

Clinical Prediction Model for Predicting Risk of Failure from Non-Pharmacological Treatment in Smoking Cessation

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Abstract

In Thailand, smoking cessation treatment primarily relies on counseling. Identifying patients at risk of treatment failure early could help healthcare providers tailor more effective interventions. This study aimed to develop a clinical prediction model to assess the risk of failure in non-pharmacological smoking cessation therapy. Retrospective cohort data were collected from medical records at the Rangsit FahSai Clinic, Rangsit University, between June 18, 2014, and November 16, 2023. The primary outcome was treatment failure at six months post-treatment. Stepwise backward logistic regression was used to develop the model. Discriminative performance was assessed using the area under the receiver operating characteristic (ROC) curve, while calibration was evaluated with calibration plots and the Hosmer-Lemeshow goodness-of-fit test. A total of 316 participants were included, with an 81.3% treatment failure rate. Clinical prediction factors included stage of change, severity of nicotine dependence, gender, having a spouse/partners/children, and health issues. The model showed acceptable discrimination (AUC = 0.76, 95% CI [0.69, 0.82]) and accurate predictions, as indicated by the calibration plot and the Hosmer-Lemeshow goodness-of-fit test ($p = 0.479$). Patients scoring 5.5 or higher on the 11-point prediction model should be considered for pharmacological interventions to improve cessation outcomes.

Keywords

Clinical prediction model; non-pharmacological; risk scores; smoking cessation; treatment failure

Introduction

Smoking cessation services are a crucial undertaking for all divisions of medical personnel across Thailand (Rungreunghiranya & Krobthong, 2021). Even though there are several smoking cessation services in Thailand, the number of current smokers has been decreasing slightly. In 2007, there were 10.8 million smokers, accounting for 21.2% of the population, which declined to 9.8 million smokers, or 16.5%, in 2024 (National Statistical Office, 2025). One reason for this might be the emergence of new tobacco products and the increased accessibility of tobacco products through online commerce. Another factor is the relatively low success rate of smoking cessation programs. According to an interview with the Vice President of the Medical Professional Alliance for Tobacco Control, the Medical Association of Thailand, there were 589 Fahsia Clinics (smoking cessation clinics) in Thailand between 2004 and 2020, with a success rate of only about 20% (Matichon, 2020). When considering treatment strategies, most involve counseling by medical professionals without pharmacological treatment.

Current clinical guidelines recommend combining smoking cessation with stop-smoking aids and counseling by healthcare personnel, as this approach has proven to be more effective than counseling alone (CDC, 2021; Tobacco Use and Dependence Guideline Panel, 2008). In addition, non-pharmacological methods may be insufficient to relieve withdrawal symptoms in some patients, which disrupts their quality of life and reduces their motivation to quit, particularly during the first four weeks of treatment, a time when relapse is most likely (Metz et al., 2005). However, in real-life practice, pharmacological treatment is not widely used. The limited use of medications for smoking cessation in Thailand is primarily due to difficulties in access. Most standard smoking cessation medications, except cytisine, are not included on the national essential medicines list (National Drug Information, 2024), meaning patients who require alternatives to cytisine must pay out of pocket. Additionally, smoking cessation services at primary healthcare centers or health hotlines typically do not have these medications, requiring patients who need them to be referred to higher-level healthcare facilities.

Most smoking cessation guidelines offer general recommendations and rarely consider the specific characteristics of patients who might succeed or fail with treatment. (Centers for Disease Control and Prevention [CDC], 2021; European Network for Smoking and Tobacco Prevention [ENSP], 2020; Tobacco Use and Dependence Guideline Panel, 2008). The type of tobacco dependence is unique to each individual and is not solely due to physical effects or nicotine dependence; it is also influenced by psychological and behavioral patterns (Longyhore & Dombrowski, 2020; Rungreunghiranya & Krobthong, 2021). Moreover, various personal factors can impact the success or failure of treatment, such as age (Kim & Cho, 2014; Lin et al., 2023; Monsó et al., 2001; Qiu et al., 2020; Sornpaisarn et al., 2022), gender (Esen et al., 2020; Perkins, 2012), health status (Lin et al., 2023; Qiu et al., 2020; Sornpaisarn et al., 2022; Tin et al., 2012; Zhu et al., 2022), family or relationships (Caponnetto & Polosa, 2008; Kim & Cho, 2014), alcohol or substance use (Caponnetto & Polosa, 2008), quantity and duration of smoking (Fu et al., 2022; Klemperer et al., 2020; Qiu et al., 2020; Sornpaisarn et al., 2022), the severity of nicotine dependence (Esen et al., 2020; Lin et al., 2023; Zhou et al., 2009), motivation (Fu et al., 2022; Klemperer et al., 2020; Zhu et al., 2022), stage of change (Lin et al., 2023; Zhou et al., 2009), and history of past smoking cessation (Fu et al., 2022; Rungreunghiranya & Krobthong, 2021; Zhou et al., 2009). As a result, treatment strategies should be personalized to account for each individual's unique characteristics.

Developing a clinical prediction score to predict the risk of non-pharmacological treatment failure in advance, using only basic and personalized information from a patient's first clinic visit, will help therapists select the most suitable treatment from the start. A review of the literature reveals that previous studies on risk prediction tools have limitations for practical use. For example, most studies have been conducted in hospital outpatient settings, where medications may also be used (Lai et al., 2021; Zhu et al., 2020). One study focused primarily on quitting using e-cigarettes (Fu et al., 2022). Some studies used machine learning algorithms to develop models without clearly specifying the relative weights of each predictive factor (Fu et al., 2022; Lai et al., 2021; Zhu et al., 2020). Additionally, some studies included numerous predictive factors that required patient compliance with follow-up visits and medication use, making the context of these studies different from the purpose of this research (Lai et al., 2021; Zhu et al., 2020). Moreover, studies conducted in other countries may not be directly applicable to Thailand due to differences in context and culture. Another challenge is that many tools do not provide appropriate cutoff scores to support interpretation or decision-making (Fu et al., 2022; Lai et al., 2021; Zhu et al., 2020).

As highlighted earlier, the objective of this study is to develop a clinical prediction score to identify patients at risk of failure with non-pharmacological treatments. Our score was created as a risk score to identify high-risk patients who may require pharmacological intervention. The results of this study will provide concrete clinical decision-making criteria for predicting treatment failure based on the individual characteristics of each substance user. These criteria can help healthcare professionals choose the most suitable treatment approach from the outset, thereby improving treatment success rates and shortening the overall duration of care.

Materials and methods

Study design and participants

This study developed a prognostic prediction model. It used a retrospective cohort design, with data collected from the medical records of individuals seeking smoking-cessation treatment at Rangsit FahSai Clinic, Rangsit University, between June 18, 2014, and November 16, 2023. The inclusion criteria were individuals aged 18 and older, who are current smokers wanting to reduce or quit smoking, and who received non-pharmacological treatments. The exclusion criteria involved individuals who discontinued treatment or lost contact within the first two weeks, as well as those who primarily used other forms of tobacco, such as e-cigarettes or hand-rolled cigarettes.

The sample size estimate was performed using Stata version 16.0 with the *pmsampsize* command for multivariable prediction model studies with a binary outcome. The parameters used included a c-statistic of 0.816 (Zhu et al., 2020), 11 candidate predictors, and an event prevalence of 0.8. The analysis revealed that a sample size of at least 306 participants was required.

This study was approved by the Ethics Committee for Research Involving Human Subjects, Thammasat University (Approval number 115/2566).

Settings and interventions

Rangsit FahSai Clinic, a private university clinic in Pathum Thani, Thailand, specializes in smoking cessation. The clinic's staff includes doctors, pharmacists, psychologists, and nurses, with psychologists leading non-pharmacological treatments, intensive counseling, and motivational interviewing for all patients. Follow-up occurs weekly via phone or in-person meetings until the patient successfully quits smoking. Once a patient quits smoking, they will receive weekly phone follow-ups for the first two months, then biweekly follow-ups for the next two to four months, and monthly follow-ups for the next six months.

Candidate predictors

The candidate predictors were derived from a review of research studies and theoretical frameworks, as well as from medical record data. If two or more factors were correlated, we selected the one considered more relevant and practical. Finally, a total of 11 predefined factors were selected: 1) gender (male/female) (Esen et al., 2020; Perkins, 2012); 2) age (Lin et al., 2023; Qiu et al., 2020; Sornpaisarn et al., 2022); 3) health issues/health problems (present/absent) (Lin et al., 2023; Sornpaisarn et al., 2022; Zhu et al., 2022); 4) close contacts who smoke (yes/no); 5) having spouse/partner/children (yes/no) (Caponnetto & Polosa, 2008; Kim & Cho, 2014); 6) alcohol/substance use (yes/no) (Caponnetto & Polosa, 2008); 7) attempted to quit in the past year (yes/no) (Fu et al., 2022; Zhou et al., 2009); 8) motivation (internal/external) (Sherman, 2013a); 9) cumulative smoking amount (pack-year); 10) Stage of change based on the Transtheoretical Model (TTM) (contemplation/preparation) (Sherman, 2013a, 2013b); and 11) Severity of nicotine dependence measured by the Heaviness of Smoking Index (HSI) (low/moderate/high) (Rungreunghiranya & Krobthong, 2021).

Outcome

The outcome was evaluated once, at the end of the sixth month. Clinic staff were evaluated through patient interviews. The primary outcome was treatment failure, which is defined as patients who are unable to remain smoke-free (0 cigarettes) continuously for at least one month by the end of the six-month treatment period or patients who could not be reached for follow-up.

Statistical analysis

To compare differences between groups for categorical variables, the exact test was used; for continuous variables with normal distributions, the independent t-test was applied; and for continuous variables with non-normal distributions, the Wilcoxon rank-sum test was used. Missing values were imputed using multiple imputations by chained equations, assuming that the missing data were missing at random. For missing outcome data in patients who could not be contacted at the end of the 6-month treatment period, it was assumed that the patient was unable to quit smoking, with the assumption that the treatment outcome had not changed since the last contact.

The model was developed using stepwise backward logistic regression, selecting predictors with p values $< .10$. The risk score was determined by using the coefficient with the lowest p value as the divisor, rounded to the nearest .5 or a whole number. The discrimination was

analyzed using independent *t*-tests and calculating the area under the receiver operating characteristic (ROC) curve. Internal validity was evaluated using ROC analysis with bootstrap resampling (200 replications). The calibration was assessed using a calibration plot comparing the model's predicted values with the actual data and testing the Hosmer-Lemeshow goodness-of-fit.

Results

A total of 316 participants undergoing non-pharmacological smoking cessation treatment in this study included 257 individuals who failed the treatment (81.3%). Of these, 73 participants (73.1%) were unable to stop smoking continuously for at least one month, and 184 participants (58.2%) could not be contacted for follow-up. The significantly different characteristics between the failure group and the success group were age, spouse /partner, health issues, stage of change, and severity of nicotine dependence (Table 1).

Table 1: Baseline Characteristics of Participants

Characteristic	Total (<i>n</i> = 316)	Failure (<i>n</i> = 257)	Success (<i>n</i> = 59)	<i>p</i> value*
Gender				
Male	280 (88.6)	225 (87.6)	55 (93.2)	0.262
Female	36 (11.4)	32 (12.5)	4 (6.8)	
Age (years): median (IQR)	21 (19, 31)	21 (19, 28)	22 (20, 42)	0.041
Education				
Below secondary school	19 (8.44)	18 (9.6)	1 (2.7)	0.327
Above secondary school or equivalent	206 (91.6)	170 (90.4)	36 (97.3)	
No Spouse /partner	224 (74.4)	189 (77.8)	35 (60.3)	0.011
No children	236 (82.8)	201 (84.8)	35 (72.9)	0.058
No health issues	257 (81.3)	215 (83.7)	42 (71.2)	0.040
Having close contacts who smoke	143 (46.6)	115 (45.8)	28 (50.0)	0.657
Alcohol consumption	220 (71.4)	176 (70.7)	44 (74.6)	0.632
Substance use	58 (19.2)	47 (19.2)	11 (19.3)	1.000
Number of cigarettes smoked: median (IQR)	10 (6, 20)	6 (20, 10)	10 (5, 15)	0.620
Age of smoking initiation (years): mean (SD)	17.23 (4.7)	17.24 (4.7)	17.19 (4.7)	0.937
Duration of smoking: median (IQR)	6 (3, 14)	6 (3, 12)	6 (4, 20)	0.391
Cumulative smoking amount (pack-years): median (IQR)	3 (1.2, 9.8)	3 (1.25, 9)	3.25 (1, 11.48)	0.876
Attempted to quit smoking in the past year	103 (42.4)	82 (41.8)	21 (44.7)	0.745
Motivation				
External	29 (9.8)	26 (10.8)	3 (5.4)	0.317
Internal	267 (90.2)	214 (89.2)	53 (94.6)	
Stage of change				
Contemplation	98 (32.1)	94 (37.9)	4 (7.0)	< 0.001
Preparation	207 (67.9)	154 (62.1)	53 (93.0)	
Time to first cigarette after waking				
Within 5 minutes	102 (34.3)	89 (37.1)	13 (22.8)	0.086
6-30 minutes	67 (22.6)	54 (22.5)	13 (22.8)	
More than 30 minutes	128 (43.1)	97 (40.4)	31 (54.4)	

Characteristic	Total (n = 316)	Failure (n = 257)	Success (n = 59)	p value*
Severity of nicotine dependence				
Mild	143 (47.8)	107 (44.0)	36 (64.3)	0.023
Moderate	134 (44.8)	116 (47.7)	18 (32.1)	
Severe	22 (7.4)	20 (8.2)	2 (3.6)	

Note: SD=standard deviation, IQR = interquartile range; *Exact test for categorical variables; independent t-test for age of smoking initiation; Wilcoxon rank-sum test for age, number of cigarettes smoked, duration of smoking, and cumulative smoking amount, and $p < .05$ considered statistical significance.

Education had the most missing data, followed by smoking cessation history in the past year. The remaining variables had less than 10% missing data. The comparison of data before and after imputation (analyzed using Multiple Imputations by Chained Equations) showed that the strength of the associations was comparable. The significant factors associated with treatment failure from univariable logistic regression were age, no spouse /partner/children, no health issues, contemplation stage, time to first cigarette within 5 minutes, and moderate nicotine dependence (Table 2).

Table 2: Comparison of the Strength of Associations Between Factors and Treatment Failure Before and After Imputation

Characteristic	Missing (%)	Before imputation*		After imputation**	
		Crude OR [95% CI]	p value	Crude OR [95% CI]	p value
Age	6.0	0.98 [0.96, 1.00]	0.044	0.98 [0.96, 1.00]	0.018
Education	28.8				
Below secondary school		3.81 [0.49, 29.48]	0.200	1.01 [0.44, 2.30]	0.990
Above secondary school or equivalent		reference	-	reference	-
No spouse or partner / No children	4.8	2.30 [1.25, 4.22]	0.007	2.24 [1.23, 4.06]	0.008
No close contacts who smoke	2.9	1.18 [0.66, 2.11]	0.571	1.24 [0.70, 2.18]	0.460
Alcohol/substance use	2.5	0.82 [0.43, 1.57]	0.552	0.86 [0.45, 1.64]	0.645
Number of cigarettes smoked	0.6	1.02 [0.98, 1.06]	0.449	1.01 [0.97, 1.05]	0.506
Age of smoking initiation	9.5	1.00 [0.94, 1.07]	0.937	0.97 [0.94, 1.06]	0.917
Duration of smoking	1.9	0.98 [0.96, 1.00]	0.113	0.98 [0.96, 1.00]	0.097
Cumulative smoking amount (pack-year)	2.2	0.99 [0.97, 1.02]	0.574	0.99 [0.97, 1.01]	0.374
Attempted to quit in the past year	23.1	0.89 [0.47, 1.69]	0.723	0.92 [0.52, 1.64]	0.788
Motivation	6.3				
External		reference	-	reference	-
Internal		2.15 [0.63, 7.36]	0.224	2.10 [0.61, 7.19]	0.237
Stage of change	3.5				
Preparation		reference	-	reference	-
Contemplation		8.09 [2.84, 23.07]	< 0.001	8.20 [2.89, 23.34]	< 0.001
Time to first cigarette	6.0				
Within 5 minutes		2.19 [1.08, 4.44]	0.030	2.19 [1.08, 4.45]	0.029
6–30 minutes		1.33 [0.64, 2.75]	0.446	1.34 [0.67, 2.68]	0.403
More than 30 minutes		reference	-	reference	-
Severity of nicotine dependence	5.4				

Characteristic	Missing (%)	Before imputation*		After imputation**	
		Crude OR [95% CI]	p value	Crude OR [95% CI]	p value
Mild		reference	-	reference	-
Moderate		2.17 [1.16, 4.05]	0.015	1.93 [1.06, 3.50]	0.030
Severe		3.36 [0.75, 15.11]	0.113	3.41 [0.76, 15.24]	0.109

Note: OR = odds ratio; *Univariable logistic regression was used for crude OR, **Multiple imputations by chained equations were used for imputations, and $p < .05$ was considered statistically significant.

According to the baseline characteristics, a total of 11 predefined factors were selected: gender, age, health issues, close contacts who smoke, spouse/partner/children, alcohol/substance use, attempt to quit in the past year, motivation, cumulative smoking amount (pack-years), stage of change, and severity of nicotine dependence. These factors were incorporated into a stepwise backward logistic regression model with a p value threshold of $< .1$ to develop the final model. The final model identified the following predictors, ordered by strength of association: stage of change, severity of nicotine dependence, gender, having a spouse/partner/children, and health-related issues (Table 3).

Table 3: The Final Model With Assigned Risk Scores

Predictor	OR [95% CI]	Coefficient	p value*	Score
Gender				
Male	reference	reference	-	0
Female	3.12 [0.99, 9.81]	1.14	0.051	1.5
Having a spouse/partner/children				
Yes	reference	reference	-	0
No	2.62 [1.27, 5.38]	0.96	0.009	1.5
Health issues				
Yes	reference	reference	-	0
No	2.04 [0.99, 4.21]	0.71	0.054	1
Severity of nicotine dependence				
Mild	reference	reference	-	0
Moderate	2.28 [1.19, 4.36]	0.83	0.012	1
Severe	7.06 [1.41, 35.32]	1.95	0.017	3
Stage of change				
Preparation	reference	reference	-	0
Contemplation	7.96 [2.75, 23.09]	2.07	<0.001	3

Note: OR = odds ratio; * Stepwise backward logistic regression with $p < .1$ was used.

The total model score, calculated by summing the scores of all factors, ranges from 0 to 11 and corresponds to the average probability of treatment failure (Table 4).

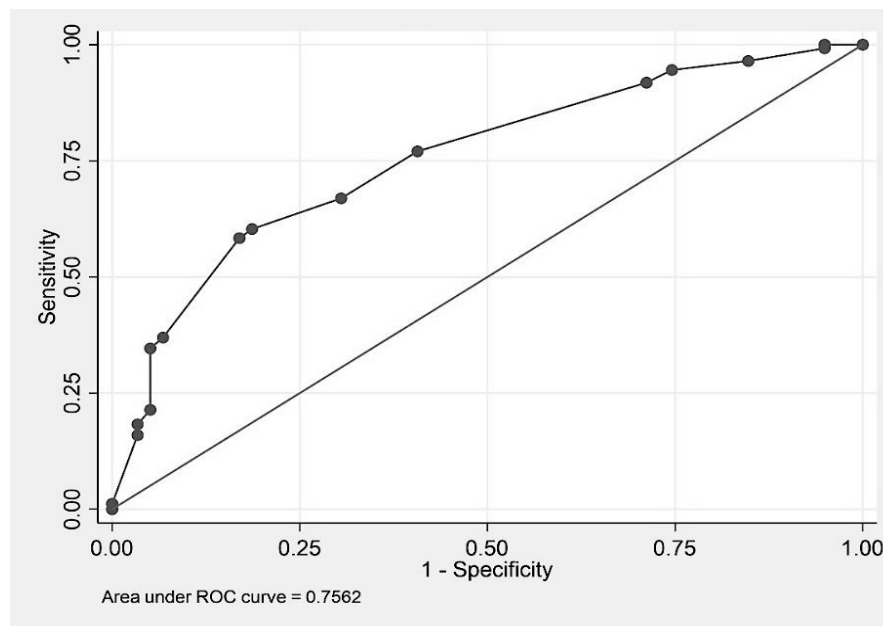
Table 4: The Average Probability of Treatment Failure at Different Total Scores

Total score	Risk of failure (%)
0	11
1	18
2	29
3	42
4	57
5	71
6	81
7	89
8	93

Total score	Risk of failure (%)
9	96
10	98
11	99

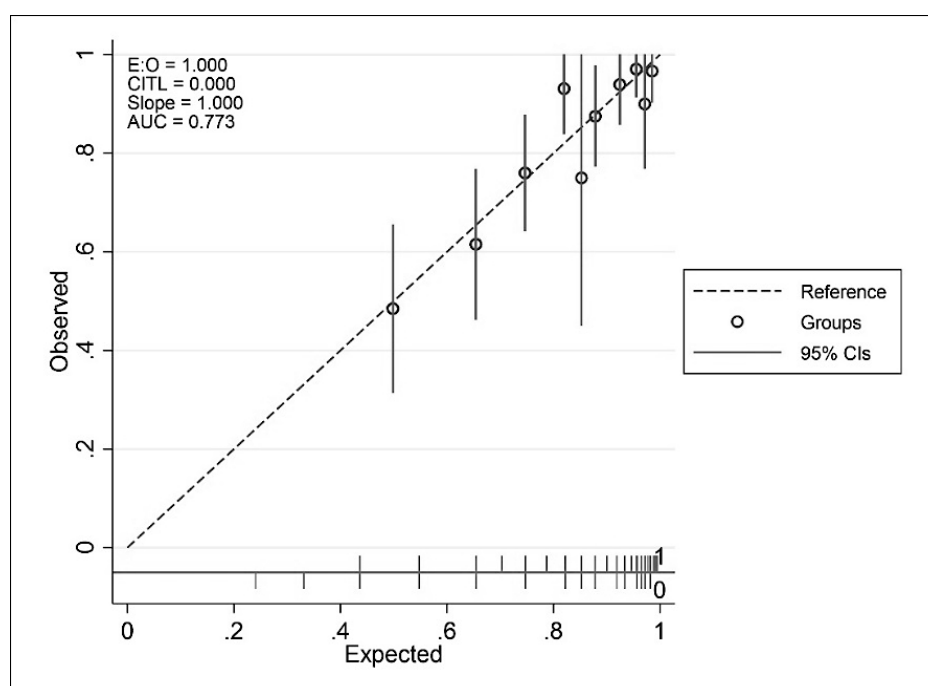
The total risk scores differed significantly between individuals who failed to quit smoking and those who succeeded. The mean score for the failure group was 6.95 ± 1.87 , compared to 5.27 ± 1.54 for the success group ($t = -6.41$, $p < .001$). Discrimination analysis revealed an ROC = 0.76, 95% CI [0.69, 0.82] (Figure 1).

Figure 1: ROC curve for Model Discrimination



The ROC for the bootstrap data was 0.71 (95% CI [0.64, 0.78]), which was closely consistent with the original data. The calibration test results indicated that the model's predictions aligned well with the actual data (Figure 2). Additionally, the Hosmer-Lemeshow goodness-of-fit test yielded a p value of 0.479, indicating that the model is not significantly different from the observed events.

Figure 2: The Calibration Plot for Model Validation



The appropriate cutoff score for categorizing patients into two risk groups is 5/5.5, which provides high sensitivity and an acceptable level of specificity (Table 5). Patients with a total risk score of < 5.5 are classified as low risk, while those with a score ≥ 5.5 are at high risk for treatment failure and should be considered for smoking cessation medication. Nonetheless, when applying the suggested cutoff scores, the plausibility of the predictors should be evaluated for each patient individually. The diagnostic performance is outlined in Table 6.

Table 5: Diagnostic Accuracy at Various Cutoff Scores

Cutoff point	Sensitivity	Specificity	Classified	LR+	LR-
≥ 5	91.83%	28.81%	80.06%	1.29	0.28
≥ 5.5	77.04%	59.32%	73.73%	1.89	0.39
≥ 6	66.93%	69.49%	67.41%	2.19	0.48
≥ 6.5	60.31%	81.36%	64.24%	3.23	0.49

Note: LR = likelihood ratio

Table 6: Diagnostic Performance Using a Cutoff Score of 5.5 or Higher

Diagnostic Measure	Estimate (%) [95% CI]
%Sensitivity	77.0 [71.4, 82.0]
%Specificity	59.3 [45.7, 71.9]
%PPV	89.2 [84.3, 92.9]
%NPV	37.2 [27.5, 47.8]
LR+	1.89 [1.38, 2.60]
LR-	0.39 [0.28, 0.53]

Note: PPV = positive predictive value, NPV = negative predictive value, LR = likelihood ratio

Discussion

The objective of this research was to develop a predictive instrument that relies solely on personal factors available during the patient's initial visit. The tool features clear interpretation guidelines and recommendations to ensure ease of use by interdisciplinary professionals in practice. These may include pharmacists, psychologists, nurses, or other public health personnel trained to provide smoking cessation services, whether in smoking cessation clinics, pharmacies, community health centers, or smoking cessation hotlines from various institutions. The developed model includes five key predictive factors, ranked by their calculated risk scores as follows: stage of change (according to TTM), severity of nicotine dependence (assessed by HSI), gender, having a spouse/partner/children, and health issues.

Stage of change or readiness to quit smoking is a key factor that clearly impacts treatment success, aligning with previous research, which found that individuals who are not planning to quit smoking within the next month have a higher likelihood of failure compared to those who are ready to quit smoking (Lin et al., 2023; Zhou et al., 2009). Smoking cessation medications and behavioral interventions can help reduce physical barriers such as cravings and withdrawal symptoms. Additionally, healthcare providers should assist patients in recognizing the benefits of quitting and linking the negative consequences of smoking to current or future concerns. Helping patients plan how to overcome their obstacles can strengthen motivation and help them become ready for treatment more quickly.

The severity of nicotine dependence is a factor strongly associated with the pathological effects of smoking. Most assessment tools, such as the Fagerstrom Test for Nicotine Dependence (Sherman, 2013b) and HSI (Rungreunghiranya & Krobthong, 2021), include essential questions that reflect the physical addiction caused by nicotine binding to receptors, such as the number of cigarettes smoked or the time it takes to smoke the first cigarette after waking up. As a result, individuals with higher nicotine dependence are more likely to experience treatment failure, as supported by both theoretical models and research findings (Caponnetto & Polosa, 2008; Esen et al., 2020; Lin et al., 2023; Monsó et al., 2001; Zhou et al., 2009). Therefore, individuals with severe nicotine dependence should be treated with medication combined with behavioral interventions to help reduce cravings and alleviate withdrawal symptoms that may occur (CDC, 2021).

This study found that females are 3.12 times more likely to fail treatment than males. While existing research has not yet definitively concluded whether gender is associated with smoking cessation success (Caponnetto & Polosa, 2008; Esen et al., 2020; Gourlay et al., 1994; Monsó et al., 2001), several studies suggest that females require special attention during the treatment process (Caponnetto & Polosa, 2008; Esen et al., 2020; Perkins, 2012). This is because women are influenced by multiple factors that may contribute to treatment failure or relapse, such as weight gain after quitting, emotional changes, the role of social support, and influences from those around them during the treatment process (Caponnetto & Polosa, 2008; Esen et al., 2020; Perkins, 2012).

Individuals without a spouse, partner, or children are at higher risk of treatment failure, consistent with several previous studies (Caponnetto & Polosa, 2008; Gourlay et al., 1994; Kim & Cho, 2014; Sornpaisarn et al., 2022). Having a spouse, partner, or children provides significant internal motivation for behavior change and offers essential support in overcoming obstacles. Similarly, those who are unaware of or fail to recognize the health risks associated

with smoking tend to experience higher treatment failure rates, as health issues can serve as a strong internal motivator or key reason for seeking smoking cessation treatment (Choi et al., 2012; Lin et al., 2023; Monsó et al., 2001; Qiu et al., 2020; Soares de Azevedo & Fernandes, 2011; Sornpaisarn et al., 2022; Tin et al., 2012; Zhu et al., 2022). However, this finding may contradict Thailand's clinical guidelines, which suggest using smoking cessation medications for individuals with chronic diseases (Rungreunghiranya & Krobthong, 2021). The guidelines primarily focus on the overall health impact, recognizing that smoking worsens chronic conditions. In contrast, this study examines treatment failure, suggesting that individuals without health problems may lack sufficient motivation to quit, making them more likely to fail in treatment.

The developed model demonstrates acceptable discriminatory power (Mandrekar, 2010), as indicated by the ROC curve and statistically significant differences in mean risk scores between the two groups. Additionally, the model demonstrated strong predictive accuracy. The positive predictive value (PPV) indicated that patients with a score of 5.5 or above are nearly 90% likely to experience treatment failure. As a result, this model is suitable for preliminary screening to help clinical personnel identify patients who need medication or be referred for more intensive treatment to receive appropriate medications. A prompt decision by the clinical staff can enhance success rates.

The model developed in this study differs from similar previous studies in several aspects. For example, the study by Lai et al. (2021) focused on smoking cessation in outpatient settings in Taiwan, which involved medication use. In contrast, this study focuses on a non-hospital clinic setting without medication. Lai et al. used machine learning techniques with a specialized program to analyze multiple predictors. In contrast, this study uses only five predictors, and the results can be calculated manually without specialized software or computer systems.

Additionally, this model demonstrated higher discriminatory power (ROC: 0.76 vs. 0.66) (Lai et al., 2021). Another similar study, conducted by Zhu et al. (2020) in China, examined smoking cessation in a hospital-based quit-smoking clinic. The two studies differ in their treatment context and interventions. Zhu et al. incorporated non-personal factors, like the number of clinic visits, which could be assessed at follow-up. Although their model demonstrated good discrimination (ROC: 0.82), it lacks a recommended score cutoff and a clear interpretation for end users.

This study has several limitations: 1) Since it is a retrospective study based on existing database records, some data were missing, which could have impacted the study findings, 2) smoking cessation outcomes was assessed at six months, making it uncertain whether patients could maintain long-term abstinence, 3) The study was conducted at a private university smoking cessation clinic, where non-pharmacological treatments were the primary intervention. As a result, the findings are most relevant to smoking cessation services in pharmacies, community health centers, or clinics that primarily use non-pharmacological interventions. However, they may not be generalized to other populations, such as patients in smoking cessation clinics at large hospitals, or those receiving both medication and psychotherapy. Future research should consider prospective data collection in various healthcare settings and explore a broader range of treatment approaches.

Conclusion

The developed model includes five clinical prediction factors, as follows: stage of change, severity of nicotine dependence, gender, having a spouse/partner/children, and health issues. Individuals who achieve a total score of 5.5 or above should be considered for pharmacological interventions to support smoking cessation. The model demonstrated acceptable discrimination and accurate predictions.

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