After completion of checklist prescribed tasks, PCPs referred patients to nephrology. CKD patients had multiple comorbidities and ML recognition of CKD provided a facile insight into comorbid burden. Operational results of this program have exceeded expectations and the program is being expanded to the entire health system. This paradigm of ML-driven, checklist-enabled care can be used agnostic of EMR platform to deliver value in CKD through structured engagement of complexity in health systems.

Keywords: kidney, primary care, nephrology, machine learning, quality improvement

Introduction

Defects in care of patients with chronic kidney disease (CKD) and end-stage renal disease (ESRD) are highly prevalent, pervasive, and profoundly impact health care costs.[1–3] Defects in value have been defined as any barrier, error, or lapse in care that could result in a suboptimal outcome.[4] Financial incentives for patients with CKD prioritize pay for late-stage CKD and ESRD medical care, specifically in hemodialysis centers, rather than improving preventive care and slowing the progression of renal disease.[3] This neglect of upstream care of CKD that precedes ESRD is a foundational defect in care delivery that uncovers an opportunity to control comorbidity in primary care settings, optimize recognition of CKD, refer to nephrologists, reduce expensive acute care utilization, and optimize use of value-enhancing care such as home dialysis and transplantation.[5,6] This article describes a pilot project to develop and deploy a system of care for patients with CKD within a health system. Specifically, this article describes how informatics was used to identify patients with CKD at risk for high costs, connect such people to primary care and standardize their primary care and referral to nephrology, and from nephrology to transplant.

Background

In the United States, CKD affects 1 in 3 adults with diabetes (DM) and 1 in 5 adults with hypertension (HTN), affecting more than 10% of the population overall.[1] ESRD, a condition that will progress to death absent dialysis or transplantation, canonically follows CKD by many months to years. This prosodic progression from CKD to ESRD has been the focus of research and therapeutics in the field. In fact, most guidelines for CKD care focus on stalling progression of CKD, but most patients with CKD present with abrupt incident ESRD in acute care settings requiring urgent dialysis. Unfortunately, most of these patients usually have missed many opportunities to diagnose disease and delay disease progression, have multiple complications, and often start dialysis with a central venous catheter, a major risk factor for mortality.[1,3]

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Most patients with renal disease go years before they are diagnosed with CKD and have multiple associated comorbid conditions including many complications associated with DM, HTN, obesity, atherosclerosis, and heart failure (CHF).[7] Most patients with CKD receive medical care for multiple conditions from many providers without clinical recognition of CKD and the majority die before reaching ESRD.[7] Notably, 70% of the longitudinal total cost of care for CKD patients resides in missed opportunities to manage comorbid conditions.[1,7] Although 2 therapies for ESRD, namely home dialysis and transplantation, significantly improve value for patients with CKD, these therapies are used infrequently. This scenario is a direct consequence of perverse financial incentives in a fee-for-service reimbursement paradigm in the United States that under-incentivizes upstream care while over-incentivizing the use of in-center hemodialysis.[1,3] In-center hemodialysis is expensive, robs patients of an opportunity to earn a living wage, and drives up utilization costs.[1,3,8,9]

The authors have previously applied a framework to understand the impact and drivers of defects in their health system. Defects can be defined as ''anything clinically, operationally, or experientially that a provider would not want to happen, including in diagnosing, initiating treatment, adjusting treatment, nurturing therapeutic alliances at the individual provider and system level, and avoiding preventable service utilization.''[4] The authors' experience suggested solutions that allowed implementation of several tactical changes within their health system's accountable care organization (ACO) and employee health plan to drive value.[4] Using this framework, the authors first looked specifically for defects in CKD care that had clear, actionable solutions that could be implemented immediately. Second, simple checklists were designed and deployed that would promote facile implementation of best practices by default. Third, the checklists were pilot tested in a primary care provider (PCP) practice with the ultimate goal of developing a scalable model.

The goal of this paper is to describe: (1) an approach to uncovering defects in value in the care of CKD; (2) an analytic model to identify CKD patients at risk for high utilization; (3) a person-centered care process to manage patients with CKD; and (4) a pilot test of an intervention to partner nephrologists with PCPs to implement a CKD defects in value checklist. The first section describes the classification of defects in CKD care. The second section describes how an analytic operating system with visualization layer (ie, dashboard interface) was built to track, monitor, and act on these defects. With a focus on value, allowed medical spend in the authors' ACO was examined as a way to address patients with highest need that would be amenable to intervention. The third section describes a pilot in which insights from the data were used and an intervention was co-created with PCPs to eliminate defects and optimize care for patients with CKD.

Methods

Clinical setting

The inquiry and intervention were conducted in the University Hospitals (UH) ACO that serves the Greater Cleveland area and Northeast Ohio. UH is a super-regional health system that cares for more than 1.2 million patients – 580,000 of whom are in the UH ACO – annually through an integrated network of 10 acute care hospitals, more than 50 health centers and outpatient facilities, and 200 physician offices in 16 counties in Northeastern Ohio. Nearly two thirds of all UH patients rely on Medicare or Medicaid to pay for their care. This includes 146,000 Medicaid managed care patients, 320,000 commercially insured patients, 58,000 Medicare Advantage patients, and 59,000 Medicare Shared Savings Program patients. ACO patients were included in this study if they were ages 18 years or older, and had sufficient data to calculate 2019 total allowed medical spend.

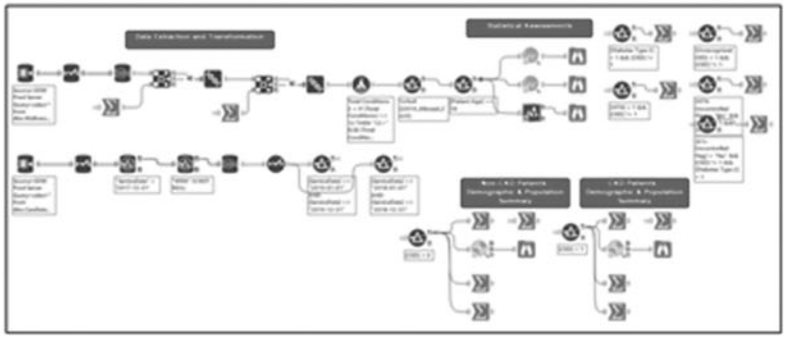
Data structure and machine learning model

The Enterprise Data Warehouse (EDW) was used to develop an operational construct for CKD by building a supervised machine learning algorithm with Alteryx Designer (Alteryx, Inc., Irvine, CA) and integrating the algorithm into the Power BI Reporting system to classify patients with known and unknown CKD and ESRD (Figure 1). A combination of laboratory values was used that yielded estimated glomerular filtration rates (eGFRs), clusters of comorbidity using International Classification of Diseases, Tenth Revision (ICD-10) codes, scheduling data, and Current Procedural Terminology (CPT) codes drawing on the work of Navaneethan et al.[10] Next examined was whether or not algorithmically defined CKD was accompanied by clinically recognized CKD as defined by both an eGFR value and ICD-10 code for CKD. Algorithmically, unrecognized CKD was defined as a patient with CKD identified from laboratory values without an ICD-10 for CKD. Data examined included: laboratory values, ICD-10 codes for comorbid conditions, and CPT and diagnosis-related group (DRG) codes to categorize both acute care and ambulatory utilization.[11,12] Further, completion of an annual wellness visit was used as a surrogate for the adequacy of preventive health care in the ambulatory setting.

The EDW centralizes the different clinical products belonging to Allscripts (Allscripts Healthcare, LLC, Chicago, IL) (ie, Touchworks, Sunrise) electronic medical record (EMR) system into one centralized 3-layer data lake. The clinical systems feeding data into the EDW also include the laboratory and pharmacy information systems, and scheduling and financial systems. In addition to the clinical and administrative data, data were incorporated from Ohio's Health Information Exchange, adjudicated claims, insurer member enrollment files, Ohio death records, and social determinants of health (mapped to ACO patients to facilitate population health management activities).

Key variables

Classification and cost of services in claims and EMR data. In the EMR and claims data, health care services were grouped by service date and classified as inpatient, emergency department (ED), or outpatient/ambulatory (OP). Out-of-network utilization was extracted from adjudicated claims data because UH's EMR can only collect data from in-network sources. Both in-network and out-of-network encounters were aggregated to calculate 90-day readmission rates. Wellness visits were defined based on CPT codes (G0438, G0402, G0439, 99385, 99386, 99387, 99391, 99392,



	CKD Patients	Non-CKD Patients
Patient Count	33,322	234,364
Average Age	76.4	55.0
Female	52.6%	58.1%
Avg. Chronic Conditions	10.8	3.6
Avg. Elixhauser Score	10.0	2.8
Avg. Charlson Score	5.4	1.3
Insurance		
Medicare	85.8%	35.0%
Medicare Adv.	2.6%	1.5%
Commercial	10.2%	62.6%
Medicaid	1.3%	0.8%
Pop Health Risk Level		
Highly Complex	73.8	12.9%
High Risk	22.3	27.8%
Rising Risk	3.6	27.9%
Low Risk	0.2	31.4%
BMI Category		
Obese	32.6%	31.1%
Overweight	23.8%	24.8%
Other	43.6%	44.1%
2019 Avg. Medical Spend	$ 24,011.98	$ 7,214.68
2019 Avg. Rx Spend	$ 6,799.21	$ 2,261.87

553,547 patients enrolled in population health management at University Hospitals.

267,686 patients have a full year of 2019 allowed medical spend data.

CKD patients **3x** more medical and pharmacy spend per year.

CKD Patients with 1+ Additional Chronic Conditions

Total Conditions	Patient Count	12mo Avg. Spend
2	372	$ 3,277.00
3	842	$ 4,025.41
4	1,328	$ 5,913.60
5	1,676	$ 6,103.06
6	2,108	$ 8,600.71
7	2,323	$ 10,721.21
8	2,450	$ 13,054.09
9	2,660	$ 15,588.90
10	2,566	$ 18,726.73
11	2,575	$ 21,518.65
12+	14,354	$ 38,820.51

Non-CKD Patients with 2+ Chronic Conditions

Total Conditions	Patient Count	12mo Avg. Spend
2	36,000	$ 3,744.45
3	29,376	$ 4,902.22
4	23,202	$ 6,804.63
5	17,693	$ 8,563.52
6	13,752	$ 10,855.92
7	10,536	$ 12,433.82
8	8,097	$ 15,512.83
9	6,107	$ 17,908.28
10	4,692	$ 19,192.12
11	3,488	$ 23,474.12
12+	7,875	$ 31,296.36

FIG. 1. Machine learning model for identifying patients with CKD. Data model on the left showing data sources and informatic build. Tables depict comorbid burden by presence or absence of CKD and by CKD stage as well as annual spend based on claims data. Avg, average; BMI, body mass index; CKD, chronic kidney disease; Rx, prescription.

99393, 99394, 99395, 99396, 99397, 99381, 99382, 99383, 99384, 99461). Allowed medical spend or the maximum reimbursement the member's health policy allows for a specific service was derived from adjudicated claims for 2019 services. The cost applied to hospital OP and ED visits included both hospital and physician services. Cost per visit was applied to each office, home health, or laboratory visit. OP dialysis services in patients without evidence of kidney transplant were excluded from ESRD costs because of significant underrepresentation in the source data, which do not include data from freestanding outpatient units.

Other study variables. Age, sex, race, and insurance program information were sourced from EMR data and verified for accuracy with payor enrollment files. A total of 50 comorbidities, defined by ICD-10 codes, were aggregated to produce an average chronic condition score. Key disease cohorts of comparison include patients with CKD, DM, HTN, CHF, stroke, and pulmonary disease. Certification of diagnosis had to occur in 2019, 2018, or 2017 to be included.

Mapping system defects, goals, and solutions

To identify and resolve defects in the care system, a team of subject matter experts was brought together, including PCPs, nephrologists, the population health team, care navigators, data scientists, and clinical pharmacists. In addition to classifying defects by subject matter experts, input from the data science team on costs attributable to these defects were incorporated where feasible. Defects and opportunities for intervention were classified under the following categories: (1) maintaining wellness in health, (2) getting well by managing disease or recovering from illness episode, and (3) sustaining recovery after acute decompensation (see Supplemental Data, available with the article online).

Next, the team was engaged in a solution-building exercise that yielded a mapping of defects in care to actionable clinical workflows. The team constructed a driver diagram to help visualize and converge on a deployable solution[9] (see Supplemental Data). The stated outcome goal in this diagram was to reduce the cost of care for patients with CKD and ESRD by 30% through decreased utilization of unplanned acute care. The key change component categories were: systems to recognize CKD, wellness and preventive care workflows, primary care workflows to refer and hand off patients, care navigation, inpatient disease-specific workflows, genetics and pharmacogenetics, dialysis access and education, and transplant referral.

The expert team then detailed these workflows for primary care and nephrology specialty practices (see Supplemental Data). For example, primary care workflows should incorporate systems to assess ageing-related eGFR changes versus true kidney disease, complete wellness services, manage CKD comorbidities, assess and manage psychosocial needs, and refer to specialists by protocol. Nephrology workflows should include disease-specific management and diagnostic testing, patient engagement with CKD education and goals of therapy, medical and social work preparedness for dialysis and/or transplant, and co-management protocols with the PCP.

These team-based system mapping exercises culminated in designing a pragmatic framework to guide patient-centered care. This framework (Figure 2) comprises 4 key processes: (1) identify patients at risk through informatics-based case-finding algorithms; (2) trigger EMR-based alerts to notify patients and providers to take action; (3) act to optimize team-based patient care in primary care and nephrology; and (4) learn continuously to improve data and clinical processes.

The CKD Checklist in Primary Care was developed as a quick-reference tool to implement the expert team's primary care recommendations into practice (Figure 3). The 1-page checklist structured goals of care for patients with CKD, including wellness care, managing comorbidities such as DM and HTN; assessments including frailty, cognition, and social support needs; and goals of care including advanced directives. A list of diagnostic testing is specified when the PCP is preparing a patient for nephrologist referral.

This framework and checklist were pilot tested in a site in the UH system with a co-located primary care practice, nephrologist, laboratory, radiology, pharmacy, and also a nearby aligned dialysis facility. A nephrologist was co-located at this practice location with a view to allowing unlimited access to consultation to the primary care teams. Proximity of a dialysis facility would allow facile referral for CKD education as well as ESRD modality planning. In this design the patient would have had age- and gender-appropriate health screenings completed in such a way that would make transplant evaluation and listing possible in an expedited time frame. This team approach relieved the PCP of the full burden of care. As examples, patient navigators facilitated interactions to promote patient and physician engagement. Pharmacists supported medication reviews and adjustments for eGFR. This design allowed patients and their families to access resources in a time-efficient manner that minimized lost time away from life and work. In sum, a patient-centered convergence of resources was designed that would optimize for the desired outcome of comorbidity management and planning for transitions of care related to advanced CKD in the ambulatory setting.

Results

The UH ACO population in this study included 267,829 adult patients in total, with a CKD cohort of 33,365 (Table 1). Age and racial characteristics are shown in Table 1. Average number of chronic conditions was higher in the CKD cohort compared with the overall sample; rates of each of the studied comorbid conditions were higher in the CKD cohort, including 97% with HTN and 86% with pulmonary disease. Ninety-day readmission rates and inpatient length of stay were higher in the CKD cohort as well.

Health care utilization and spend by CKD characteristic are described in Tables 2 and 3. Average number per patient of inpatient visits, 30-day readmissions, and ED visits all increased with CKD stage of disease (Table 2). Costs per patient were more than twice as high for patients with CKD ($24,011) than for patients with DM or HTN but without CKD (Table 3). Unrecognized CKD was noted in 9158 patients with average annual spend of $8199. Total medical spend for all CKD patients in the sample was more than $800 million.

Patients with CKD who had completed a wellness visit averaged $18,902 in annual medical spend vs. $25,457 among those who had not completed a wellness visit in the

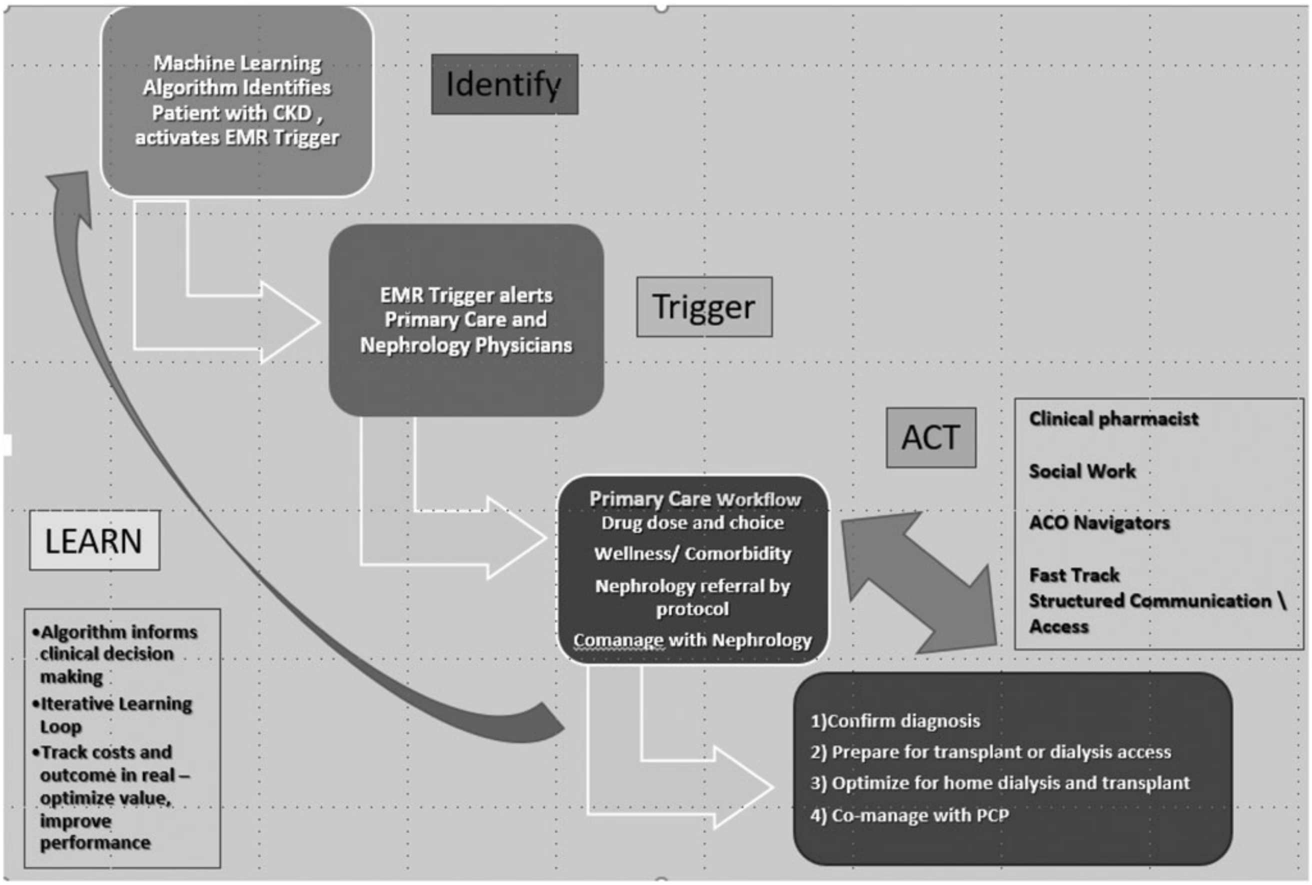


FIG. 2. Framework for improving CKD early identification and care. ACO, accountable care organization; CKD, chronic kidney disease; EMR, electronic medical record; PCP, primary care provider.

same year (data not shown). Among non-CKD patients, wellness visit completion was associated with an annual spend of $5583 vs. $8382 among those without wellness visit completion.

Pilot test results for the CKD checklist intervention were based on patients seen in a nephrology clinic after a referral from the pilot primary care site. Nineteen patients were included during the first 3 months despite a near complete lockdown on face-to-face visits during the pandemic (see Supplemental Data). Fifteen of the patients seen were between Stages 2 and 3b CKD. Fifteen patients had HTN, and 6 had DM. Actions taken in their care included medication adjustment for 5 patients and continued CKD monitoring for 13 patients. There also were 5 preemptive transplant referrals and 3 nonurgent dialysis starts in this time period from the pilot practice site.

Discussion

This study used a novel informatics-driven approach to identify and make visible defects in care for patients with CKD and to begin to eliminate those defects. Specifically, first, the data system was leveraged to obtain a data understanding of a disease state, CKD. The premise was that biochemically classified CKD is a lead measure that better triggers clinically relevant intervention and timely access to care than administrative data. Administrative data such as ICD-10 codes, DRGs, and claims data, which reflect products of clinical care that has already been delivered, are necessarily lag markers of CKD. Thus, the expert team combined traditional administrative data along with measures of eGFR to arrive at a CKD classifier with a view to maximize the chance of recognizing and managing patients with comorbidity. This approach differs from generation of lists of patients using claims data, diagnostic codes, or procedure codes as these measures are subject to the time constants of the revenue cycle. Using a biochemical anchor to the CKD classifier would allow better alignment of case finding with the time constants of care delivery. As the initial design of the model was iterated, the expert team came to understand that using traditional operator-intensive methods of generating patient lists using traditional statistical programming and analyses would not work given time constraints of clinical relevance and the diversity of data sources. The team also came to realize very quickly that the human resources could be used much more efficiently in directly enabling care delivery rather than serving rote reporting tasks that were largely irrelevant clinically.

Further, the health system had several clinical pathways in deployment. However, adherence to these was more in the breach than in compliance given the absence of an automated case-finding approach that triggered appropriate clinical actions. The health system also was not burdened by legacy reporting systems prior to the build of the data model

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Chronic Kidney Disease (CKD) in Primary Care

Checklist for managing patients diagnosed with CKD. See Up To Date® for detailed guidelines.

☐ Differentiate Between Aging and True Disease

- eGFR averages 100 ml/min at age 40 and declines by 7 ml/min per decade on average; also varies by race and gender (see table below)

☐ Complete a Wellness Assessment

- USPTSF age and gender appropriate screenings
- Vaccinations(1,2,3):Influenza; Hepatitis B; Pneumococcal PCV13 or PPSV23
- Smoking cessation

☐ Manage Comorbidity

- Hypertension (goal <130/80; refer to Hypertension CPG)
- Diabetes Mellitus (goal HgbA1C <7% ; recommend SGLT2i and/or LA GLP1-RA) (4)
- Lipids (goal LDL<100; refer to Cholesterol Management CPG)
- Anemia (Hgb <13 male, <12 female)
- Avoid or eliminate nephrotoxic drugs (i.e., NSAIDs, radiographic contrast, aminoglycoside, antibiotics, amphotericin B)
- Adjust drug choice and dose by eGFR
- Post-discharge medication reconciliation

Request Clinical Pharmacy assistance as needed

☐ Assess Frailty & Cognition

- Assess fall risk
- Use cognitive testing as per clinical situation (i.e. MoCA, Karnofsky; see Up To Date® for test calculator)

☐ Assess Social Support Needs

- Assess patient for social determinants of health (SDOH) needs and connect to social support resources.
- SDOH assessment: **food and housing security, transportation, financial resources, health literacy**
- Self-care capability, caregiver support
- Connectivity resources
  - Preferred communication channel; cell phone access (+data plan); able to receive messages, use telemedicine with camera

☐ Goals of Care

- Advanced Directives
- Shared Decision-Making regarding ESRD treatment choices should be made in co-management with Nephrology

☐ Referral to Nephrology

- See table below for indications for referral to Nephrology
- Initial referral should include results of ACR, eGFRs, and Ultrasound of kidneys
- If aged >50 years, add serum and urine protein electrophoresis

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Last updated: 10/13/2020

FIG. 3. CKD checklist in primary care. ACR, albumin-creatinine ratio; CKD, chronic kidney disease; CPG, clinical process guideline; eGFR, estimated glomerular filtration rate; ESRD, end-stage renal disease; LA GLP1-RA, long-acting glucagon-like peptide 1 receptor agonists; LDL, low-density lipoprotein; MoCA, Montreal Cognitive Assessment; NSAID, nonsteroidal anti-inflammatory drug; PCV13, 13-valent pneumococcal conjugate vaccine; PPSV23, 23-valent pneumococcal polysaccharide vaccine; SGLT2i, sodium/glucose cotransporter-2 inhibitors; USPSTF, US Preventive Services Task Force.

Table 1. Characteristics of the Study Population

	All patients	*CKD cohort*
Patient Count	267,829	33,365
Average Age	57.7	76.4
Gender		
Female	57.4%	52.6%
Male	42.6%	47.4%
Race		
White	80.4%	79.8%
Black	9.1%	13.1%
Other	10.5%	7.1%
2019 Readmission Rate, 90 Day	23.4%	32.3%
2019 Avg. Length of Stay per Admit	3.7	5.2
GFR Values - ACO 2019 Population		
Have GFR Value in Medical Record	63.3%	71.9%
No GFR Value in Medical Record	36.7%	28.1%
Avg. Chronic Conditions	4.5	10.8
% w/Diabetes	20.0%	49.3%
% w/Hypertension	44.5%	96.7%
% w/Heart Failure	12.5%	49.0%
% w/Stroke	14.1%	41.3%
% w/Pulmonary Disease	55.4%	85.9%

ACO, accountable care organization; Avg, average; CKD, chronic kidney disease; GFR, glomerular filtration rate.

and thus was well positioned for ab initio deployment of machine learning versus a more traditional approach of reporting whether or not care pathways were adhered to. As the approach was designed, the stakeholders strongly aligned around a collaborative care delivery structure moving forward rather than the stentorian pass-fail reporting of quality of the past.

Machine learning was used to make predictions around CKD as follows: identify patients within the system and classify them by comorbid burden and wellness completion. Data insights from machine learning were then used to trigger actions within the EMR (Figure 2).[13] Next, subject matter expert input was used in formulating clinical actions around the data insights with tactical, clinically deployable checklists and workflows. Preliminary observations show the promise of this approach while awaiting further evaluation of the efficacy of the intervention in driving outcomes. This is an area of active investigation as the initial success is iterated.

Notable findings that are likely generalizable to most health systems include:

Table 3. Health Care Spend by Patient Subgroups

	Patient count	*2019 Total medical spend*	*2019 Avg. medical spend*
CKD Patients	33,365	$ 800,127,188.73	$ 24,011.98
Unrecognized CKD	9158	$ 75,093,012.89	$ 8199.72
Diabetes w/o CKD	37,147	$ 430,591,480.72	$ 11,591.55
Hypertension w/o CKD	116,319	$ 1,171,385,932.25	$ 10,070.46

Avg, average; CKD, chronic kidney disease.

i) Leveraging knowledge that advancing CKD stages associates with comorbid clustering allows scripted person-centered care.

ii) Absence of wellness visits associates with increased medical spend across the board. Thus, wellness visits can be used as a point of value optimization.

iii) Structured attention to laboratory data, orders for imaging, and medication reconciliation can be used to optimize nephrology referral.

A recent publication from UCLA describes deployment of teams of subspecialists to deliver care for CKD patients with complex needs. However, this approach did not employ an automated detection and triggering method and also did not use standardized workflows or checklists.[6] Further, this approach somewhat disintermediates the PCP practice as the medical home of the patient, whereas in the approach described herein, the PCP practice remains the medical home of the patient.

The primary limitation of this work is the narrow time horizon of the inquiry and a limited scope of the first deployment. This approach is in the process of being generalized across the health system and a cluster randomized trial is being planned across the nephrology and primary care practices. Specifically, future lines of inquiry will focus on cardiorenal disease in Stage 4 and 5 CKD, linking the CKD data structure to the transplant data structure as well as the cost and billing structures. A further confounder of the ability to measure impact of the interventions on cost and acute care utilization was the disruption of access to care and steep increase in acute care utilization among CKD patients during the COVID-19 pandemic. The approach to solving for defects in care also is provider-centric and patients' perspectives on defects in care are being used during iterations.

Table 2. Health Care Utilization by Chronic Kidney Disease Stage

CKD stage	*Patient count*	*2019 avg. IP visits*	*2019 avg. 30 day readmits*	*2019 avg. ED visits*
CKD Stage 1 - Normal	234,364	0.08	0.01	0.36
CKD Stage 2 - Mild Loss	2776	0.40	0.05	1.05
CKD Stage 3a - Mild to Moderate	7065	0.39	0.05	1.09
CKD Stage 3b - Moderate to Severe	5106	0.46	0.05	1.20
CKD Stage 4 - Severe	2280	0.82	0.14	1.69
CKD Stage 5 - Kidney Failure	1244	1.12	0.22	2.18

Avg, average; CKD, chronic kidney disease; ED, emergency department; IP, inpatient.

Summarizing, at-risk patients with CKD were identified using the automated trigger. The algorithm identified patients with CKD stage 3 or above and sent an email to encourage patients to visit their PCPs. This email thus directly engaged patients. Simultaneously, a list of these patients was sent to their PCPs. A structured checklist for PCP management of patients was then used to help ensure that patients were receiving appropriate therapy for HTN and/or DM, that medication doses were based on eGFR, that comorbid conditions were addressed, that wellness measures were completed, and physiology (eg. blood pressure, blood glucose) was controlled. To increase referral to nephrology, the PCP visit was scripted to refer to nephrology and nephrology workup and documentation were standardized. This model also is envisaged to feed an iterative learning loop that would help improve performance in its future state (Figure 2). Results thus far within the system suggest that this model has worked in directing early-stage referrals of CKD cases from PCPs to nephrologists and that meaningful clinical actions such as medication dose and choice are being addressed as well as regimented monitoring of CKD. Based on this initial success, leadership of the primary care program has requested that this program be disseminated system-wide.

A path forward

This journey uncovered several avenues for value delivery in health systems based on optimizing care for patients with CKD using informatics as an accelerator of change. The first and foremost is to avoid the parochial trap that the medical care of the CKD patient revolves around kidney care. Rather, an opportunity was seen for a more secular approach:

i) Identifying CKD uncovers complexity and populations likely to incur higher medical spend. Wellness visits could provide an opportunity to ''make CKD visible'' in primary care settings through triggers based on the algorithm that was used to identify patients with CKD.

ii) Primary care workflows could be tailored to include optimization of wellness among CKD patients while retaining their place as the medical home for these patients through standardized workflows and simple checklists.

iii) Designing formal hardwired linkages within health systems between primary care practices and nephrology to optimize referral of CKD patients to nephrology and structured channels of communication.

iv) This first phase of deployment will then be followed by a drive toward zero defects in the care of the CKD patient.

Conclusion

The authors see this approach to machine learning-driven CKD care as a way to solve for value delivery in health care by using machine learning around CKD as a facile way to trawl for complexity in the population. CKD also uncovered defects in value. These defects in value are most often a consequence of the way the care system is organized, or fails to be organized, and are largely invisible to clinicians, whose focus is – unfortunately for the most part – transactional and reactive rather than relational and proactive. This approach would identify patients with CKD and comorbid clustering using a deterministic algorithm that would then be used to initiate an EMR-based trigger that would initiate actions in the primary care and nephrology setting either sequentially or simultaneously. These clinical actions are scripted to solve for ideal care delivery in the majority of clinical settings using clinically relevant, tactically facile checklists. Standardized care across the ambulatory continuum would then accrue savings by reducing expensive unplanned acute care utilization. Such a care delivery paradigm can be built with prescribed iterative learning that would sustain gains over time.

Authors' Contributions

Drs. Srinivas, Coran, Thatcher, Patton, Palakodeti, Zeiger, Sarabu, Pronovost: Conception, data acquisition, analysis, interpretation, drafting, revision, final approval, accountable for content. Dr. Dunn: Conception, analysis, interpretation, drafting, final approval, accountable for content. Ms. Dobbs: Conception, data acquisition, interpretation, drafting, final approval, accountable for content. Ms. Reese: Conception, data interpretation, drafting, final approval, accountable for content. Dr. Runnels: Conception, data acquisition, interpretation, drafting, revision, final approval, accountable for content. Drs. Srinivas, Palakodeti, Runnels, and Pronovost, and Ms. Reese: Obtained funding.

Author Disclosure Statement

The authors declare that there are no conflicts of interest.

Funding Information

This study was funded internally by the University Hospitals Accountable Care Organization.

Supplementary Material

Supplementary Data

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