Journal of Current Science and Technology, January-March 2026 Vol. 16 No. 1, Article 164

ISSN 2630-0656 (Online)

Cite this article: Wanitchakorn, S., & Suriya, S. (2026). Multi-factor model for renal risk prediction in HIV patients initiating dolutegravir: A Thai secondary hospital cohort study. *Journal of Current Science and Technology*, *16*(1), Article 164. https://doi.org/10.59796/jcst.V16N1.2026.164

Journal of Current Science and Technology

Journal homepage: https://jcst.rsu.ac.th

Multi-Factor Model for Renal Risk Prediction in HIV Patients Initiating Dolutegravir: A Thai Secondary Hospital Cohort Study

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Received 11 August 2025; Revised 19 September 2025; Accepted 19 September 2025; Published online 20 December 2025

Abstract

Effective renal risk stratification for patients initiating dolutegravir (DTG) is crucial, as standard estimated glomerular filtration rate (eGFR**)** monitoring may be insufficient to prevent long-term kidney disease. This study aimed to develop and validate a multi-factor risk model to identify patients susceptible to a significant eGFR reduction (≥25%), thereby enabling targeted monitoring and preventive care. A retrospective cohort study at a Thai secondary care hospital analyzed 1,100 people with HIV who initiating DTG-based regimens between 2021 and 2023. The cohort was randomly divided into a training (n = 880) and a validation (n = 220) dataset. A multi-factor logistic regression model was developed, and its performance was compared against a model using only baseline eGFR. A significant eGFR reduction occurred in 17.82% of the cohort. Five independent risk factors were identified: age >40 years, BMI >23 kg/m², CD4 count <400 cells/μL, baseline eGFR <90 mL/min/1.73 m², and elevated alanine aminotransferase (ALT >40 U/L). The comprehensive 5-factor model demonstrated significantly better predictive performance (AUC 0.780; 95% CI 0.716 – 0.844) than the model using eGFR alone (AUC 0.651; 95% CI 0.571 – 0.730). Identifying at-risk patients is a critical first step in preventing long-term renal disease. This study provides a practical, novel renal risk prediction tool for DTG users, highlighting its clinical utility for proactive care. Future work should focus on prospective validation and integration into clinical workflows.

Keywords**:** *chronic kidney disease; dolutegravir; eGFR; HIV; predictive model; proactive care; renal risk stratification*

1. Introduction

Dolutegravir (DTG), an integrase inhibitor, is a cornerstone of modern antiretroviral therapy (ART) for people with HIV (PWH), recommended globally for its high efficacy and robust resistance profile (Deeks et al., 2013; Walmsley et al., 2013; Cottrell et al., 2013). However, DTG therapy presents a significant clinical challenge: it can increase serum creatinine by 10 – 15% by inhibiting its tubular secretion (Ruxrungtham et al., 2022; World Health Organization, 2019). Although this initial estimated glomerular filtration rate (eGFR) decline is an expected pharmacological effect; however, the long-term clinical outcome is not uniform. For some patients, this is a transient and reversible effect, while for others, it may represent the beginning of a progressive path towards chronic kidney disease (CKD).

Prior studies have identified several risk factors for CKD among people living with HIV, including older age, lower baseline eGFR, hypertension, diabetes, and low CD4 counts (Kalayjian et al., 2012; Ryom et al., 2014). Beyond HIV, predictive models incorporating demographic, metabolic, and laboratory parameters have been developed for CKD in other populations (Tangri et al., 2011; Matsushita et al., 2020). More recent HIV-specific models have attempted to stratify CKD risk

using routine clinical parameters (Mocroft et al., 2015). However, few studies have validated such models in real-world Asian populations or in the context of DTG initiation.

This uncertainty creates a critical need for better risk prediction. Current clinical practice in many settings relies solely on basic eGFR monitoring, a strategy that may be insufficient to identify which patients are on a trajectory towards irreversible adverse renal outcomes. This is particularly concerning in resource-limited settings like Thailand, where real-world data on this issue are scarce and access to advanced renal care is limited (Koteff et al., 2013).

This raises the question of whether incorporating additional routine clinical parameters together with eGFR could create a more effective risk stratification tool. Establishing a better predictive model could empower clinicians to shift from a reactive to proactive approach to renal care. A more accurate identification of high-risk patients would allow for the implementation of preventative strategies, such as closer monitoring, medication review, and targeted patient counseling, to preserve long-term kidney function.

This study, therefore, aimed to establish and validate a predictive tool. We first identified the prevalence and key predictive factors of significant eGFR decline in a Thai hospital setting. Subsequently, we developed a multi-factor predictive model and compared its performance against the current standard of care relying on eGFR alone to establish a more robust prediction tool for clinical decision-making.

2. Objectives

This study aimed to develop and validate a clinically applicable multi-factor risk model to identify patients susceptible to a significant eGFR reduction (≥25%), thereby enabling targeted monitoring and preventive care.

3. Materials and Methods

3.1 Study Design and Subjects

This retrospective cohort study was conducted at a secondary care hospital in Thailand, utilizing electronic medical records of people with HIV (PWH) from October 2021 to October 2023. Data collection, data extraction and all analyses were performed only after the ethics approval had been granted. Eligible participants were Thai adults (aged ≥18 years) who initiated a DTG-based regimen and remained on it for at least 12 months with a medication adherence of ≥95%. Patients were excluded if they were pregnant or had active malignancy, autoimmune diseases, other pre-existing renal conditions, or incomplete medical records.

3.2 Ethics Statement

This study received ethical approval from the Ethical Committee for Human Research, Pakchongnana Hospital, Thailand on 8 May 2023 (Approval number: ECPC-2566008). All procedures adhered to the ethical guidelines of the Helsinki Declaration. The study has been registered with the Thai Clinical Trials Registry (TCTR20230904001).

3.3 Sample Size Calculation

The minimum required sample size for model development was calculated based on a binary outcome (Riley et al., 2019). Assuming an anticipated Cox–Snell R-squared of 0.21, 10 candidate predictors, and an estimated event prevalence of 10% from prior literature (Valdivia-Cerda et al., 2021), the calculation yielded a minimum of approximately 1,080 participants, a prevalence later confirmed in a Thai cohort (Sacdalan et al., 2025) and consistent with our preliminary data. To ensure robustness and account for potential data incompleteness or loss during retrospective collection, the study targeted a total of 1,100 participants

3.4 Data Collection and Definitions

Demographic characteristics, clinical parameters, and laboratory test results were systematically extracted from the medical records of PWH (identified by ICD-10 code B24). Data was collected at baseline (defined as the date of DTG-based regimen initiation) and 12 months, using a structured case record form (CRF). Sociodemographic characteristics collected included age at DTG initiation, sex, current smoking status, and alcohol consumption. Clinical and medical history comprised duration since HIV diagnosis (years), BMI (kg/m^2), CD4+ T-cell count at diagnosis and baseline (cells/μL), documented opportunistic infections (OIs), and baseline comorbidities. Renal function was assessed using the estimated glomerular filtration rate (eGFR, mL/min/1.73 m^2), calculated using the Chronic Kidney Disease Epidemiology Collaboration (CKD-EPI) equation. Baseline eGFR was categorized as <90 or ≥90 mL/min/1.73 m^2 (de Boer et al., 2022). A decline is defined as ≥25% decrease from baseline,

as this is a clinically significant threshold commonly used in research to indicate progressive kidney disease (Srisopa et al., 2023).

Elevated ALT (Alanine aminotransferase): Defined as a baseline value greater than 40 Unit per Liter (U/L), based on the hospital normal laboratory reference range (Rinella et al., 2023).

3.5 Primary Outcome

The primary outcome for the predictive model was significant renal function decline, assessed using the eGFR at the 12-month follow-up. The eGFR was calculated via the CKD-EPI equation (mL/min/1.73 m^2). A significant decline was specifically defined as a ≥25% reduction from baseline eGFR to the 12-month measurement.

3.6 Statistical Analysis and Model Development

Participants with missing data were excluded from the analysis. All statistical analyses were performed using IBM SPSS Statistics for Windows (Version 27.0). For model development, eligible participants were randomly allocated into a training dataset (80% of the cohort, n = 880) and a validation dataset (20%, n = 220). Stratified random sampling was applied to ensure a balanced distribution of the primary outcome in both datasets.

Candidate predictors for the model were first identified through univariable logistic regression ($p < 0.05$). A stepwise backward elimination approach was then used on the training dataset to build the most robust, parsimonious multi-factor model (Model 1). To test our hypothesis that a multi-factor approach is better than the current standard of care, we compared the performance of our comprehensive model (Model 1; 5-predictor model) with a second model that used only baseline eGFR as a predictor (Model 2). As the primary outcome was assessed at a fixed 12-month endpoint, binary logistic regression was deemed an appropriate analytical method. Model performance was evaluated in the validation dataset using the area under the receiver operating characteristic (AUC ROC) curve, accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).

4. Results

Of the 1,455 patient records initially reviewed, 1,100 PWH met the inclusion criteria and were included in the final analysis. This cohort was randomly divided into a training dataset (n = 880) and a validation dataset (n = 220) using stratified sampling (Figure 1).

4.1 Baseline Characteristics

The study cohort, predominantly male (58.55%), had a mean age of 44.40 ± 11.30 years and a mean BMI of 22.46 ± 3.59 kg/m^2. The majority of PWH (62.45%) had an HIV diagnosis duration of >5 years, and 48.73% had a CD4 count <400 cells/μL at diagnosis. Baseline eGFR averaged 102.36 ± 16.94 mL/min/1.73 m^2.

The training and validation datasets were generally comparable ($p > 0.05$), although statistically significant differences were observed in baseline levels of dyslipidemia, ALT, and triglycerides (Table 1; see Supplementary Table S1 for full distribution of comorbidities).

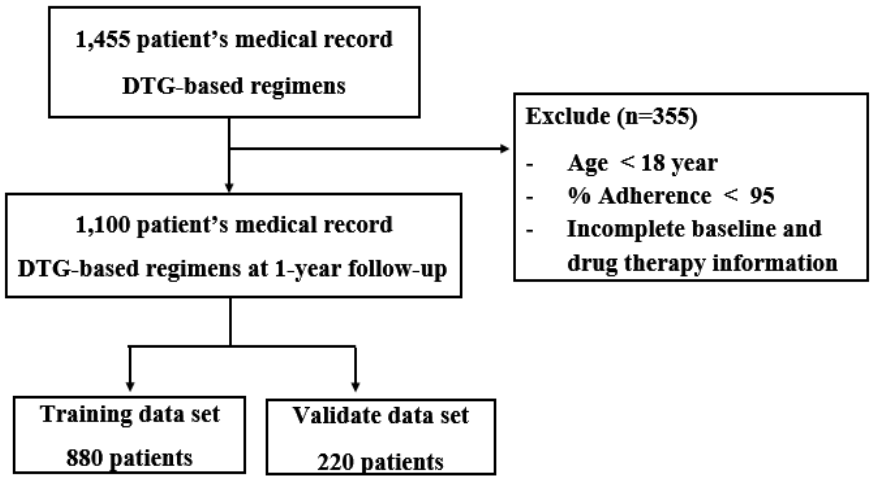

Figure 1 Flow diagram of medical record selection for HIV patients included in the study

Table 1 Sociodemographic and baseline clinical characteristics of study participants on dolutegravir-based regimens (n = 1,100).

Variables	Total (n = 1,100) Mean ± SD	Training data set (n = 880) Mean ± SD	Validate dataset (n = 220) Mean ± SD	*p*-value
eGFR decline 25 % from baseline (n, %)	196 (17.82)	159 (18.07)	37 (16.82)	0.314
Age (years)	44.40 ± 11.30	44.17 ± 11.43	45.31 ± 10.81	0.301
Male (n, %)	644 (58.55)	516 (58.63)	128 (58.18)	0.903
BMI (kg/m^2)	22.46 ± 3.59	22.44 ± 3.60	22.51 ± 3.56	0.563
Current smoking (n, %)	42 (3.82)	37 (4.20)	5 (2.27)	0.181
Alcohol use (n, %)	267 (24.27)	219 (24.89)	48 (21.82)	0.342
Comorbidities (n, %)				
Hypertension	184 (16.73)	152 (17.27)	32 (14.55)	0.332
Dyslipidemia	94 (8.54)	91 (10.34)	3 (1.36)	<0.001*
Diabetes Mellitus	36 (3.27)	29 (3.30)	7 (3.18)	0.932
Duration since HIV diagnosis (n, %)				
<2 years	49 (4.45)	43 (4.89)	6 (2.73)	0.437
2 to 5 years	364 (33.09)	295 (33.52)	69 (31.36)	
5 to 10 years	519 (47.18)	408 (46.36)	111 (50.45)	
>10 years	168 (15.27)	134 (15.23)	34 (15.45)	
Previous antiretroviral regimen (n, %)				
Naive:3TC/DTG/TDF (300/50/300)	31 (2.82)	23 (2.61)	8 (3.63)	
TDF/FTC/EFV(300/200/600)	620 (56.36)	512 (58.18)	108 (49.09)	0.231
3TC/AZT/NVP(300/500/400)	367 (33.36)	280 (31.82)	87 (39.55)	
3TC/TDF/NVP(300/300/400)	60 (5.45)	47 (5.34)	13 (5.91)	
3TC/AZT/EFV(300/600/600)	6 (0.55)	5 (0.57)	1 (0.45)	
LPV/r/3TC/AZT(400/100/300/600)	10 (0.91)	8 (0.91)	2 (0.91)	
TDF/FTC/EFV(300/200/400)	6 (0.55)	5 (0.57)	1 (0.45)	
CD4 cell count at diagnosis (n, %)				
<400 cells/μL	536 (48.73)	422 (47.95)	114 (51.81)	0.305
≥400 cells/μL	564 (51.27)	458 (52.05)	106 (48.18)	
Baseline CD4 count, cells/μL	430.34 ± 216.51	290.07 ± 180.54	316.37 ± 162.76	0.691
Blood chemistry				
FBS (mg/dL)	93.91 ± 18.12	94.10 ± 18.52	93.12 ± 16.41	0.575
ALT (U/L)	36.58 ± 26.56	37.27 ± 26.88	33.85 ± 25.10	0.020*
TC (mg/dL)	199.26 ± 37.94	199.22 ± 38.03	199.40 ± 37.69	0.853
TG (mg/dL)	139.79 ± 75.37	142.87 ± 79.60	127.48 ± 53.66	0.001*
LDL (mg/dL)	121.79 ± 31.44	121.53 ± 31.60	122.86 ± 30.83	0.833
eGFR (mL/min/1.72m^2)	102.36 ± 16.94	102.80 ± 17.17	100.59 ± 15.89	0.115

Note. Continuous variables are presented as mean ± SD, and categorical variables are presented as frequency (percentage). Comparisons between the training and validation datasets were performed using the independent Student's *t*-test for continuous variables, Chi-square test for categorical variables, and Fisher's exact test when expected cell counts were <5. Statistically significant *p*-values (<0.05) are highlighted and marked with an asterisk (*). Abbreviations: BMI; body mass index, FBS; fasting-blood sugar, ALT; alanine transaminase, TC; total cholesterol, TG; triglyceride, LDL; low-density lipoprotein, eGFR; estimated glomerular filtration rate, SD; standard deviation, 3TC; lamivudine, AZT; zidovudine, DTG; dolutegravir, EFV; efavirenz, FTC; emtricitabine, LPV/r; lopinavir/ritonavir, NVP; nevirapine, TDF; tenofovir disoproxil fumarate.

4.2 Prevalence of Significant eGFR Decline

A significant eGFR decline at 12 months was observed in 196 participants, representing an overall prevalence of 17.82% in the cohort. In the training dataset, 159 participants (18.07%) experienced the outcome, while 37 participants (16.82%) experienced it in the validation dataset.

4.3 Predictor Identification and Model Development

To build the predictive model, univariable logistic regression was first performed on the training dataset to identify nine candidate predictors. Subsequently, a backward stepwise multivariable logistic regression was used to create the final parsimonious model (Model 1). This process identified five independent predictors significantly

associated with eGFR decline: age >40 years, BMI >23 kg/m², CD4 count <400 cells/μL, baseline eGFR <90 mL/min/1.73 m², and elevated ALT levels (ALT >40 U/L) (Table 2).

4.4 Model Performance Comparison

To test our hypothesis that a multi-factor approach is better, the performance of the comprehensive 5-factor model (Model 1) was compared against a model using only baseline eGFR (Model 2) (Figure 2). When assessed on the validation dataset, Model 1 demonstrated significantly better predictive performance, with an Area Under the ROC Curve (AUC) of 0.780 (95% CI 0.716 – 0.844). In contrast, the model using only eGFR (Model 2) showed markedly lower discriminatory ability, with an AUC of 0.651 (95% CI 0.571 – 0.730). While Model 2 had slightly lower sensitivity, accuracy, specificity, and overall AUC, this limits its clinical utility. The full performance metrics for both models are detailed in Figure 3 and Figure 4.

Table 2 Univariate and multivariable logistic regression analysis of predictors of renal function decline among participants on DTG-based regimens (n = 1,100)

Predictors	Crude OR		Adjust OR	
	OR (95% CI)	***p*-value**	**OR (95% CI)**	***p*-value**
Age range (n, %)				
<40	reference			
≥40	3.272 (2.216 – 4.830)	<0.001*	3.206 (2.062 – 4.985)	<0.001*
Current smoking	0.088 (0.012 – 0.645)	0.017*	0.166 (0.019 – 1.415)	0.166
Duration since HIV diagnosis (years)				
<2	reference			
2 to 5	4.743 (1.439 – 15.634)	0.011*	1.377 (0.362 – 5.235)	0.638
5 to 10	4.124 (1.259 – 13.511)	0.019*	0.996 (0.259 – 3.825)	0.996
>10 years	3.470 (1.013 – 11.885)	0.048*	0.751 (0.187 – 3.014)	0.686
Previous opportunistic infections				
Pneumocystis pneumonia	1.064 (0.796 – 1.423)	0.674		
Cryptococcosis	1.461 (0.865 – 2.467)	0.157		
Tuberculosis	1.087 (0.611 – 1.933)	0.777		
Candidiasis	1.430 (0.942 – 2.171)	0.093		
Toxoplasmosis	0.373 (0.087 – 1.607)	0.186		
BMI level (kg/m^2)				
<23.0	reference			
≥23.0	1.660 (1.238 – 2.226)	0.001*	2.137 (1.551 – 2.944)	<0.001*
First antiretroviral regimen				
First DTG	reference	0.728		
First non -DTG	1.030 (0.871 – 1.218)			
CD4 cell count at diagnosis, cells/μL				
≥400	reference			
<400	2.242 (1.659 – 3.030)	<0.001*	2.388 (1.731 – 3.297)	<0.001*
eGFR level, mL/min/m^2				
≥90	reference			
<90	2.445 (1.806 – 3.311)	<0.001*	1.638 (1.177 – 2.278)	0.003*
Alanine transaminase				
Normal ALT (≤40 U/L)	reference			
Elevated ALT (>40 U/L)	3.501 (1.721 – 7.122)	<0.001*	2.606 (1.164 – 5.831)	0.020*

Note. Odds ratios (ORs) and 95% confidence intervals (CIs) were estimated using both univariate (crude OR) and multivariable (adjusted OR) logistic regression analyses. Crude ORs reflect the unadjusted association of each predictor with renal function decline, whereas adjusted ORs account for potential confounders included in the final multivariable model. Categorical predictors were coded as binary or grouped variables, with the reference category set at OR = 1.00. Statistically significant p-values (<0.05) are highlighted in bold and marked with an asterisk (*). Abbreviations: OR = odds ratio; CI = confidence interval; BMI = body mass index; eGFR = estimated glomerular filtration rate; ALT = alanine transaminase; TG = triglyceride.

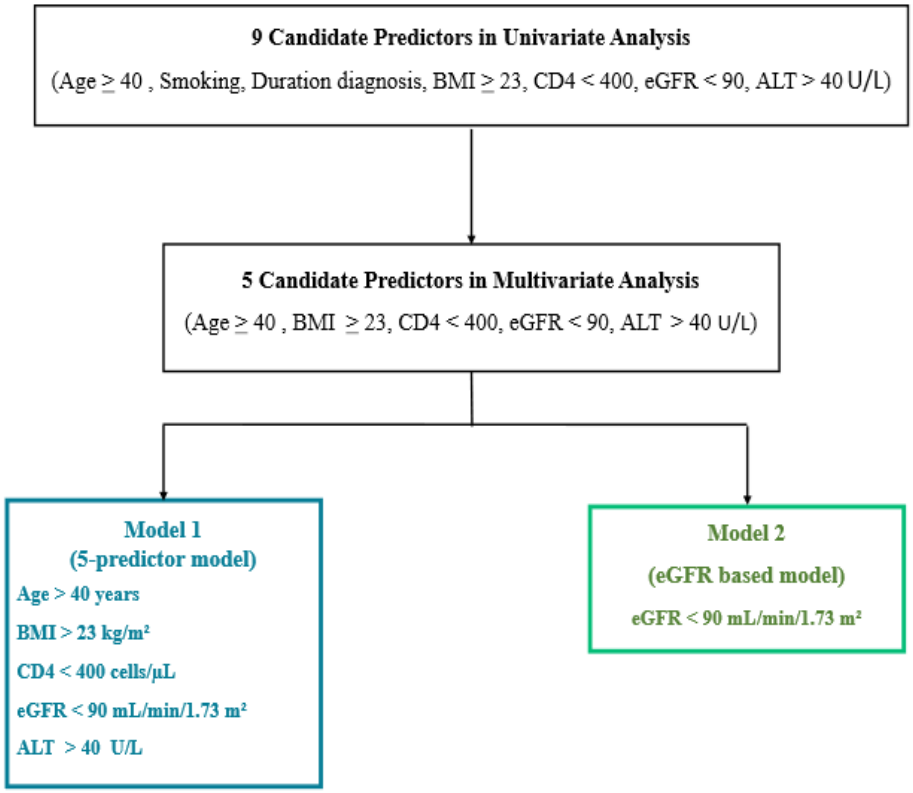

Figure 2 Candidate predictors and final models for risk of renal function decline in participants on DTG. Nine variables were tested in univariate logistic regression; five remained significant in multivariable analysis. Two models were derived: Model 1 (five predictors: age ≥40 years, BMI ≥23 kg/m², CD4 <400 cells/µL, eGFR <90 mL/min/1.73 m², ALT >40 U/L) and Model 2 (parsimonious model with eGFR <90 mL/min/1.73 m² alone)

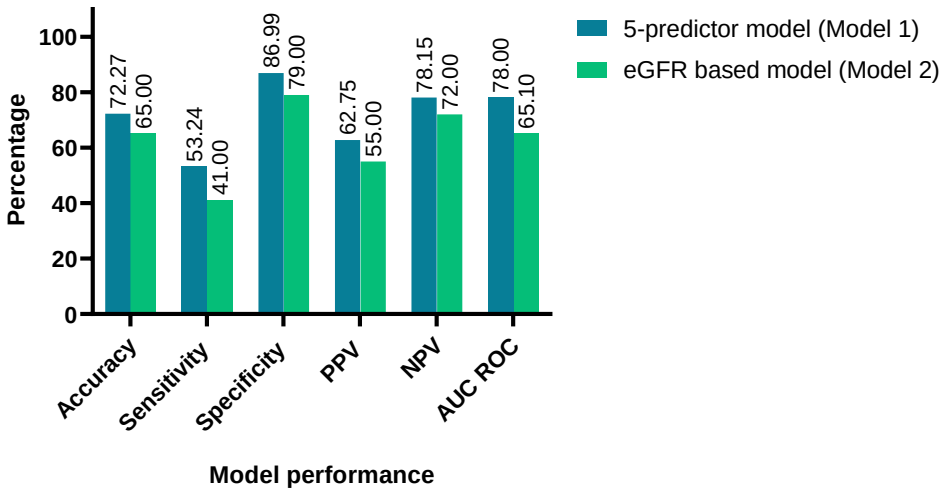

Figure 3 Performance of the five-predictor model (Model 1) and the eGFR-based model (Model 2) for predicting renal function decline in participants on DTG. Model performance was assessed by accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the receiver operating characteristic curve (AUC ROC)

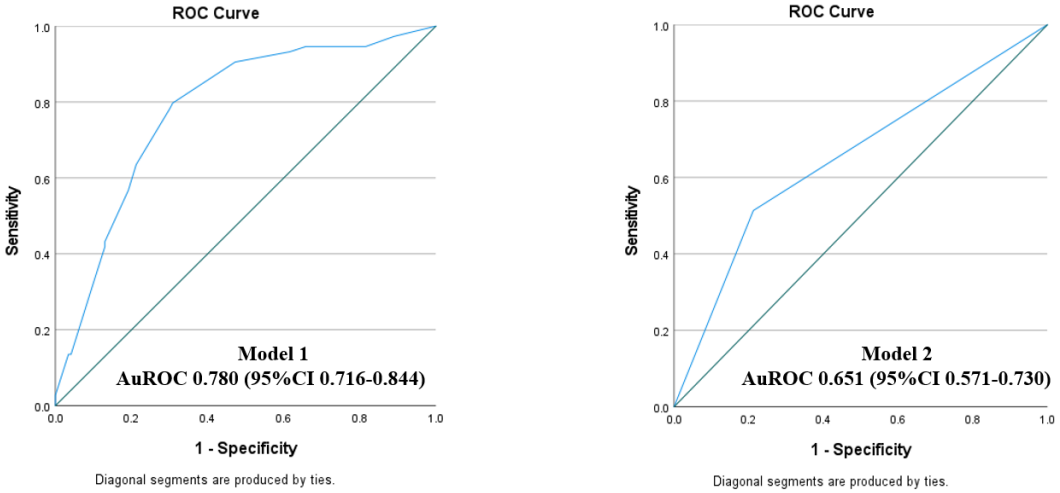

Figure 4 Receiver operating characteristic (ROC) curves of the five-predictor model (Model 1, left) and the eGFR-based model (Model 2, right) for predicting renal function decline in participants on DTG. The solid blue line represents each model's ROC curve; the diagonal line indicates random classification (AuROC = 0.500). Model 1 achieved an AuROC of 0.780 (95% CI: 0.716 – 0.844), and Model 2 an AuROC of 0.651 (95% CI: 0.571 – 0.730).

5. Discussion

This study developed and validated a multi-factor model for identifying PWH at risk of a significant eGFR decline after initiating DTG. The model, built from routine clinical parameters, performs significantly better than relying on eGFR alone, which is the current standard of care. This work addresses a critical gap by providing clinicians in resource-limited settings, like Thailand, with a practical tool to shift from reactive monitoring to a proactive approach to renal care.

The primary clinical implication of this model is its ability to guide preventative strategies and targeted pharmaceutical care. By identifying high-risk individuals at the beginning, clinicians can implement personalized care plans. These interventions include more frequent renal monitoring, careful review of concomitant nephrotoxic medications, and focused patient counseling to enhance awareness. This proactive stance is crucial for preserving long-term kidney function and potentially mitigating the progression to CKD.

A key strength of our model is its practicality: it incorporates five predictors age >40 years, BMI >23 kg/m², CD4 count <400 cells/μL, baseline eGFR <90 mL/min/1.73 m², and ALT >40 U/L that are part of routine clinical assessment and readily available to any clinician. Our results demonstrate that combining these simple, routine parameters provides a more holistic and accurate risk assessment than monitoring eGFR in isolation. This is because, while each factor represents a different dimension of patient vulnerability, their combination provides better predictive power. In a clinical context, a predictive model with an AUC of 0.780 suggests that it can lead to more informed and accurate clinical decisions, potentially reducing the number of patients who experience an unexpected renal decline while also preventing unnecessary interventions in those at low risk. Advancing age and lower baseline eGFR are well-established risk factors (Kalayjian et al., 2012; Ryom et al., 2014). The inclusion of BMI and CD4 count reflects the interplay between metabolic health, systemic inflammation, and renal risk (Crum-Cianflone et al., 2010; Koch, 2019; Lucas et al., 2014). The identification of elevated ALT (ALT >40 U/L) as a novel predictor warrants further discussion. Elevated ALT may reflect hepatic inflammation, metabolic dysfunction, or insulin resistance, which could contribute to renal injury via a hepato-renal axis (Ochiai et al., 2020; Strauss et al., 2025). Mechanistically, systemic inflammation, oxidative stress, or non-alcoholic fatty liver disease (NAFLD) may amplify renal susceptibility in PWH, particularly in the context of ART-induced metabolic changes. Our findings suggest that routine liver function assessment may provide additional prognostic insight for renal risk stratification in this population.

The predictive performance of this model (AUC = 0.780) compares favorably with that of other published models in HIV/renal risk prediction. For example, many existing models had AUCs ranging from 0.600 to 0.750 (Mocroft et al., 2015) making our model's performance competitive. These findings suggest our clinically applicable model offers a robust and effective tool for risk stratification, particularly in a Southeast Asian population where such data is scarce.

This study has several strengths, including its large sample size from a real-world Southeast Asian cohort and its robust validation methodology. However, the study also has limitations. First, the retrospective design prevents the inference of causality. Second, being a single-center study may limit the generalizability of our findings. Third, while baseline imbalances in some variables (dyslipidemia, ALT, and triglycerides) did not significantly affect internal validation, they may introduce heterogeneity, underscoring the need for external validation. Fourth, our reliance on creatinine-based eGFR as the sole outcome marker represents a primary limitation. This approach predicts a functional decline rather than diagnosing CKD, as we lacked data on albuminuria, a key indicator of structural damage. The CKD-EPI equation can also be influenced by non-GFR determinants like muscle mass, which our model does not capture. Additionally, the lack of cystatin C data a more reliable marker in some populations is a limitation for future prospective studies. A significant limitation is the lack of systematic data on exposure to nephrotoxic drugs like cotrimoxazole or cimetidine, which could have confounded our assessment of true renal function decline. We also acknowledge that while BMI of our cohort was predominantly moderate, extreme BMI values can affect the accuracy of the CKD-EPI equation, although this was a minimal factor in our study. Finally, while the 12-month follow-up was appropriate for observing DTG's initial impact, a longer period would be more informative for assessing long-term renal progression. We did not perform short-term creatinine monitoring to differentiate the expected initial eGFR decline from true renal impairment, a consideration for future research.

6. Conclusion

Relying solely on eGFR is a suboptimal strategy for assessing renal risk in people with HIV initiating DTG. This study provides a validated and clinically feasible 5-factor model that offers a better method for early risk stratification. By empowering clinicians to identify high-risk patients, this tool can facilitate a proactive approach to care, with the goal of preserving long-term kidney function and preventing adverse renal outcomes. Future work should focus on prospective validation and integration of this model into clinical practice

7. Abbreviations

Abbreviation	Full Term
3TC	Lamivudine
ALT	Alanine aminotransferase
ART	Antiretroviral therapy
AUC	Area under the curve
AUC ROC	Area under the receiver operating characteristic curve
AZT	Zidovudine
BMI	Body mass index
CD4	Cluster of differentiation 4
CKD	Chronic kidney disease
CKD-EPI	Chronic Kidney Disease Epidemiology Collaboration
CI	Confidence interval
CRF	Case record form
DTG	Dolutegravir
eGFR	Estimated glomerular filtration rate
EFV	Efavirenz
FTC	Emtricitabine
FBS	Fasting blood sugar
HIV	Human immunodeficiency virus
ICD-10	International Classification of Diseases, 10th Revision
LDL	Low-density lipoprotein
LPV/r	Lopinavir/ritonavir
NAFLD	Non-alcoholic fatty liver disease
NPV	Negative predictive value
NVP	Nevirapine
OI	Opportunistic infection
OR	Odds ratio
PPV	Positive predictive value
PWH	People with HIV
ROC	Receiver operating characteristic
SD	Standard deviation
TCTR	Thai Clinical Trials Registry
TC	Total cholesterol
TDF	Tenofovir disoproxil fumarate
TG	Triglyceride

8. Acknowledgements

The authors extend our sincere appreciation to the executive leadership, the director of the strategy and planning subdivision, the director of the Department of Pharmacy, the HIV/AIDS clinic, and all participating medical personnel at Pakchongnana hospital for their invaluable support and for facilitating this study's data collection and conduct within their institution. We also thank the faculty of pharmacy, Thammasat University, for their support in this research.

9. CRediT Statement

Siriyaporn Wanitchakorn: Conceptualization, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization.

Sutthipun Suriya: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Supervision, Project Administration, Funding Acquisition.

10. References

Cottrell, M. L., Hadzic, T., & Kashuba, A. D. (2013). Clinical pharmacokinetic, pharmacodynamic and drug-interaction profile of the integrase inhibitor dolutegravir. *Clinical pharmacokinetics*, *52*(11), 981-994. https://doi.org/10.1007/s40262-013-0093-2

Crum-Cianflone, N., Roediger, M. P., Eberly, L., Headd, M., Marconi, V., Ganesan, A., ... & Infectious Disease Clinical Research Program HIV Working Group. (2010). Increasing rates of obesity among HIV-infected persons during the HIV epidemic. *Plos One*, *5*(4), Article e10106. https://doi.org/10.1371/journal.pone.0010106

de Boer, I. H., Khunti, K., Sadusky, T., Tuttle, K. R., Neumiller, J. J., Rhee, C. M., ... & Bakris, G. (2022). Diabetes management in chronic kidney disease: A consensus report by the American Diabetes Association (ADA) and Kidney Disease: Improving Global Outcomes (KDIGO). *Diabetes Care*, *45*(12), 3075-3090. https://doi.org/10.2337/dci22-0027

Deeks, S. G., Lewin, S. R., & Havlir, D. V. (2013). The end of AIDS: HIV infection as a chronic disease. *The Lancet*, *382*(9903), 1525-1533. https://doi.org/10.1016/S0140-6736(13)61809-7

Kalayjian, R. C., Lau, B., Mechekano, R. N., Crane, H. M., Rodriguez, B., Salata, R. A., ... & Kitahata, M. M. (2012). Risk factors for chronic kidney disease in a large cohort of HIV-1 infected individuals initiating antiretroviral therapy in routine care. *Aids*, *26*(15), 1907-1915. https://doi.org/10.1097/QAD.0b013e328357f5ed

Koch, V. H. (2019). The effects of obesity on kidney function: A challenge for nephrologists. *Brazilian Journal of Nephrology*, *41*(2), 162-165. https://doi.org/10.1590/2175-8239-JBN-2019-0064

Koteff, J., Borland, J., Chen, S., Song, I., Peppercorn, A., Koshiba, T., ... & Piscitelli, S. C. (2013). A phase 1 study to evaluate the effect of dolutegravir on renal function via measurement of iohexol and para-aminohippurate clearance in healthy subjects. *British Journal of Clinical Pharmacology*, *75*(4), 990-996. https://doi.org/10.1111/j.1365-2125.2012.04440.x

Lucas, G. M., Ross, M. J., Stock, P. G., Shlipak, M. G., Wyatt, C. M., Gupta, S. K., ... & Kalayjian, R. C. (2014). Clinical practice guideline for the management of chronic kidney disease in patients infected with HIV: 2014 update by the HIV Medicine Association of the Infectious Diseases Society of America. *Clinical Infectious Diseases*, *59*(9), e96-e138. https://doi.org/10.1093/cid/ciu617

Matsushita, K., Jassal, S. K., Sang, Y., Ballew, S. H., Grams, M. E., Surapaneni, A., ... & Coresh, J. (2020). Incorporating kidney disease measures into cardiovascular risk prediction: Development and validation in 9 million adults from 72 datasets. *EClinicalMedicine*, *27*, Article 100552. https://doi.org/10.1016/j.eclinm.2020.100552

Mocroft, A., Lundgren, J. D., Ross, M., Law, M., Reiss, P., Kirk, O., ... & D: A: D study group, the Royal Free Hospital Clinic Cohort, and the INSIGHT, SMART, and ESPRIT study groups. (2015). Development and validation of a risk score for chronic kidney disease in HIV infection using prospective cohort data from the D: A: D study. *PLoS Medicine*, *12*(3), Article e1001809. https://doi.org/10.1371/journal.pmed.1001809

Ochiai, H., Shirasawa, T., Yoshimoto, T., Nagahama, S., Watanabe, A., Sakamoto, K., & Kokaze, A. (2020). Elevated alanine aminotransferase and

low aspartate aminotransferase/alanine aminotransferase ratio are associated with chronic kidney disease among middle-aged women: A cross-sectional study. *BMC Nephrology*, *21*(1), Article 471. https://doi.org/10.1186/s12882-020-02144-6

Riley, R. D., Snell, K. I., Ensor, J., Burke, D. L., Harrell Jr, F. E., Moons, K. G., & Collins, G. S. (2019). Minimum sample size for developing a multivariable prediction model: PART II-binary and time-to-event outcomes. *Statistics in Medicine*, *38*(7), 1276-1296. https://doi.org/10.1002/sim.7992

Rinella, M. E., Neuschwander-Tetri, B. A., Siddiqui, M. S., Abdelmalek, M. F., Caldwell, S., Barb, D., ... & Loomba, R. (2023). AASLD Practice Guidance on the clinical assessment and management of nonalcoholic fatty liver disease. *Hepatology*, *77*(5), 1797-1835. https://doi.org/10.1097/HEP.0000000000000323

Ruxrungtham, K., Chaivooth, S., Chetchotisakd, P., Chariyalertsak, S., Kiertiburanakul, S., Phanuphak, P., ... & Nookai, S. (2022). *Thailand national guidelines on HIV/AIDS treatment and prevention 2021/2022.* Division of AIDS and STIs, Department of Disease Control. Retrieved form https://www.thaiaidssociety.org/wp-content/uploads/2023/03/HIV-AIDS-Guideline-2564_2565_ED2.pdf

Ryom, L., Mocroft, A., Kirk, O., Ross, M., Reiss, P., Fux, C. A., ... & Lundgren, J. D. (2014). Predictors of advanced chronic kidney disease and end-stage renal disease in HIV-positive persons. *Aids*, *28*(2), 187-199. https://doi.org/10.1097/QAD.0000000000000042

Sacdalan, C., Austin, C., Varma, A., Pinyakorn, S., Kroon, E., Colby, D. J., ... & SEARCH 010/RV254 study group. (2025). Impaired creatinine-based estimated glomerular filtration rate in Thai individuals switching to dolutegravir: Illustrating the role of cystatin C testing to aid clinical decision making. *AIDS Research and Therapy*, *22*(1), Article 15. https://doi.org/10.1186/s12981-025-00712-0

Srisopa, S., Kornjirakasemsan, A., Treebupachatsakul, P., & Sonthisombat, P. (2023). Incidence and risk factors of tenofovir disoproxil fumarate induced nephrotoxicity and renal function recovery, a hospital case-control study. *Infection & Chemotherapy*, *55*(2), 226–236. https://doi.org/10.3947/ic.2023.0001

Strauss, K. L. E., Phoswa, W. N., Hanser, S., & Mokgalaboni, K. (2025). HIV infection and antiretroviral therapy impair liver function in people living with HIV: Systematic review and meta-analysis. *Pharmaceuticals*, *18*(7), Article 955. https://doi.org/10.3390/ph18070955

Tangri, N., Stevens, L. A., Griffith, J., Tighiouart, H., Djurdjev, O., Naimark, D., ... & Levey, A. S. (2011). A predictive model for progression of chronic kidney disease to kidney failure. *Jama*, *305*(15), 1553-1559. https://doi.org/10.1001/jama.2011.451

Valdivia-Cerda, V., Alvarez-Zavala, M., Sánchez-Reyes, K., Cabrera-Silva, R. I., Ruiz-Herrera, V. V., Loza-Salazar, A. D., ... & González-Hernández, L. A. (2021). Prevalence and risk factors of chronic kidney disease in an HIV positive Mexican cohort. *BMC Nephrology*, *22*(1), Article 317. https://doi.org/10.1186/s12882-021-02526-4

Walmsley, S. L., Antela, A., Clumeck, N., Duiculescu, D., Eberhard, A., Gutiérrez, F., ... & Nichols, G. (2013). Dolutegravir plus abacavir–lamivudine for the treatment of HIV-1 infection. *New England Journal of Medicine*, *369*(19), 1807-1818. https://doi.org/10.1056/NEJMoa1215541

World Health Organization. (2019). *Update of recommendations on first- and second-line antiretroviral regimens.* Retrieved form https://apps.who.int/iris/bitstream/handle/10665/325892/WHO-CDS-HIV-19.15-eng.pdf

Supplement data

Table S1 Distribution of recorded comorbidities among study participants in the total cohort, training dataset, and validation dataset

Variables	Total (n = 1,100)	Training data set (n = 880)	Validate data set (n = 220)
Comorbidities (n, %)			
Hypertension	184 (16.73)	152 (17.27)	32 (14.55)
Dyslipidemia	94 (8.54)	91 (10.34)	3 (1.36)
Diabetes Mellitus	36 (3.27)	29 (3.30)	7 (3.18)
Asthma	28 (2.55)	22(2.50)	6 (2.72)
Thyroid	12 (1.09)	9 (1.02)	3 (1.36)
Gout	4 (0.36)	3 (0.34)	1 (0.45)
Epilepsy	3 (0.27)	2 (0.23)	1 (0.45)