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A Dynamic Predictive Model for the Progression of Chronic Kidney Disease to Kidney Failure

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BACKGROUND: Predicting the progression of CKD is important for treatment decisions and for informing patient provider communication. We have previously developed a highly accurate *static* prediction model for the progression of CKD that used one time values. In this analysis, we describe a *dynamic* prediction model for CKD progression that includes changes in laboratory variables between visits as additional predictors of outcome.

METHODS: We developed the dynamic prediction model using longitudinally collected data from patients with CKD Stages 3 to 5 referred to nephrologists. Our static model included age, gender, and eGFR, urinary ACR, serum albumin, phosphorous, calcium and bicarbonate. The dynamic model added change in laboratory variables between visits. We used cox proportional hazards models and compared discrimination (IDI), calibration (Hosmer Lemeshow Chi Square), model fit (AIC) and net reclassification (NRI) at 3 years.

RESULTS: We studied 3,004 patients with an average of 5 visits (range 1-22) over a median follow up period of three years. The addition of change in eGFR, as well as an interaction term of the change in eGFR and subsequent eGFR were independently associated with the outcome, and improved model fit and discrimination (Table 1).

Table 1: Performance characteristics of static vs dynamic model

Visit	N	Static Model Chi Square	Dynamic Model Chi Square	Static Model AIC	Dynamic Model AIC	IDI	NRI
1	3,004	140	N/A	3988	N/A	N/A	N/A
2	2,582	327	156	3455	3447	1.0 (-0.7, 3.0)	9.1 (-0.7, 27.3)
3	2,250	179	37	3123	3112	3.2 (1.1, 5.4)	19.6 (5.3, 37.8)
4	1,965	180	21	2770	2743	2.8 (+0.1, 6.1)	10.4 (+6.4, 27.4)
5	1,721	156	11	2449	2435	2.8 (4.5, 6.2)	22.4 (6.7, 42.2)
6	1,512	193	7	2303	2269	4.6 (1.0, 7.4)	42.8 (21.8, 62.1)

Improvements in model fit, calibration and reclassification were also noted after 5 visits. (HL chi square <20 for dynamic model, continuous NRI 22.4 %). Changes in the remaining laboratory parameters did not significantly improve model performance (p IDI > 0.10).

CONCLUSIONS: A dynamic predictive model combining changes in eGFR between nephrology clinic visits can improve risk prediction for kidney failure over a static model that uses only a single eGFR. Integration of dynamic models in electronic health records deserves further study.