

Enhancing Clinical Outcomes in Diabetic Kidney Disease (DKD) through Risk Prediction and Case Management in Patients with Diabetes

Mao Cheng-Hsien* ^{1, 2}, Chen Po-Wei¹, Chuang Ke-Yung¹, Hsieh Yu-Ling³, Hsiao Shu-Tai¹, Chou Pesus⁴
1Taipei Medical University Hospital, 2Institute of Health and Welfare Policy, National Yang Ming Chiao Tung University, 3 Far Eastern Memorial Hospital, 4Community Medicine Research Center & Institute of Public Health, National Yang MingChiao Tung University, Taipei, Taiwan

Mao Cheng-Hsien
CEO, Department of Healthcare Quality,
Taipei Medical University Hospital
EMAIL : cheng.h.mao@gmail.com



INTRODUCTION

The incidence and prevalence of end-stage renal disease (ESRD) in Taiwan have persistently ranked among the world's highest for over a decade, with Diabetic Kidney Disease (DKD) being the primary cause. DKD presents a critical microvascular complication of diabetes. Our goal is to efficiently monitor DKD progression by integrating an information alert system and implementing targeted interventions. Additionally, we leverage machine learning to develop a predictive model for DKD onset within three years of a Type 2 Diabetes Mellitus (T2DM) diagnosis, aiming to proactively mitigate future comorbidities.

METHOD

This retrospective cohort study conducted in Taiwan, we aimed to develop risk prediction models for T2DM outpatients at Taipei Medical University Hospital between January 1, 2018, and June 30, 2023. Inclusion criteria required no evidence of DKD at baseline, defined as urinary albumin/creatinine ratio (UACR) > 30 mg/g, or eGFR < 60 mL/min/1.73m², with a 3-year follow-up. Exclusions were applied to those aged < 18, with acute infections, malignancies, or pregnancy. **We** employed 54 potential variables extracted from Electronic Medical Records (EMR) for predictive modeling, utilizing five machine learning algorithms: eXtreme Gradient Boosting(XGBoost) , Support Vector Machine(SVM), Random Forest(RF),Logistic Regression(LR), Decision Tree. Model performance was assessed using the Area Under the Curve (AUC). Patient data underwent 5-fold cross-validation, with partitioned into training (80%) and testing (20%) sets.

Our approach presents a management and multifactorial intervention strategy for DKD progression based on guidelines from the American Diabetes Association (ADA) and Kidney Disease Improving Global Outcomes (KDIGO). Screening for DKD (UACR and eGFR) is recommended at the initial diabetes diagnosis and annually thereafter. Our care framework includes three categories: (1)continuous tracking, (2)receive treatment, and (3)refer to nephrology treatment. **Finally**, we implemented an alert system integration across COPE and the case management system. Specific multifactorial interventions were tailored based on progression types and DKD risk prediction level (no, low, intermediate, and high). Subsequently, the medical team tailored screening, diagnosis, lifestyle therapies, treatment goals, pharmacologic management and intervention programs according to patient needs.

RESULTS

In our analysis, a total of 18,816 patients were included, with a median age of 57.9 years (IQR, 49–65 years), and 11,609 (61.7%) were male. At the 3-year follow-up, patients were categorized based on the presence (n = 2,958, 15.3%) or absence (n = 15,858, 84.7%) of DKD. The incidence of at least one macrovascular or microvascular complication (hypertension, cardiovascular disease, diabetic retinopathy, diabetic peripheral neuropathy) was 54.2%.

The XGBoost model demonstrated the highest AUC (0.823, 95% CI 0.761–0.887). The SHAP plot based on XGBoost revealed that T2DM patients with high homocysteine (Hcy), poor glycemic control, low serum albumin (ALB), low estimated glomerular filtration rate (eGFR), high BMI, a history of chronic heart failure, and smoking had an increased risk of developing DKD over the next 3 years.

From August 1, 2023, to January 31, 2024, the information system enabled automated prediction functions for 12,732 T2DM outpatients. Notably, when the predicted category was intermediate or high, the system issued warnings 1,298 times (10.2%). Impressively, the medical team responded with execution actions to these alerts 846 times (65.2%).

Furthermore, the execution rate of laboratory tests increased compared to the previous year (1) eGFR: 6.8% (2) UACR: 14.2% (3)HbA1c: 4.3% , particularly in moderate or severe risk groups, the completion rate of these three tests exceeded 95%.

CONCLUSIONS

Our study provides empirical evidence and management strategies for patients with T2DM. The alerts system proves particularly advantageous for physicians and patients who adhere to recommended follow-up, emphasizing kidney health, function, and blood glucose control. The implementation of early warning systems for DKD holds significant clinical value. The XGBoost model with potential to support population management strategies by prediction 3-year DKD risk in individuals recently diagnosed T2DM. For those displaying susceptible factors for incident DKD, early and optimal interventions by care providers play a crucial role in delaying the progression of DKD and potentially reducing the incidence of cardiovascular events and premature mortality.

Table1:Evaluation of the performance of five machine learning algorithms

Models	AUC	Accuracy	Sensitivity	Specificity
XGBoost	0.823	0.816	0.834	0.829
SVM	0.801	0.800	0.801	0.791
RF	0.792	0.784	0.781	0.768
LR	0.808	0.792	0.810	0.808
DT	0.804	0.807	0.808	0.814

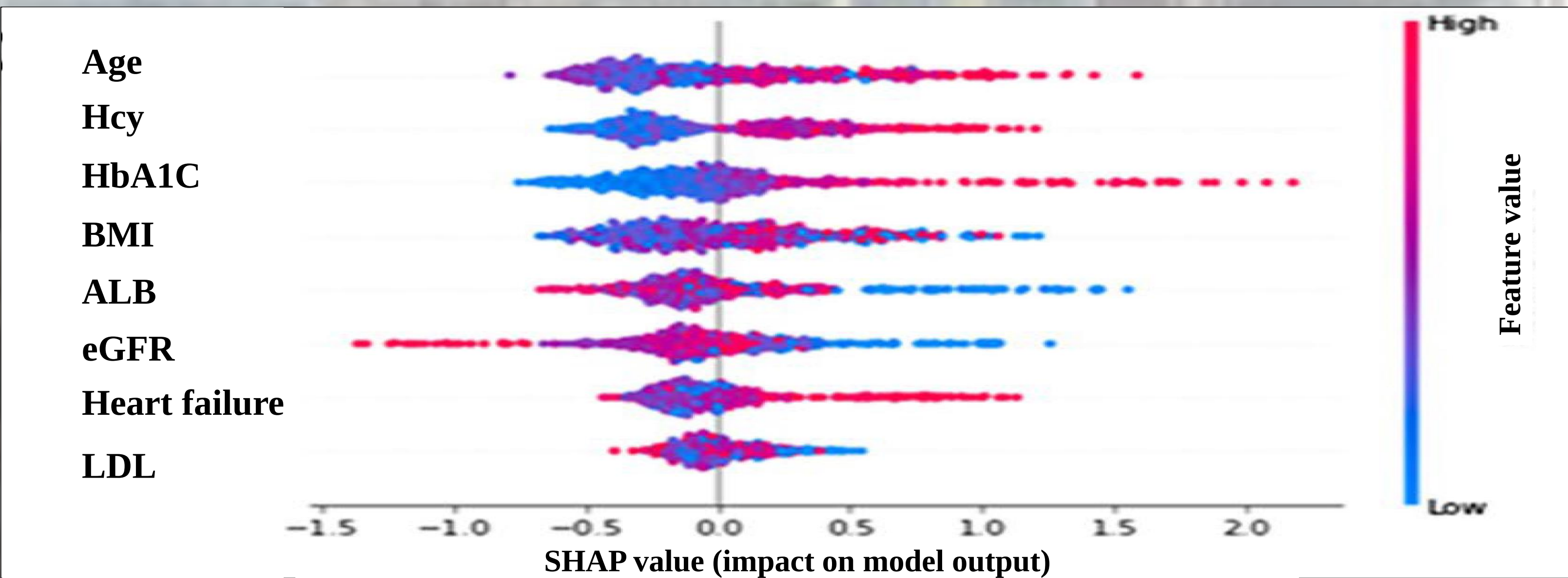


Figure 1: Importance matrix plot of the XGBoost model, depicting the importance of each variable for predicting 3-year DKD risk

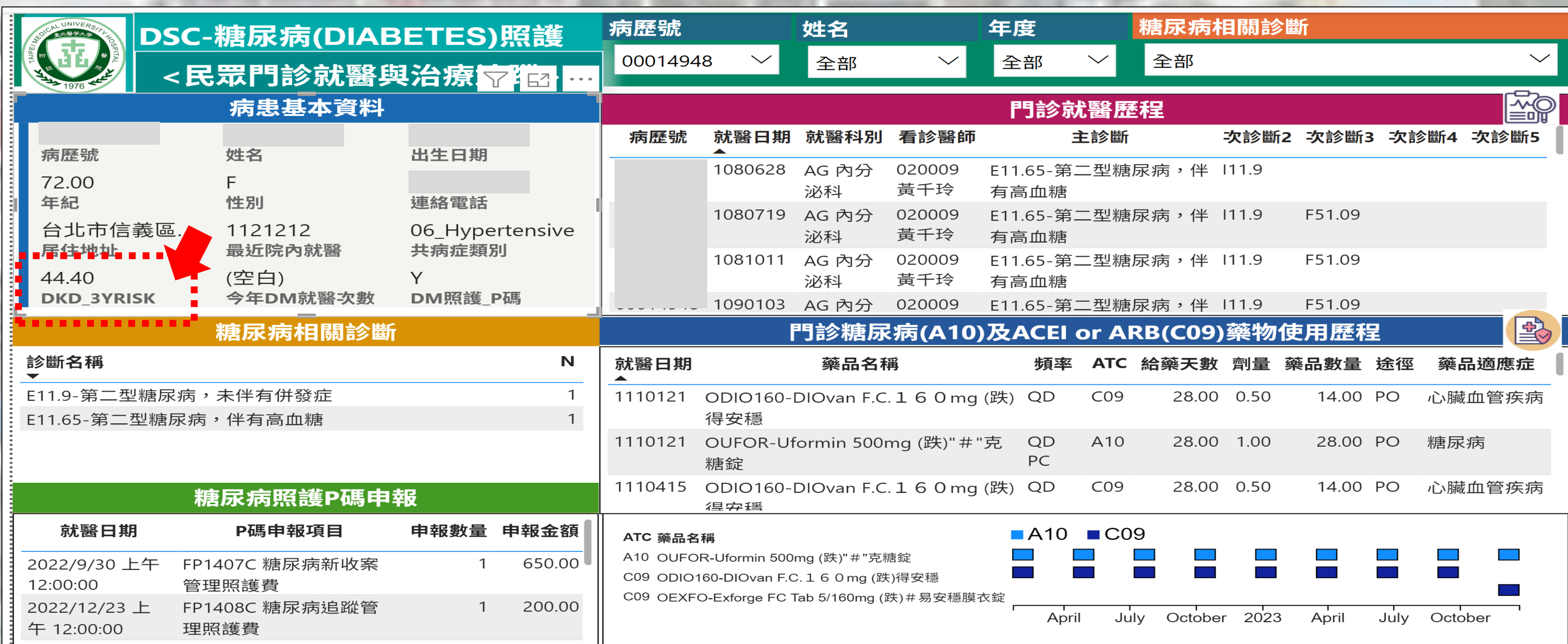


Figure2: DM case management platform and early warning system for DKD

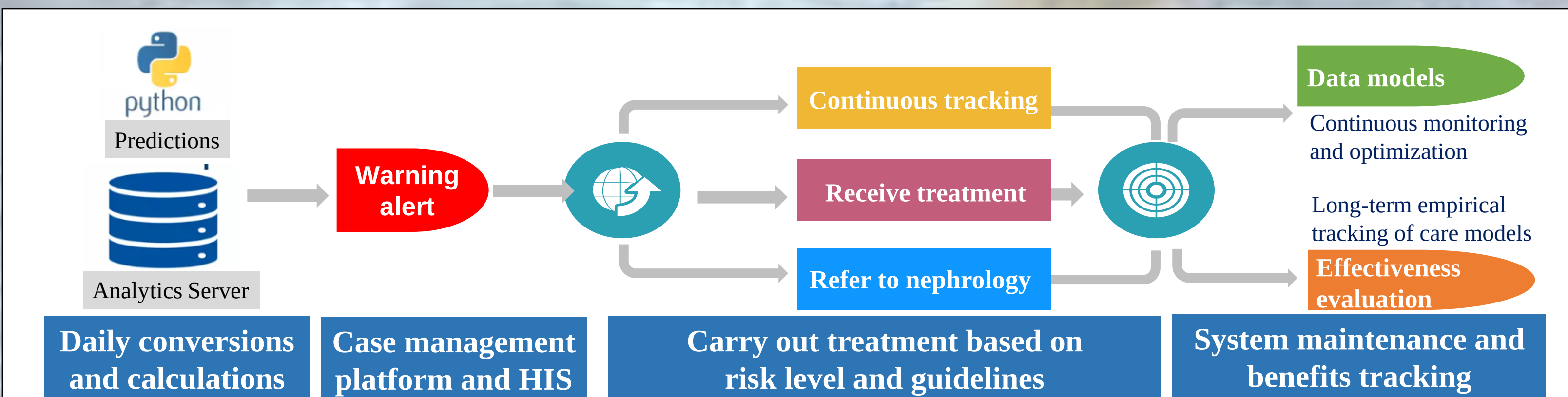


Figure3: DM case management framework for early warning, referral, treatment, and tracking processes