Original Article

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Optimizing Chemotherapy Outcomes for Elderly Thai Cancer Patients: Development of a Predictive Tool for Severe Adverse Events

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Abstract:

Objective: To develop a predictive model for grade 3–5 CAEs in older Thai cancer patients using clinical and geriatric parameters.

Material and Methods: This retro-prospective cohort study enrolled patients aged ≥60 years with solid tumors who were undergoing chemotherapy at Chulabhorn Hospital between January 2023 and June 2024. Clinical data and geriatric assessments were collected at baseline and during each treatment cycle. Predictors were identified using multilevel logistic regression, and model performance was evaluated using AUROC with internal validation.

Results: Ninety-four patients contributed 634 chemotherapy cycles, with 124 grade 3–5 CAEs (19.6%) recorded. Significant predictors included low income, ECOG performance status, white blood cell count, and absolute neutrophil count, while polypharmacy and prolonged Timed Up and Go Test (>20 seconds) showed protective trends, likely reflecting more cautious physician management. The final model achieved an AUROC of 0.72 (95% CI: 0.67–0.77), with a sensitivity of 81.2%, a specificity of 41.7%, a positive predictive value of 25.5%, and a negative predictive value of 90.0%.

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Conclusion: A Thai-specific clinical tool incorporating geriatric and clinical parameters can help identify older patients at risk of severe chemotherapy toxicity. Its high sensitivity and negative predictive value support its use as a screening tool in routine oncology care.

Keywords: aged, chemotherapy-induced adverse effects, drug-related side effects and adverse reactions, geriatric assessment, risk prediction models, Thailand

Introduction

Older cancer patients face heightened risks of chemotherapy-related adverse events (CAEs), as reported in both global and Thai contexts[1,2]. However, practical tools to preemptively identify high-risk individuals in Thailand remain unavailable in routine clinical practice[3]. The prevalence of multimorbidity, functional decline, and treatment-related vulnerability among older adults presents a growing challenge as Thailand transitions into a super-aged society[4]. Despite global advances in geriatric oncology[5,6], most predictive models have been formulated and validated within Western populations and may not be generalized to the Thai context.

Numerous known instruments—such as the Cancer and Aging Research Group (CARG) score[7] and Chemotherapy Risk Assessment Scale for High-Age Patients (CRASH)[8]—incorporate geriatric and laboratory parameters to estimate the risk of chemotherapy toxicity. These models, while evidence-based, require adaptations to local healthcare infrastructure and population characteristics to achieve clinical utility in low- and middle-income settings. Additionally, the use of performance status alone (e.g., ECOG) has been shown to underestimate vulnerability in older adults[9-11], reinforcing the need for multidimensional assessment strategies[12-14].

To address this gap, the authors aimed to develop a pragmatic, context-specific risk score for forecasting severe chemotherapy-induced toxicity in elderly Thai cancer patients. We hypothesized that integrating simple clinical and geriatric variables—accessible in outpatient settings—could yield a feasible screening tool to guide treatment decisions and supportive care planning.

Material and Methods

Study design

This retrospective-prospective cohort study was carried out from January 2023 to June 2024 at Chulabhorn Hospital in Bangkok, Thailand. Participants eligible for the study were aged 60 years or older, diagnosed with solid malignancies, and scheduled to initiate a new chemotherapy regimen. Concurrent chemoradiotherapy was permitted. Patients could be re-enrolled during subsequent lines of chemotherapy if they continued to meet eligibility criteria. Individuals unable to communicate in Thai were excluded.

Ethical considerations

The research received approval from the Institutional Review Board of the Faculty of Medicine, Thammasat University (MTU-EC-ES-0-066/67), and the Chulabhorn Research Institute (010/2561). Written informed consent was acquired from all participants before enrollment.

Clinical and geriatric assessment

Medical and geriatric evaluations were conducted by trained oncology nurses on the day of chemotherapy initiation. Geriatric assessment included functional

status, nutritional state, mobility, cognitive function, and psychosocial health. Validated Thai versions of assessment tools were used when available.

Baseline variables collected included sex, age, primary cancer site, disease stage, and chemotherapy regimen. Geriatric assessments included:

- Performance status: Eastern Cooperative Oncology Group (ECOG)
- Comorbidities: Self-report with medical record confirmation
- Function: Instrumental Activities of Daily Living (IADL)[15]
- Mood and distress: Thai 2Q depression screen[16] and distress thermometer[17]
- Cognitive function: Mini-Cog®[18,19]
- Nutrition: Body mass index (BMI), Mini Nutritional Assessment (MNA®)[20]
- Mobility: Timed up and go test[21]

Chemotherapy and outcome documentation

All patients received chemotherapy prescribed by their primary oncologists. Treatment modifications and supportive care interventions were determined at the discretion of the treating physicians. Throughout the chemotherapy course, systematic documentation was carried out concerning adverse events, treatment delays, dose reductions, discontinuation, and modifications due to toxicity or patient preferences.

The principal endpoint was the incidence of Grade 3–5 chemotherapy-induced adverse events (CAEs), as defined by the Common Terminology Criteria for Adverse Events (CTCAE), version 5.0[22]. Events were recorded from any setting, including scheduled clinic visits, unplanned outpatient assessments, and emergency department encounters. All reported adverse events were reviewed and adjudicated by two medical oncologists to ensure consistency.

Sample size calculation

The determination of sample size for this investigation was based on the number of chemotherapy-related adverse events (CAEs), rather than the number of enrolled patients. According to methodological standards for multivariable logistic regression, 10 to 20 events per candidate predictor are required to ensure model stability and validity[23]. Based on the model developed by Hurria et al.[7], which included 13 predictive variables spanning patient demographics, cancer characteristics, laboratory parameters, and geriatric assessments, a minimum of 130 events (13 variables × 10 events) was deemed necessary to support model development. This event-driven approach aligns with best practices for predictive modeling in clinical research.

Statistical analysis

Baseline demographic and geriatric evaluation data were summarized using descriptive statistics. Categorical variables were presented as frequencies and percentages, whereas continuous variables were presented as means, medians, standard deviations, and ranges. Univariable logistic regression was conducted to evaluate the relationships between baseline factors and the incidence of Grade 3–5 chemotherapy-related adverse events (CAEs). Variables exhibiting a p-value<0.20, AUROC>0.6, and credible clinical significance were chosen for multivariable analysis.

Multivariable analysis was conducted using multilevel logistic regression, accounting for repeated chemotherapy-related events within individual participants. Because a single patient could experience multiple adverse events across treatment cycles or visits, this hierarchical model structure was used to avoid clustering bias. Predictors of Grade 3–5 CAEs were identified using backward elimination, retaining variables with p-value<0.05. Adjusted odds ratios (ORs) and 95% confidence intervals (CIs) were reported. A clinical prediction model was constructed utilizing the

final multivariable model. Regression coefficients were converted into a risk score, creating a user-friendly tool for predicting severe CAEs. Model discrimination was evaluated using the area under the receiver operating characteristic curve (AUROC), the Mann–Whitney U test, histogram of the clinical risk score, and Kernel density analysis. Model performance was further evaluated using sensitivity, specificity, and positive likelihood ratios. Internal validation was conducted using bootstrap resampling (1,000 iterations) to assess model stability. All statistical analyses were performed using Stata/MP version 18.0 (StataCorp LLC, College Station, TX, USA).

Results

Patient characteristics

Ninety-four individuals participated in 592 chemotherapy treatment visits, from which 634 clinical adverse event (AE) episodes were recorded. The mean patient age was 68.8±6.3 years, with 26.6% aged ≥72 years. Most participants were male patients (53.2%), retired or unemployed (78.7%), and living with family (94.7%). Common comorbidities included hypertension (45.7%) and diabetes (17%). Polypharmacy (defined as >4 medications) was observed in 89.4% of participants. Gastrointestinal and hepatobiliary cancers were the most prevalent malignancies (57.5%), followed by breast (26.6%) and lung cancers (8.5%). Most patients received standard first-line chemotherapy (64.9%) with a typical regimen duration of 18 weeks (67%). Full baseline characteristics are shown in Table 1.

Chemotherapy-related adverse events

Among 634 clinical episodes, 124 events (19.6%) were classified as Grade 3–5 chemotherapy-related adverse events (CAEs) based on CTCAE version 5. Hematologic toxicities were frequent, with neutropenia (30.1% Grade 3, 12.3% Grade 4) and anemia (20.4% Grade 3) being the most common. Febrile neutropenia occurred in 2 episodes (100% Grade 3–4).

Non-hematologic toxicities included anorexia (16.0% Grade 3), fatigue (14.3%), mucositis (18.8%), and diarrhea (18.0%). Severe events (Grade 3–5) were captured from both scheduled and unscheduled visits, including emergency room encounters. A detailed breakdown of adverse events is presented in Table 2.

Table 1 Basic patient characteristics

	n (%)
Age (years)*	68.8±6.3
Age ≥72	25 (26.6)
Male	50 (53.2)
Couple	72 (76.6)
Education: at least a bachelor's	48 (51)
No social member activities	84 (89.4)
Retire/unemployed	74 (78.7)
Income (USD/month)	
≤297.8	26 (27.7)
297.9–1,489.4	55 (58.5)
>1,489.4	13 (13.8)
Living with family	89 (94.7)
PPC	89 (94.7)
DM	16 (17)
HT	43 (45.7)
Polypharmacy >4	84 (89.4)
ECOG PS	
0	50 (53.2)
1	32 (34)
2	12 (12.3)
Anemia	15 (16)
WBC <4,000 cell/μL	5 (5.3)
Serum albumin ≥3.5 g/dL	89 (94.7)
Types of cancer	
GI & HPB	54 (57.5)
Breast	25 (26.6)
Lung	8 (8.5)
Others	7 (7.5)
Stage	
I–II	25 (26.6)
III–IV	69 (73.4)
StCMT	52 (56.5)

Table 1 Continued

	n (%)
First-line therapy	61 (64.9)
Schedule duration(weeks)	
12	22 (23.4)
18	63 (67)
≥24	9 (9.6)
Hearing problem	9 (9.6)
Knee pain	41 (43.6)
MiniCog 4-5	59 (62.8)
Depression	10 (10.6)
SEFI	22 (23.4)
Distress >5	28 (29.8)
Falling	6 (6.6)
Mobile device assistant	12 (12.8)
BMI ≥23 (move up)	47 (50)
TUGT >20sec	31 (33)
Wt loss last 3 mo	65 (69.1)

USD=US dollar, PPC=presence of personal consultant, DM=diabetes mellitus, HT=hypertension, CrCl=creatinine clearance, ECOG=Eastern Cooperative Oncology Group, PS=performance score, Anemia=Hemoglobin ≤10 in female and ≤11 in male, WBC=white blood cell, g/dL=gram per deciliter, μL=microliter, Metastasis=distant metastasis, CCRT=concurrent chemoradiation, StCMT=start with standard chemotherapy dose, CMT≥2=multiple agents of chemotherapy, IADL=Instrumental Activities of Daily Living, Depression=presence of depression from screening, SEFI=Social effect from illness, Distress>5=Distress score>5, Falling=history of falling, BMI=body mass index, TUGT=Time up and go test, Wt loss last 3 mo=history of weight loss last 3 months

Predictors of grade 3–5 adverse events

Univariate and multilevel logistic regression analyses identified multiple significant predictors of Grade 3–5 CAEs. Patients with higher incomes (>50,000 baht/month) were significantly less likely to experience severe events (OR 0.30, 95% CI: 0.11–0.82). Poorer functional status (ECOG 2–3), TUGT >20 seconds, leukopenia (WBC <2,500/μL), and neutropenia (ANC <1,500/μL) during chemotherapy cycles were associated with increased risk.

Multilevel logistic regression confirmed these predictors, and their coefficients were used to derive a clinical prediction score. The model demonstrated good discrimination (AUROC 0.719, 95% CI: 0.67–0.77). Predictors and coefficients are detailed in Table 3, while model performance is shown in Table 4.

Model performance and comparison with ECOG score

In univariable analysis, 13 candidate variables were associated with Grade 3–5 chemotherapy-related adverse events (CAEs). Using multilevel logistic regression, a predictive model was developed based on eight significant predictors: income level, history of hypertension, schedule duration, TUGT (Timed up and go test), ECOG performance status, WBC, ANC per cycle, and polypharmacy (Table 3).

The final model achieved an AUROC of 0.72 (95% CI: 0.67–0.77), demonstrating acceptable discriminative ability (Figure 1). Internal validation with 1,000 bootstrap replications confirmed model robustness. Model calibration was assessed descriptively using a histogram of predicted versus observed events (Figure 3). Discrimination was further supported by the Mann–Whitney U test (p-vaue<0.001).

At the optimal cutoff (≥ −2.04), separation between patients with and without Grade 3–5 CAEs was observed (Figure 4). At this threshold, the model yielded a sensitivity of 81.2%, specificity of 41.7%, positive predictive value (PPV) of 25.5%, and negative predictive value (NPV) of 90.0% (Table 4). These findings suggest the model is best suited for screening to rule out high-risk patients, given its high NPV but limited PPV.

When compared to ECOG performance status alone, the model demonstrated significantly superior predictive ability, with AUROC values of 0.719 (95% CI: 0.67–0.77) vs. 0.577 (95% CI: 0.52–0.63), respectively (p-vaue<0.001, Figure 2).

Table 2 Common chemotherapy-related adverse events

	Grading of AEs (no. of symptom events, %)					
	1	2	3	4	1-2	3-5
HAE						
Neutropenia	0	42 (57.5)	22 (30.1)	9 (12.3)	42 (57.5)	31 (42.5)
Anemia	0	39 (79.6)	10 (20.4)	0	39 (79.6)	10 (20.4)
Low plt	7 (46.7)	6 (40.0)	2 (13.3)	0	13 (86.7)	2 (13.3)
FN	0	0	1 (50.0)	1 (50.0)	0	2 (100.0)
NHAE						
Anorexia	48 (45.3)	41 (38.7)	17 (16.0)	0	89 (84.0)	17 (16.0)
Fatigue	50 (55.0)	28 (30.8)	13 (14.3)	0	78 (85.7)	13 (14.3)
Mucositis	15 (31.3)	24 (50.0)	9 (18.8)	0	39 (81.3)	9 (18.8)
HFS	8 (40.0)	4 (20.0)	9 (42.9)	0	12 (57.1)	9 (42.9)
PN	30 (46.2)	28 (43.1)	7 (10.8)	0	58 (89.2)	7 (10.8)
Diarrhea	12 (30.8)	20 (51.3)	6 (15.4)	1 (2.6)	32 (82.0)	7 (18.0)
Sepsis	0	0	2 (100.0)	0	0	2 (100.0)

AEs=adverse events, no.=number, HAE=hematologic adverse event, NHAE=non-hematologic adverse events, Low plt=Thrombocytopenia, FN=febrile neutropenia, HFS=hand foot syndrome, PN=peripheral neuropathy

Table 3 Significant predictors of grade 3-5 chemotherapy adverse events

Parameter	Gr 3-5, N (%) (n=117)	Gr 1-2, N (%) (n=475)	OR (95%CI)[1]	β^1	p-value	AUROC (95% CI)
Income level (Baht/month)						
≤10,000	32 (27.4)	125 (26.3)	Ref.			
10,001-50,000	77 (65.8)	270 (56.8)	0.74 (0.42-1.32)	-0.296	0.310[1]	
>50,000	8 (6.8)	80 (16.8)	0.30 (0.11-0.82)	-1.194	0.019[1]	
Hypertension						
No	80 (68.4)	257 (54.1)	Ref.			
Yes	37 (31.6)	218 (45.9)	0.75 (0.42-1.33)	-0.289	0.321[1]	
Schedule duration (weeks)						
12	26 (22.2)	92 (19.4)	Ref.			
18	87 (74.4)	324 (68.2)	1.62 (0.84-3.14)	0.485	0.150[1]	
≥24	4 (3.4)	59 (12.4)	0.74 (0.20-2.72)	-0.295	0.655[1]	
TUGT (sec)						
≤20	82 (70.09)	292 (61.47)	Ref.			
>20	35 (29.91)	183 (38.53)	0.41 (0.22-0.77)	-0.894	0.006[1]	
WBC (cell/μL), cycle						
≥2,500	96 (82.1)	460 (96.8)	Ref.			
<2,500	21 (17.9)	15 (3.2)	3.86 (1.47-10.13)	1.351	0.006[1]	
ANC (cell/μL), cycle						
≥1,500	81 (69.2)	428 (90.1)	Ref.			
<1,500	36 (30.8)	47 (9.9)	2.03 (1.02-4.02)	0.706	0.044[1]	
ECOG performance score, cycle						
0	49 (41.9)	247 (52)	Ref.			
1	36 (30.8)	163 (34.3)	1.00 (0.58-1.75)	0.005	0.987[1]	
2-3	32 (27.4)	65 (13.7)	3.14 (1.45-6.79)	1.143	0.004[1]	

Table 3 Continue

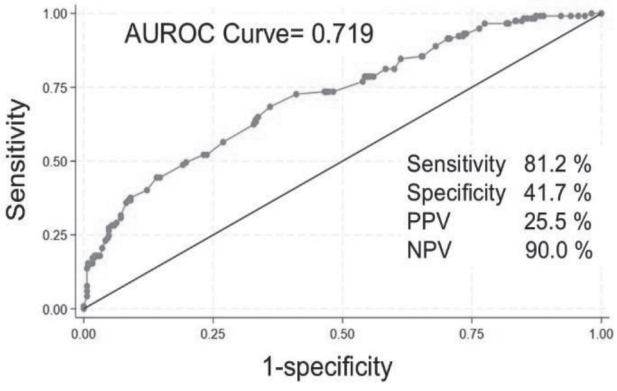
Parameter	Gr 3–5, N (%) (n=117)	Gr 1–2, N (%) (n=475)	OR (95%CI)[1]	β[1]	p-value	AUROC (95% CI)
Polypharmacy						
≤4	111 (94.9)	432 (90.9)	Ref.			
>4	6 (5.1)	43 (9.1)	0.37 (0.13–1.03)	−1.003	0.058[1]	
Score						
Mean (S.D.)	−1.02 (1.01)	−1.83 (0.88)			<0.001[2]	0.719 (0.67–0.77)
Median (IQR)	−1.21 (−1.75, −0.41)	−1.75 (−2.45, −1.26)				

score=risk score= −1.457 + ((−0.296 (Income=10,001–50,000) −1.194 (Income >50,000)) + (−0.289* Hypertension) + (0.485 (Treatment duration=6 month) −0.295 (Treatment duration >6 month)) + (−0.894* Timed up and go test) + (1.351* WBC) + (0.706* ANC) + (0.005 (ECOG=1) + 1.143 (ECOG=2,3)) + (−1.003* Polypharmacy)) constant and beta coefficient derived from multilevel logistic regression
[1]Multilevel logistic regression, [2]Mann–Whitney U test

Table 4 Predictive model with cut-off point, sensitivity, specificity, PPV, NPV, and LR

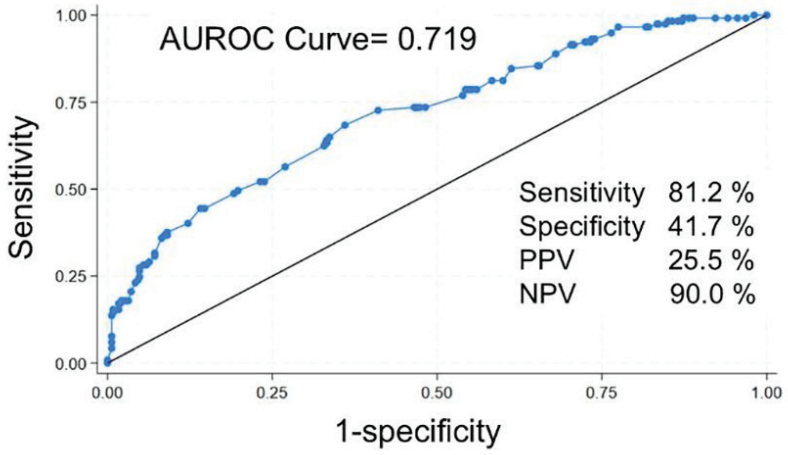
Score	Total (N=592)	Gr 1–2	Gr 3–5	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	LR+	LR−
Cutoff				81.2	41.7	25.5	90.0	1.39	0.45
<−2.0413	220 (37.16)	198 (41.68)	22 (18.80)						
≥−2.0413	372 (62.84)	277 (58.32)	95 (81.20)						

PPV=positive predictive value, NPV=negative predictive value, LR=likelihood ratio, ECOG=Eastern Cooperative Oncology Group, TUGT=time up and go test, WBC=white blood cell, ANC=absolute neutrophil count



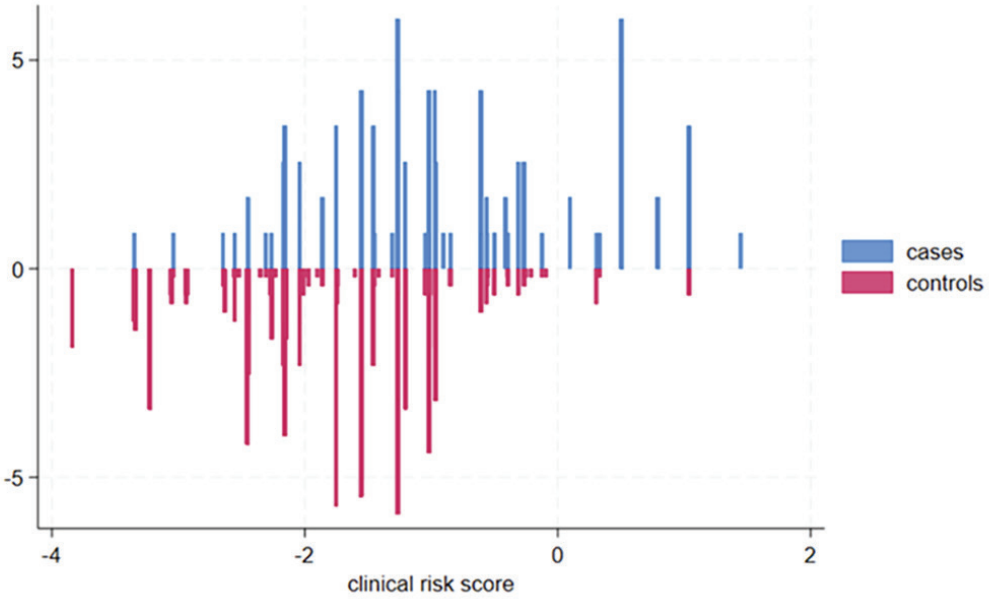
AUROC=area under the receiver operating characteristics, PPV=positive predictive value, NPV=negative predictive value

Figure 1 Performance of the predictor score, area under the receiver operating characteristics (AUROC) curve model, and QR code of clinical risk scoring from this study; https://cae-score.vercel.app/



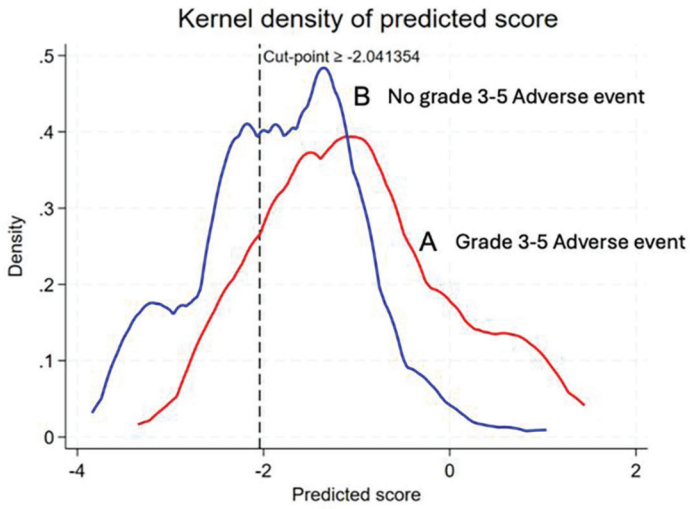
AUROC=area under the receiver operating characteristics; ECOG=Eastern Cooperative Oncology Group

Figure 2 Comparison of performance of the predictor score, AUROC Curve and 95% Confidence band between the new predictive score and ECOG performance score



The results of the internal validation used by the Bootstrap method (1,000 sampling times). The X-axis represents the predictive probability of chemotherapy adverse events by the model. The Y-axis represents the adverse events at the cycle level. The predictive model showed excellent internal validation, according to the calibration plot.

Figure 3 Histogram of the clinical risk score



Kernel density plot of predicted cycle-level risk scores for grade 3–5 adverse events (A, red) and no grade 3–5 adverse events (B, blue). The dashed vertical line indicates the optimal cut-point (≥ −2.04) used to classify patients at higher risk of severe adverse events. The figure shows the separation of predicted score distributions between the two groups.

Figure 4 Kernel analysis of predicted score

Discussion

This research established a clinical prediction model utilizing eight characteristics to identify older cancer patients at risk for Grade 3–5 chemotherapy-associated adverse events (CAEs), achieving an area under the receiver operating characteristic curve (AUROC) of 0.72. Unlike existing models, such as CARG (AUROC 0.72)[7] or CRASH (C-statistic 0.65)[8], our model was developed in a Thai setting with a distinct patient population and real-world treatment context. While the CARG and CRASH models emphasize functional status and laboratory data, our model incorporates both clinical and sociodemographic variables relevant to Thai oncology practice. Previous models were derived primarily from Western populations with different demographic, clinical, and healthcare characteristics. For example, Kim et al. developed a model using a South Korean population with a lower predictive accuracy (AUROC 0.642) and a different cancer distribution, further underscoring the importance of localized tools[24]. Our study contributes to the expanding literature by providing a context-specific tool with reasonable discrimination (AUROC 0.72) and high negative predictive value (NPV 90%), making it especially useful for screening. A comparison of the predictive variables and the model performance is presented in Table 5.

The final model includes both medical and functional factors (e.g., ECOG score, TUGT, polypharmacy, ANC, WBC), as well as contextual parameters (e.g., income level, chemotherapy schedule). Among these, the inclusion of income level serves as a proxy for socioeconomic status, which may influence treatment access, health literacy, and adherence—all of which affect toxicity risk[25]. Significantly, TUGT over 20 seconds correlated with a diminished probability of Grade 3–5 CAEs, which may reflect more cautious treatment approaches in frailer patients rather than

better physiological tolerance[13,26]. Similarly, polypharmacy was found to be a protective factor, possibly due to more vigilant monitoring or proactive dose adjustments in patients with multiple comorbidities[27,28].

Table 5 Comparison of variables associated with grade 3–5 chemotherapy adverse events

	Present	Hurria	Extermann	Kim
Year	2024	2011	2012	2018
Country	Thailand	US	US	Korean
n	592	500	518	301
Inclusion Age	60	65	70	70
Model Perform	AUROC 0.72	AUROC 0.72	C-stat 0.65	C-stat 0.64
Age		√		
Income	√			
Type		√		
GI	50			40
Breast	27			1
Lung	9	30	21	25
StCMT		√		
CMT≥2	√			
Regimen			√	
Duration	√			
nHb		√		
WBC	√			
Protein ≥6.7				√
LDH			√	
CrCl		√		
Hearing		√		
Falling		√		
ECOG PS	√			
TUGT	√			
Med assist		√		
Social def		√		
Walk 1 block		√		
DBP			√	
Polypharmacy	√			
No stress				√
HP				√
Obey command				√
MMSE			√	√
MNA			√	
Fluid/day				√

GI=gastrointestinal, StCMT=start with standard chemotherapy dose, CMT≥2=multiple agents of chemotherapy, Regimen=chemotherapy regimen, Duration=schedule duration, nHb=normal hemoglobin, WBC=white blood cell, LDH=lactate dehydrogenase, CrCl=creatinine clearance, Hearing=hearing impairment, Falling=history of falling last 6 months, ECOG=Eastern Cooperative Oncology Group, PS=performance score, TUGT=Time up and go test, Med assist=medical intake assist require, Social def=social deficiency from illness, Walk 1 block=limited in walking one block, DBP=diastolic blood pressure, No stress=no stress in last three months, HP=health perception, Obey command=obey command accomplish, MMSE=Mini-Mental State Exam score 25-30, MNA=Mini-Nutritional Assessment, Fluid/day=oral fluid/day more than 3 cups, Model Perform=model performance, AUROC=Area Under the Receiver Operating Characteristic, C-stat=C-statistic

Two illustrative cases from our study support the clinical applicability of the model. Using our tool, a 68-year-old man with hypertension and diabetes was identified as high-risk. After receiving XELOX, he developed Grade 3 hand-foot syndrome, resulting in treatment discontinuation. Similarly, a 70-year-old woman flagged as high-risk developed sepsis after one cycle of FOLFIRI and required hospitalization. These examples demonstrate how the early identification of at-risk patients can guide more vigilant care and timely intervention.

The performance characteristics of the model—particularly its high sensitivity (81.2%) and NPV (90%)—support its use as a screening tool, particularly in busy clinical settings where comprehensive geriatric assessment may not be feasible[5,29,30]. Although the positive predictive value (PPV) was modest (25.5%), the model is well-suited for ruling out high-risk patients, allowing oncologists to focus resources on those most vulnerable[31,32].

Importantly, the model incorporates event-level data across multiple chemotherapy cycles using multilevel logistic regression. This approach is rarely applied in resource-limited settings and adds value by accounting for repeated measures and real-world treatment patterns over time[33–35].

There are also limitations that should be acknowledged. The model was derived from a single-institution cohort and has not yet undergone external validation, which may limit its generalisability. Interestingly, two variables—polypharmacy and TUGT >20 seconds—showed protective trends (adjusted OR <1), likely reflecting physician treatment decisions such as pre-emptive dose reductions or enhanced supportive care; these should be interpreted as hypothesis-generating rather than true protective factors. Formal calibration tests (e.g., Hosmer–Lemeshow) were not appropriate for the hierarchical models; instead, calibration was assessed descriptively using a histogram (Figure 3). Decision curve analysis was not conducted, since the model was designed primarily to assess predictive performance rather than clinical utility. Finally, prophylactic G-CSF use was not systematically recorded, which restricts the interpretation of hematologic adverse event risks.

Despite these limitations, our findings offer a contextually relevant tool for screening older Thai patients at risk of chemotherapy-related toxicity, while underscoring the need for external validation and refinement to enhance its clinical utility.

Conclusion

This study established and internally verified a predictive model tailored for Thai elderly cancer patients to identify those at risk of experiencing severe chemotherapy-related adverse events. By incorporating clinical, laboratory, and functional variables relevant to the Thai context, the model achieved good discrimination and strong negative predictive value, supporting its use as a screening tool. This tool may support early risk recognition, inform safer chemotherapy planning, and enhance shared decision-making in routine oncology care.

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Conflict of interest

The authors declare no conflicts of interest related to this study.

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Supplementary Table 1 Final multivariable model coefficients, intercept, and cutoff

Predictor Variable	Coefficient (β)	Standard Error	Adjusted OR (95% CI)	p-value
Low income (≤10,000 THB/month)	+0.85	0.32	2.34 (1.25–4.39)	0.008
ECOG performance status ≥2	+0.76	0.29	2.15 (1.20–3.86)	0.010
White blood cell count <4,000 /mm^3	+0.92	0.37	2.50 (1.20–5.22)	0.015
Absolute neutrophil count <2,000 /mm^3	+1.05	0.41	2.86 (1.28–6.40)	0.011
Polypharmacy (≥5 concurrent medications)	–0.58	0.25	0.56 (0.34–0.91)	0.021
TUGT >20 seconds	–0.67	0.27	0.51 (0.30–0.85)	0.009
Hypertension (history)	+0.61	0.26	1.84 (1.10–3.08)	0.020
Chemotherapy schedule <21 days	+0.72	0.30	2.05 (1.14–3.67)	0.016

Model intercept: –1.92
Optimal cutoff: ≥ –2.04 (derived by Youden Index)
Model performance: AUROC=0.72 (95% CI: 0.67–0.77); Sensitivity 81.2%; Specificity 41.7%; PPV 25.5%; NPV 90.0%