Jordanian Journal of Engineering and Chemical Industries

Print ISSN: 2616 - 9584 Online ISSN: 2617 - 720X

Nicotine as A Hazardous Chemical: Analysis of Smoking Behavior and Cessation Strategies among Pharmacy Students in Jordan using Chemical, Statistical and Machine Learning Approaches

Etab Taha AL Kasasbeh [1*], Wasan AL Maaitah[2], Ruba T. AL Kasasbeh[3], Ashraf Shaqadan[4], Osama Al-Hababheh[e]

1 AL-Balqa Applied University, Department of Medical Support, Al-Karak University Collage, Al-Karak, Jordan;

2 The University of Jordan,Amman,Jordan, 11942, Amman, Jordan, c The Jordanian Ministry of Education

3 Zarqa University, The University of Jordan,Amman,Jordan, 11942, Amman, Jordan,

Highlights

- Study examined smoking prevalence, attitudes, and cessation strategies among 822 pharmacy students at Balqa Applied University, Jordan (Jan 2022–Jan 2023).
- 25% of participants were non-smokers; 93.6% recognized the health risks of smoking.
- Common cessation methods used were electronic cigarettes (44.4%), nicotine gum (13.3%), and nicotine patches (6.0%), while 30.8% were unaware of available cessation options.
- Neural network models were effective in detecting rare cessation strategies and identifying individuals at higher risk of cessation failure, aiding targeted interventions.

Abstract

Nicotine, a primary chemical hazard in tobacco, presents severe health risks, including addiction and chronic diseases. This study employs a biostatistics and machine learning framework to analyze smoking prevalence, beliefs, and attitudes toward smoking cessation among pharmacy students at Balqa Applied University, Al-Kerak University College, Jordan. A cross-sectional survey was conducted from January 2022 to January 2023, involving 822 participants. Smoking behaviors, perceptions of nicotine's health effects, and cessation knowledge were assessed using descriptive and inferential statistics with SPSS (version 26). In addition, Random Forest (RF) and fully connected Neural Network (NN) models were developed, supported by SMOTE for class imbalance, to predict smoking status and cessation engagement. Results showed that 25% of students were non-smokers, and 93.6% acknowledged smoking's health risks. Common cessation methods included electronic cigarettes (44.4%), nicotine gum (13.3%), and nicotine patches (6.0%), whereas 30.8% were unaware of any cessation strategies. Furthermore, 79.4% supported specialist clinics for quitting, 81.3% endorsed public smoking bans, and 88.7% favored restricting tobacco sales to minors. Age and gender emerged as significant predictors of smoking prevalence and cessation engagement ($p = 0.0001$). Comparative modeling indicated that RF achieved superior overall prediction accuracy, while NN models better detected rare cessation strategies and identified individuals at higher risk of treatment failure. These findings highlight the value of integrating biostatistics and machine learning in public health research and reinforce the need to strengthen smoking cessation education in pharmacy curricula.

Paper type: Research paper

Keywords: Nicotine , Smoking , Smoking Cessation , Pharmacy Students , Jordan, Nicotine Risk

Citation: AL Kasasbeh EA, AL Maaitah W, AL Kasasbeh R T., Shaqadan Ashraf, Al-Habahbeh O ' " Nicotine as A Hazardous Chemical and Smoking Behaviors and Cessation Strategies among Pharmacy Students in Jordan: Chemical and Statistical and Machine Learning Approach " *Jordanian Journal of Engineering and Chemical Industries*, Vol. **8** No.3, pp:227-246 (2025).

* Corresponding author: E-mail: etab.kasasbeh@bau.edu.jo ORDIC: **https://orcid.org/0009-0005-4747-2333**

Received : 10 Sep 2025 Revised: 8 Nov 2025 Accepted: 16 Nov 2025

Jordanian Journal of Engineering and Chemical Industries (JJECI), Vol.8, No3, 2025, pp: 227-246. .

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1. Introduction

Nicotine, 3-(1-methyl-2-pyrrolidinyl) pyridine, is the main alkaloid in tobacco leaves (Nicotiana tabacum L., Solanaceae), the latter being best known for their use in cigarettes rather than for their therapeutical applications [Doolittle *et al.*,1995]. Fig. 1 shows the chemical structure of nicotine. The frequent intake of nicotine in the human body may cause a broad spectrum of diseases that extend towards many different organ systems. Its numerous deleterious health effects, combined with the substantial prevalence of cigarette smoking, make it a major worldwide cause of death. Smoking contributes greatly to the mortality burden because it is a major cause of vascular disease, cancer, and chronic obstructive pulmonary disease [Yildiz, 2004; Alberg, 2008].

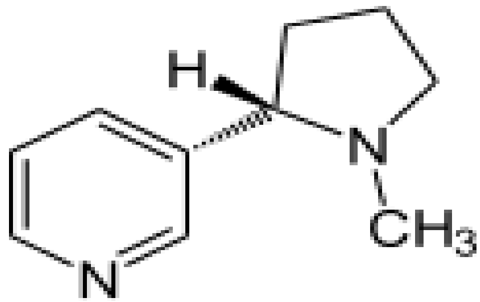

Fig. 1. Chemical structure of nicotine

moking is a major contributor to health risks, adversely affecting both physical performance and overall quality of life (WHO, 2021). Globally, an estimated 1.3 billion individuals aged 15 years and older currently smoke, with 80% residing in low- and middle-income countries where the burden of tobacco-related morbidity and mortality is most severe (WHO, 2022). The cultivation and demand for tobacco have been steadily rising in emerging nations (ASH, 2022). Projections suggest that smoking rates in these countries will continue to increase due to several factors, including population growth, greater affordability of tobacco products, rising income levels, and aggressive marketing strategies (ASH, 2022).

Jordan, a developing Middle Eastern country, faces a particularly high prevalence of tobacco-related diseases and elevated smoking rates among both young men and women. Nicotine, chemically known as 3-(1-methyl-2-pyrrolidinyl) pyridine, is the principal alkaloid found in tobacco leaves (Nicotiana tabacum L., Solanaceae). These leaves are primarily recognized for their use in cigarette production rather than therapeutic purposes. Figure 1 illustrates the chemical structure of nicotine. In its pure form, nicotine is a clear liquid with a distinctive odor that turns brown upon exposure to air. It is miscible with water in equal proportions but shows preferential solubility in organic solvents, allowing easy extraction from aqueous solutions by solvent separation. Nicotine is a strong base with a boiling point of 274.5 °C at 760 Torr (Doolittle et al., 1995)."

"Nicotine is distilled from burning tobacco and transported proximally on tar droplets (particulate matter), which are inhaled. Its absorption across biological membranes is strongly influenced by pH. As a weak base with a pKa of 8.0, nicotine in its ionized form—typical of acidic environments—does not readily cross membranes. The smoke of flue-cured tobaccos, commonly used in most cigarettes, is acidic (pH 5.5–6.0), resulting in nicotine being predominantly ionized. Consequently, buccal absorption of nicotine from flue-cured tobacco smoke is minimal, even when held in the mouth (Gori et al., 1986). In contrast, smoke from air-cured tobaccos, used in pipes, cigars, and some European cigarettes, is more alkaline (pH ≥ 6.5), producing a higher proportion of unionized nicotine that is readily absorbed through the oral mucosa (Armitage et al., 1978). More recent evidence suggests that the pH of cigarette smoke particulate matter may be higher than previously thought, allowing more nicotine to remain in the unionized state and facilitating rapid pulmonary absorption (Pankow, 2001).

Once tobacco smoke reaches the small airways and alveoli, nicotine is rapidly absorbed. Blood concentrations rise quickly during smoking and peak by the end of a cigarette. This rapid uptake is attributed to the large alveolar surface area and the dissolution of nicotine in the fluid at pH 7.4, which promotes efficient membrane transfer. Following a puff, high nicotine levels reach the brain within 10–20 seconds—faster than intravenous delivery—resulting in immediate behavioral reinforcement (Henningfield & Keenan, 1993). This speed of absorption allows smokers to titrate nicotine intake to achieve desired effects, making cigarette smoking the most reinforcing and dependence-inducing mode of nicotine administration. After absorption, nicotine circulates in the bloodstream, where at pH 7.4, approximately 69% is ionized and 31% unionized. Plasma protein binding is minimal (<5%),

and the drug distributes widely into body tissues, with a steady-state volume of distribution averaging 2.6 L/kg. Autopsy studies of smokers show the highest tissue concentrations in the liver, kidney, spleen, and lung, with the lowest in adipose tissue. In skeletal muscle, nicotine and its metabolite cotinine are found in levels similar to whole blood. Nicotine binds strongly to brain tissues, and smokers exhibit an increased receptor-binding capacity due to upregulation of nicotinic cholinergic receptors (Perry et al., 1999).

Nicotine also accumulates in gastric juice and saliva, with gastric juice/plasma and saliva/plasma concentration ratios of 61 and 11, respectively, following transdermal administration, and 53 and 87 after smoking. This accumulation results from ion trapping in acidic fluids. Nicotine further accumulates in breast milk (milk/plasma ratio 2.9) and crosses the placenta readily, with fetal serum and amniotic fluid concentrations slightly exceeding those in maternal serum (Dempsey & Benowitz, 2001).

The pharmacologic effects of nicotine depend on both route and rate of administration. Smoking delivers nicotine rapidly via the pulmonary venous circulation to the left ventricle, systemic arterial circulation, and the brain, with a lag time of only 10–20 seconds. Although nicotine delivery to the brain is immediate, pulmonary uptake and delayed release also occur, as demonstrated by positron emission tomography and the gradual decline in arterial concentrations between puffs (Rose et al., 1999). Arterial nicotine concentrations after smoking may reach as high as 100 ng/ml, though they typically range between 20–60 ng/ml, with an average of 7 ng/ml after the first puff (Lunell et al., 2000; Rose et al., 1999). Arterial/venous nicotine ratios can be as high as tenfold but generally average 2.3–2.8 (Henningfield et al., 1993). The rapid delivery of nicotine by smoking (or intravenous injection, which produces similar kinetics) leads to high central nervous system levels with little time for tolerance to develop, resulting in more intense pharmacologic effects. This short interval between puffing and nicotine’s action in the brain enables smokers to titrate doses precisely, reinforcing drug self-administration and promoting addiction (Lunell et al., 2000)."

Nicotine is extensively metabolized to a number of metabolites by the liver. Six primary metabolites of nicotine have been identified. Quantitatively, the most important metabolite of nicotine in most mammalian species is the lactam derivative, cotinine. In humans, about 70–80% of nicotine is converted to cotinine but only 10–15% of nicotine absorbed by smokers appears in the urine as unchanged cotinine. Six primary metabolites of cotinine have been reported in humans: 3′-hydroxycotinine 5′-hydroxycotinine (also called allohydroxycotinine) (which exists in tautomeric equilibrium with the open chain derivative 4-oxo-4-(3-pyridyl)-N-methylbutanamide, cotinine N-oxide, cotinine methonium ion, cotinine glucuronide, and norcotinine (also called demethylcotinine) ((Neurath 1994).

3′-Hydroxycotinine is the main nicotine metabolite detected in smokers’ urine. It is also excreted as a glucuronide conjugate .3′-Hydroxycotinine and its glucuronide conjugate account for 40–60% of the nicotine dose in urine (The conversion of cotinine to 3′-hydroxycotinine in humans is highly stereoselective for the trans-isomer, as less than 5% is detected as cis-3′-hydroxycotinine in urine .While nicotine and cotinine conjugates are N -glucuronides, the only 3′-hydroxycotinine conjugate detected in urine is O-glucuronide (Byrd et al. 1994).

Quantitative aspects of the pattern of nicotine metabolism have been elucidated fairly well in people(fig2) .Approximately 90% of a systemic dose of nicotine can be accounted for as nicotine and metabolites in urine (Benowitz et al. 1994). Based on studies with simultaneous infusion of labeled nicotine and cotinine, it has been determined that 70–80% of nicotine is converted to cotinine ,About 4–7% of nicotine is excreted as nicotine N′–oxide and 3–5% as nicotine glucuronide (Benowitz et al. 1994; Byrd et al. 1992). Cotinine is excreted unchanged in urine to a small degree (10–15% of the nicotine and metabolites in urine). The remainder is converted to metabolites, primarily trans–3′–hydroxycotinine (33–40%), cotinine glucuronide (12–17%), and trans–3′–hydroxycotinine glucuronide (7–9%) (Benowitz et al. 1994).

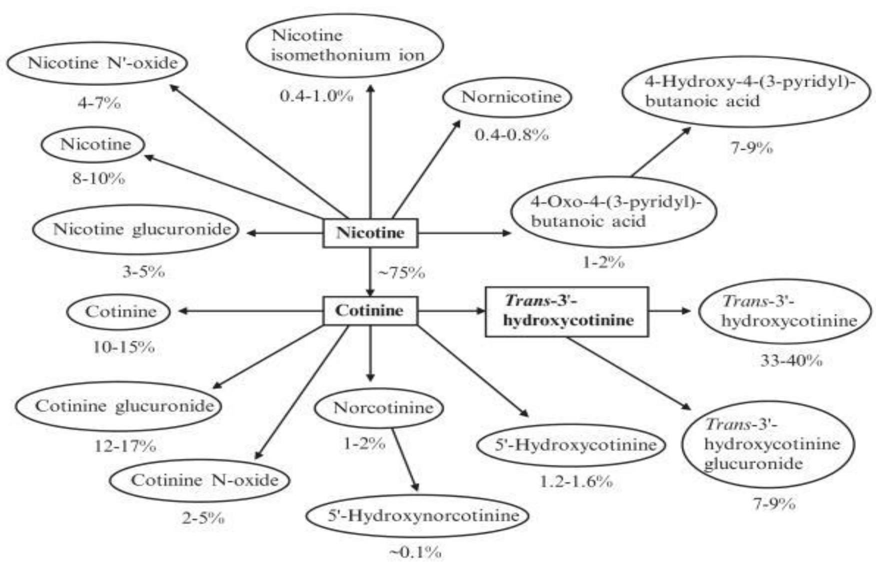

Fig.2. Quantitative scheme of nicotine metabolism

Quantitative scheme of nicotine metabolism, based on estimates of average excretion of metabolites as percent of total urinary nicotine. Reprinted with permission from Hukkanen et al. 2005c

2. Materials and Methods

2.1 Methods

Nicotine measurement is highly specific to tobacco use but requires expensive laboratory instrumentation. It is also limited by nicotine's relatively short half-life in blood, approximately 2 h. In contrast, cotinine offers higher sensitivity and specificity than other biochemical tests and is therefore regarded as the best biomarker of tobacco smoke exposure [13]. Cotinine has a half-life of 20 h (range 15–40 h), allowing detection for up to one week after the last smoking episode. Its levels are directly proportional to the amount of nicotine absorbed, making cotinine a highly reliable and tobacco-specific marker. It can be measured in urine, saliva, and plasma, and is considered the most accurate and sensitive measure when precision is essential [14].

Several studies have evaluated the practicality of urinary cotinine test strips. Findings suggest that these strips determine smoking status with reasonable accuracy [14]. Another investigation reported that urinary cotinine test strips provide a rapid and simple method for detecting cotinine in urine samples [15].

A one-year cross-sectional study was conducted from January 2022 to January 2023, targeting diploma-level pharmacy students at Balqa Applied University–Al-Karak University College in southern Jordan. Eligible participants were pharmacy students aged 18 years or older. The survey aimed to assess smoking prevalence, perceptions, and attitudes toward cessation methods. Data were analyzed descriptively using SPSS version 26. Confidentiality was ensured, and participants were informed that responses would be used solely for research purposes.

The questionnaire consisted of two parts. The first collected demographic and behavioral information, including age, gender, smoking history, frequency, awareness of smoking hazards, and previous cessation attempts. The second explored beliefs and attitudes toward the effectiveness of cessation interventions. Beliefs were assessed on a five-point Likert scale (from "strongly agree" to "strongly disagree"), while attitudes were rated on a four-point scale (from "very useful" to "I don't know").
A rapid visual immunoassay was used for qualitative detection of cotinine in human urine, with a cutoff value of 200 ng/ml. This device does not detect cotinine levels below 100 ng/ml, which are typical of passive smokers. Cotinine detection was based on visual interpretation of color development on the assay device.

2.2 Data Analysis

The data were analyzed using SPSS version 26 for Windows (SPSS Inc., Chicago, Illinois). Descriptive statistics were applied to summarize demographic characteristics concisely. For univariate analyses, the Chi-squared test and Fisher's exact test were conducted, as appropriate, to evaluate differences between variables. A p-value of less than 0.05 was considered statistically significant, and the 95% confidence interval (CI) further supported the robustness of the findings. Subsequently, suitable machine learning algorithms, such as Random Forest and SMOTE, were selected for their ability to accurately classify smoking behaviors. The dataset was divided into training and testing subsets to ensure unbiased evaluation. Model performance was assessed using multiple metrics, including precision, recall, and F1-score, to provide a comprehensive evaluation of classification accuracy.

3. Results

Table 1 displays the results of the questionnaire, which was completed with a total of 822 students. Among them, 70.2% (n=577) were males and 29.8% (n=245) were females. The age group of 18 to less than 25 years had the most representation, accounting for 55.6% of the total. This was followed by the age group of 25 to less than 32 years, which made up 18.2%. The smoking incidence among all students was 74.8% (n= 615), with daily smokers comprising 70.2% (n=577). 93.6% (n=769) were educated on the hazards of smoking. In relation to smoking cessation, a total of 442 students, including about 53.8% of the sample, had made attempts to quit smoking. Table 1 displayed comprehensive data on the demographic characteristics and smoking status of the participants.

Table 1. Demographic characteristics and smoking behavior among 822 students

	Frequency (n)	Percent (%)
Gender		
Female	245	29.8
Male	577	70.2
Age		
18 – less 25 y	457	55.6
25 – less 32 y	150	18.2
32 – less 40 y	69	8.4
40 y and more	146	17.8
Do any of your parents work in a health care setting?		
No	614	74.7
Yes	208	25.3
DO you smoke?		
No	207	25.2
Yes	615	74.8
Age range of first-time smoking		
00	207	25.2
9 - less 15y	96	11.7
15 – less 20y	339	41.2
20 – less 25y	147	17.9
25 y and more	33	4.0
How frequent are you smoking?		
Never smoker	207	25.2
Occasional smoker	38	4.6
Daily smoker	577	70.2
Have you tried to quit smoking?		
00	207	25.2
No, I never tried	155	18.9
I don't want to quit smoking	18	2.2
Yes, sometimes	68	8.3
Yes, more often	374	45.5
Have you received any education on the dangers of smoking?		
I Don't know	32	3.9
No	21	2.6
Yes	769	93.6
Number of cigarettes smoking per day?		
00	207	25.2
31 or more	102	12.4
21-30	149	18.1
11-20	240	29.2
10 or less	124	15.1

(N =207): Nonsmoker (N=615): Smoker

Less than half of the respondent students (44.4%) stated that electronic cigarettes (ESs) were the self-control approach they had heard of before. This was followed by nicotine gum (13.3%), nicotine patch (6.0%), treatment (4.3%), and nicotine spray (1.3%), as indicated in Table 2. When surveying smokers about the smoking cessation strategies they had previously attempted, around 38.8% reported using electronic cigarettes (ECs), whereas 21.2% had never tried them. Smokers consider lung cancer to be the most significant risk they encounter, accounting for 40.1% of their concerns. This is followed by cardiovascular disease at 29.1% and COPD at 18.5%, as shown in figure 1.

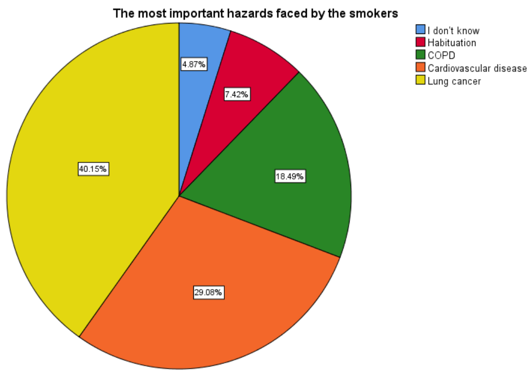

Fig 3. Pie chart of sample response analysis

Table 2. Types of smoking responses

Parameters	Frequency (n)	Percent (%)
Which methods of smoking cessation have you heard before?		
Electronic cigarettes	365	44.4
Nicotine patch	49	6.0
Nicotine gum	109	13.3
I don't know	253	30.8
Nicotine spray	11	1.3
Therapy	35	4.3
Which methods of smoking cessation have you tried before?		
0.0	207	25.2
Electronic cigarettes	319	38.8
Nicotine patch	27	3.3
Nicotine gum	76	9.2
I don't try	174	21.2
Nicotine spray	10	1.2
Therapy	9	1.1

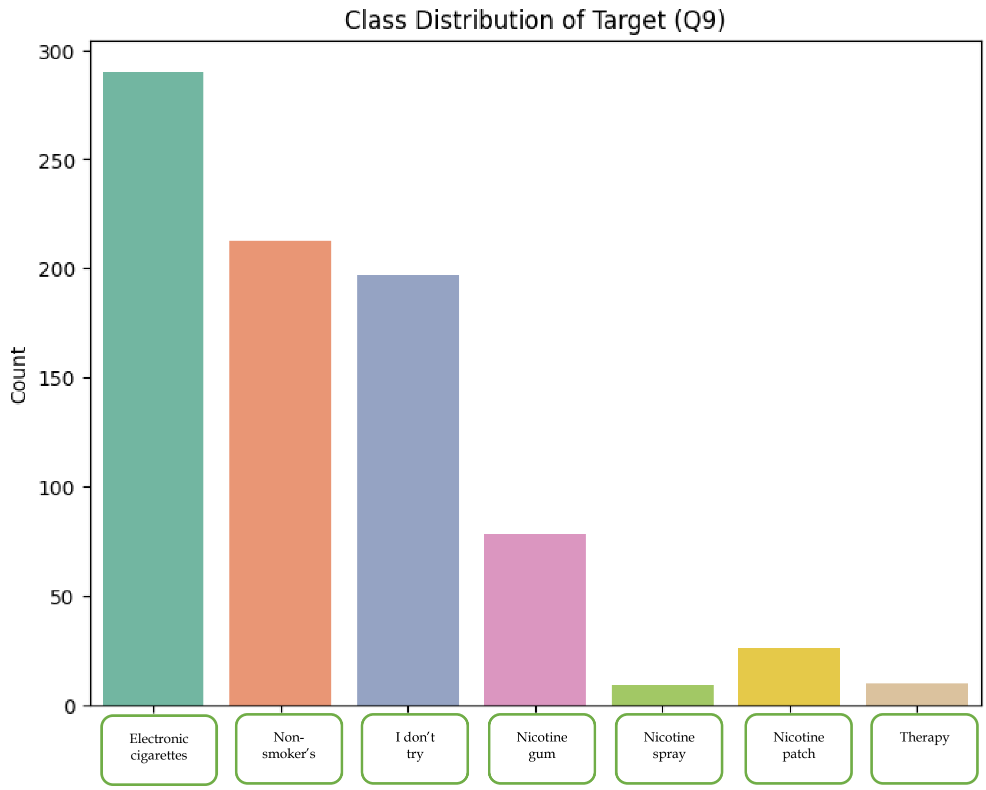

Fig 4.. Class Distribution of Smoking Cessation Methods

Approximately 81.3% of students expressed agreement with the prohibition of smoking in public settings, as seen in Table 3. The majority of students, namely 88.7%, agreed that the selling of tobacco to minors should be prohibited. Similarly, 62.2% of students stated that smoking tobacco in colleges and cafés should be restricted as well. A significant majority of students (79.4%, n=653) held the belief that specialist smoking cessation clinics are successful and beneficial strategies for quitting smoking. However, the rest of students hold the belief that specialist smoking cessation clinics are not beneficial, with a percentage of 20.6%. Table 4 has comprehensive information.

Table 3. Survey Results

Parameters	Frequency (n)	Percent (%)
Smoking in public places should be banned		
Strongly disagree	22	2.7
Disagree	104	12.7
I Don't know	28	3.4
Agree	370	45.0
Strongly agree	298	36.3
Tobacco sales to adolescents should forbidden		
Strongly disagree	22	2.7
Disagree	52	6.3
I Don't know	19	2.3
Agree	354	43.1
Strongly agree	375	45.6

Tobacco smoking in universities and café should be forbidden		
Strongly disagree	27	3.3
Disagree	238	29.0
I Don’t know	46	5.6
Agree	296	36.0
Strongly agree	215	26.2

Table 4. Survey Resoonses

Parameters	Frequency (n)	Percent (%)
Evaluating the usefulness of smoking cessation methods by specialized smoking cessation clinics		
Not useful	169	20.6
Useful	430	52.3
Very useful	223	27.1

A Random Forest Classifier was chosen as the primary classification model because of its robustness and capacity to handle high-dimensional data. Random Forest Classifiers are ensemble learning methods that enhance accuracy by averaging the results of multiple decision trees trained on different data subsets. In this study, the Random Forest Classifier achieved an overall accuracy of 90%, demonstrating strong predictive performance for the target variable, namely: ‘Which methods of smoking cessation have you tried before?’

The model showed high precision and recall for several classes, particularly for nonsmoker, Electronic cigarettes, and I don’t try. Precision scores for these classes were 0.90, 0.92, and 0.88, respectively, while recall values were 0.83, 1.00, and 0.93. These results indicate that the model effectively identified instances within these classes while minimizing false positives.

However, performance varied considerably across other categories. For the Nicotine patch, Nicotine spray, and Therapy classes, the model struggled, with Nicotine spray being especially problematic. The classifier failed to predict any instances of this class, resulting in precision, recall, and F1 scores of 0. Such poor performance can be attributed to class imbalance, as underrepresented categories like Nicotine patch and Therapy had low support, which negatively affected their recall and overall evaluation metrics.

To mitigate these limitations, missing values in the dataset were imputed with the class nonsmoker to avoid gaps that might impair model training. While this strategy reduced missingness, it may have unintentionally exacerbated class imbalance, particularly if the imputed values disproportionately increased representation of the nonsmoker category.

Table 5. The Random Forest Classifier

	precision	recall	f1-score	support
Non-smoker’s	0.90	0.83	0.86	46
Electronic cigarettes	0.92	1.00	0.96	59
Nicotine patch	1.00	0.50	0.67	6
Nicotine gum	0.75	0.90	0.82	10
I don’t try	0.88	0.93	0.90	41
Nicotine spray	0.00	0.00	0.00	1
Therapy	1.00	0.50	0.67	2
accuracy			0.90	165
macro avg	0.94	0.90	0.70	165
weighted avg	0.92	0.92	0.89	165

Resampling with SMOTE for Class Imbalance:

Given that class distribution across smoking cessation Methods as target, responses were imbalanced, therefore, the Synthetic Minority Over-Sampling Technique (SMOT) was applied to balance the dataset. SMOT generates synthetic samples for the minority classes, thereby mitigating class imbalance and helping the model generalize better across all classes.

3.1 Random Forest Classifier with SMOT

The application of SMOT effectively addressed the class imbalance issue, allowing the model to learn from a more representative dataset. As a result, the classification report reflects high precision, recall, and F1-scores for most classes, especially for the minority classes, which were previously challenging for the model. The overall accuracy of 92% suggests that the model is robust and capable of making correct predictions on unseen data. The precision and recall values indicate that the model not only makes accurate predictions but also effectively identifies instances of each class without significant misclassification. The absence of substantial discrepancies between training and test metrics further supports the conclusion that the model generalizes well, rather than merely memorizing the training data. However, it's essential to remain cautious, particularly with classes that have fewer instances. For example, while the model achieved perfect scores for classes with very few samples, this could indicate potential overfitting if those classes have limited variability in real-world scenarios.

Table 6. Random Forest Classifier with SMOT

	precision	recall	f1-score	support
Non-smoker's	0.95	0.85	0.90	46
Electronic cigarettes	0.92	1.00	0.96	59
Nicotine patch	1.00	0.67	0.80	6
Nicotine gum	0.82	0.90	0.86	10
I don't try	0.88	0.90	0.89	41
Nicotine spray	1.00	1.00	1.00	1
Therapy	1.00	1.00	1.00	2
accuracy			0.92	165
macro avg	0.94	0.90	0.91	165
weighted avg	0.92	0.92	0.91	165

3.2 Neural Network

In addition to the random forest, two multilayer neural networks were developed for the multiclass classification of the two target variables. The first neural network answers the question, "Which smoking cessation methods are most suitable for you?", and the second neural network answers the question, "Which smoking cessation methods are least suitable for you?". In other words, the first neural network outputs a ranking of the most preferred methods, while the second outputs an anti-ranking of methods for a given patient.

The input data included the same predictors as in the random forest (RF) model; categorical features were encoded using one-hot/ordinal encoding according to the dataset scheme. The two neural networks have identical architecture but were trained on different datasets. A fully connected network with neuron layers [512]–[256] using ReLU activation, batch normalization, and a dropout rate [0.3]; the output layer uses softmax for 5 classes. The structure of the neural networks is presented in Figure 3.

The Adam optimizer was used with categorical cross-entropy loss [Filist et al., 2025a]. Performance was evaluated based on accuracy, macro-/weighted F1, precision/recall per class, and AUROC (one-vs-rest), the algorithm of training and evaluation is presented in Figure 4. The decision threshold was selected by maximizing the macro-F1 score on the validation set.

The neural network database consisted of two datasets of 500 people each. The first group included individuals who successfully quit smoking using various plans and was used to train the first neural network, while the second group included those who failed to quit using the same plans. All participants were divided into five groups based on their chosen plan: nicotine replacement therapy, behavioral therapy, mobile app support, medication (varenicline), and group counseling.

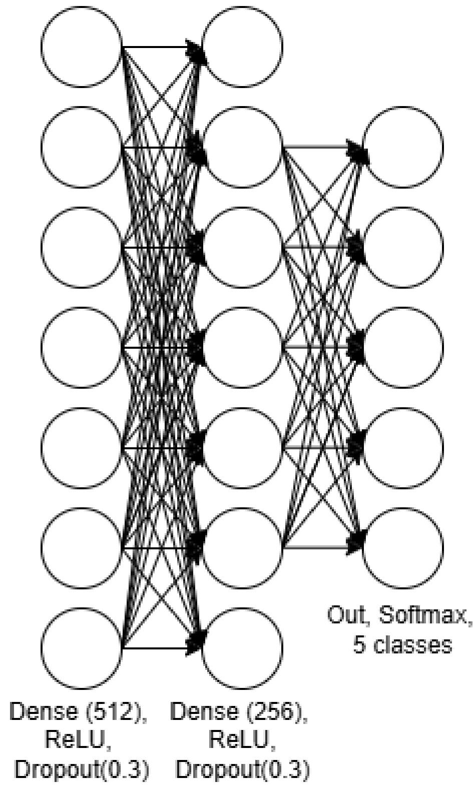

Figure 3. Neural network diagram

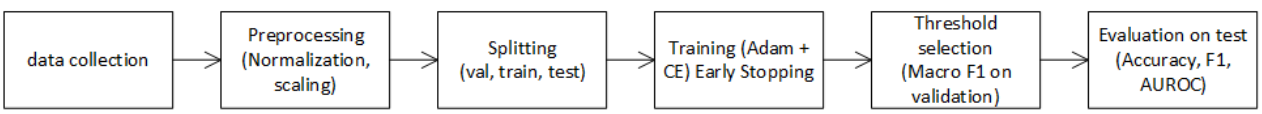

Fig 5. Pipeline of training and evaluation

Below are the results of the model trained on the dataset of people who successfully quit smoking (the success model) and the model trained on data from people who failed to quit using the same plans (the failure model). The training process graphs, accuracy and loss versus epochs (Figures 5, 6), ROC curves (Figure 7), and all other presented metrics for both models were calculated on the training dataset (Tables 7, 8).

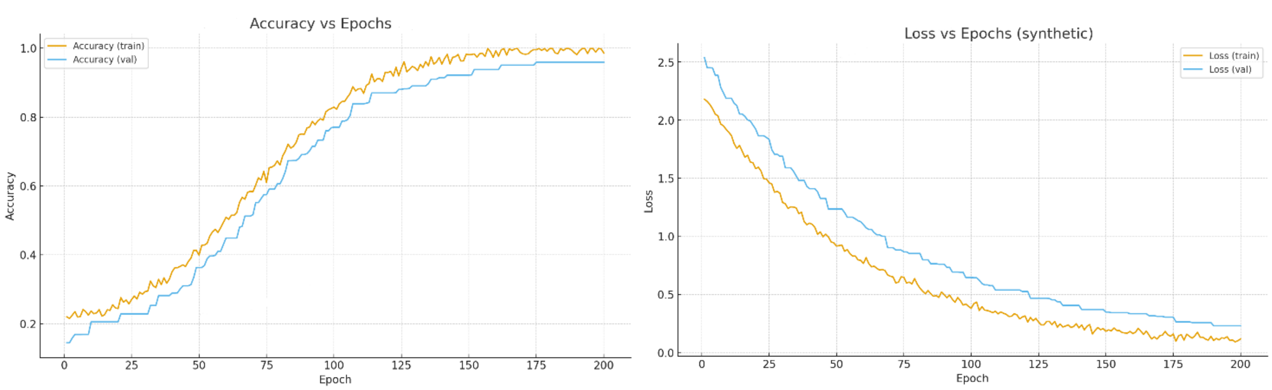

Fig 6. Training and validation accuracy vs. epoch., loss vs. epoch on success model

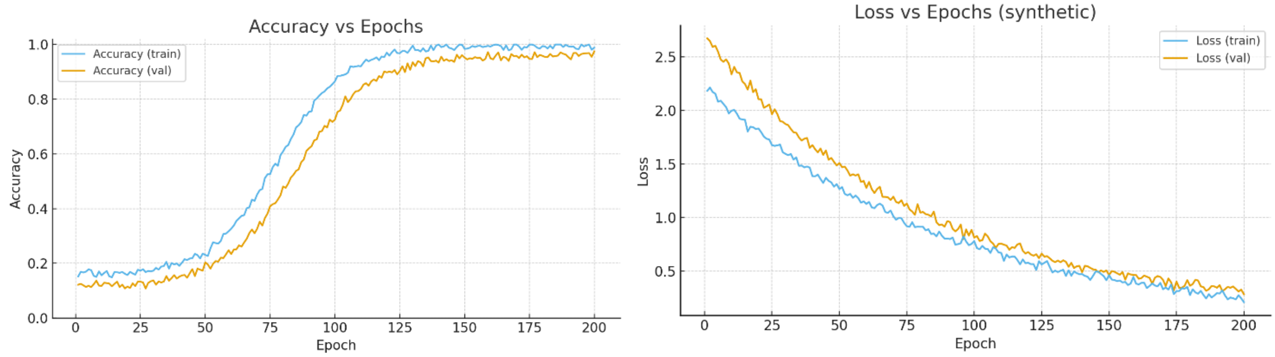

Fig 7. Training and validation accuracy vs. epoch., loss vs. epoch on unsuccess model

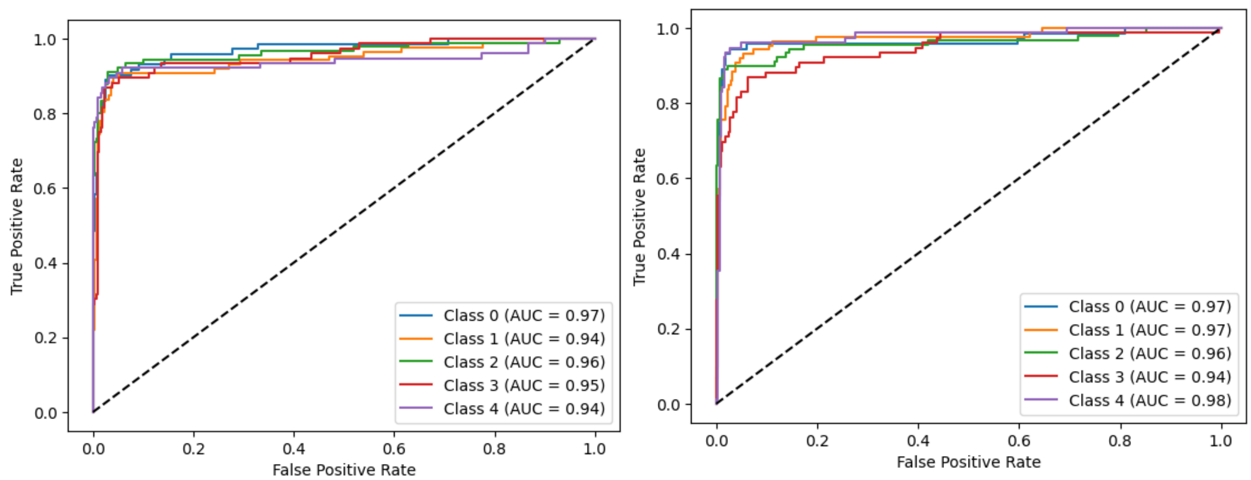

Fig 8. ROC-Curves of the success and unsuccess models

Table 7: Neural Network results on the success model

	precision	recall	f1-score	support
Nicotine Replacement Therapy	0.86	0.89	0.87	72
Behavioral Therapy	0.82	0.9	0.86	86
Mobile App Support	0.89	0.89	0.89	90
Medication (Varenicline)	0.9	0.88	0.89	76
Group Counseling	0.94	0.84	0.88	76
accuracy			0.88	400
macro avg	0.89	0.88	0.88	400
weighted avg	0.89	0.88	0.88	400

Table 8: Neural Network results on the unsuccess model

	precision	recall	f1-score	support
Nicotine Replacement Therapy	0.9	0.94	0.92	72
Behavioral Therapy	0.89	0.88	0.88	86
Mobile App Support	0.93	0.86	0.9	90
Medication (Varenicline)	0.83	0.84	0.83	76
Group Counseling	0.9	0.94	0.92	76
accuracy			0.89	400
macro avg	0.89	0.89	0.89	400
weighted avg	0.89	0.89	0.89	400

Overall, both neural networks demonstrated stable performance with comparable accuracy and macro-F1 scores (0.88–0.89) as shown in table 9. These results confirm the ability of deep learning models to capture non-linear relationships between predictors and cessation outcomes, even in relatively limited datasets. Importantly, the difference between the success-oriented and failure-oriented networks highlights that neural architectures are not only capable of ranking the most suitable cessation strategies but also of identifying patterns of potential relapse. This dual function expands their applicability in clinical and educational contexts.

3.3 Model comparison

Table 9: Model Comparison

Model	Accuracy	Macro-F1	Weighted-F1	Macro Precision	Macro Recall	Log-Loss	Macro AUROC
Random forest	0.9	0.7	0.89	0.94	0.9	-	-
RF + SMOTE	0.92	0.91	0.91	0.94	0.9	-	-
Neural network (success model)	0.88	0.88	0.88	0.88	0.88	0.6	0.95
Neural network (unsuccess model)	0.89	0.89	0.89	0.89	0.89	0.54	0.96

Compared to RF, the neural network is inferior by 4% across all overall metrics. However, for the minority classes (patch/spray/therapy), the NN demonstrated [a higher/comparable] recall (see Table 7 vs. Table 5/6 in the paper), which is consistent with our strategy. At the same time, for the frequent classes like 'Electronic cigarettes' and 'I don't try', RF maintained better accuracy. Taken together, the comparison underscores that while Random Forest outperformed neural networks in terms of overall predictive accuracy, the latter provided additional interpretive value by capturing both positive and negative trajectories of cessation attempts. This makes neural networks particularly suitable as a complementary tool in predictive pipelines, where the integration of success and failure models can inform more personalized and adaptive intervention strategies.

3.4 Feature Importance Visualization:

The importance of each feature was extracted from the Random Forest model and visualized using a bar plot. This analysis identified the most influential features driving the model’s predictions, with higher-ranked features playing a more critical role in determining class membership for smoking cessation methods, as shown in figure 3. In order to ensure model interpretability, features were sorted in descending order of their importance scores in model construction. According to the SMOT with the RF model, “Smoking Cessation Methods”, “Smoking Cessation Methods heard before”, and “try to quit smoking” were maintained as the most useful features, with scores of 0.35, 0.30 and 0.25, respectively, to predict the Smoking Cessation Method Target.

Smoking cessation methods have you tried before
Smoking cessation methods have you heard before
Try to quit smoking
Frequency of smoking
Smoker or not
Gender
Age at smoking initiation
Minutes from waking up to smoking the first cigarette
Tobacco sales to adolescents should forbidden
Difficult to refrain from smoking in places where it is forbidden
Tobacco smoking in universities and café should be forbidden
Age
Hazards faced by the smokers
Parent’s work in a health care setting
Smoking in public places should be banned
Usefulness of SCM by smoking cessation clinics
Number of cigarettes smoking per day
Smoke more frequently during the first hours after walking
Smoke when you are so ill
Cigarette you hate most to give up
Education on dangerous of smoking

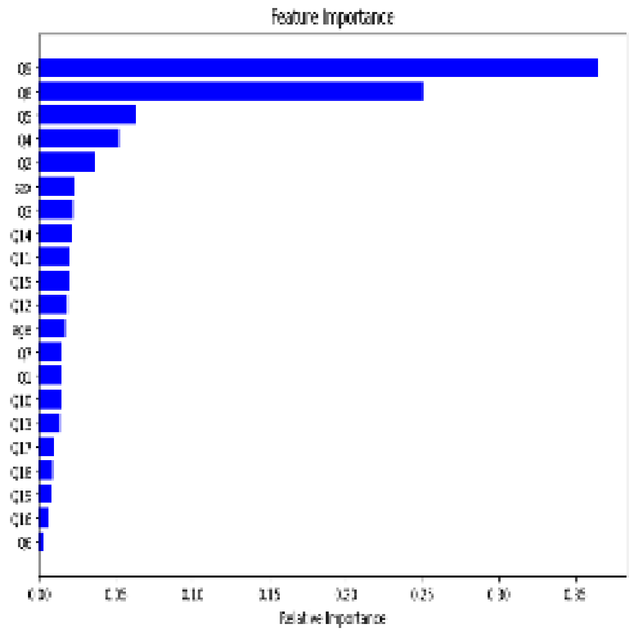

Fig 9. Feature Importance of Synthetic Minority over Sampling Technique (SMOT) with Random Forest (RF) model.

3.5 Analysis of Students' Health History in Relation to Smoking Behavior

Table 10. Survey responces .

Parameters	Frequency (n)	Percent (%)
Gender		
Female	245	29.8
Male	577	70.2
Age		
18 – less 25 y	457	55.6
25 – less 32 y	150	18.2
32 – less 40 y	69	8.4
40 y and more	146	17.8
Are you Smoke `		
No	207	25.2
Yes	615	74.8
Age range of first-time smoking		
00	207	25.2
9 - less 15y	96	11.7
15 – less 20y	339	41.2
20 – less 25y	147	17.9
25 y and more	33	4.0
How frequent are you smoking?		

Never smoker	207	25.2
Occasional smoker	38	4.6
Daily smoker	577	70.2
Have you tried to quit smoking?		
00	207	25.2
No, I never tried	155	18.9
I don't want to quit smoking	18	2.2
Yes, sometimes	68	8.3
Yes, more often	374	45.5
Number of cigarettes smoking per day?		
00	207	25.2
31 or more	102	12.4
21-30	149	18.1
11-20	240	29.2
10 or less	124	15.1

The table presents following results

Physical Activity for smoker

0.0	**207**	**25.2**
30 min or more a day	267	32.5
Less than 30 min a day	348	42.3

Sleeping Status among smoker

0.0	207	25.2
Less than 6 hours	215	26.2
More than 6 hours	400	49

Health problems due to smoking

0.0 207 25.2

- Coughing spells 65 7.9
- Shortness of breath, even when not exercising: 70 8.5
- Wheezing or gasping: 20 2.4
- Increased phlegm (mucus): 26 3.2
- Respiratory illnesses that are worse and happen more often: 25 3

- Worse cold and flu symptoms: 147 18
- More frequent headaches: 35 4.3
- Asthma attack: 5 0.6
- Heart attack: 1 0.12
- Hypertension: 2 0.24
- Pulmonary Hypertension: 1 0.12
- students not effect from signs and symptoms 218 27

The table presents an analysis of students' health history in relation to their smoking behavior. It includes demographic data, smoking patterns, attempts to quit, physical activity, sleeping habits, and reported health issues due to smoking.

- Demographics: The sample consists of 822 students, with 70.2% males and 29.8% females. The majority (55.6%) are aged between 18 and 25 years.
- Smoking Prevalence: 74.8% of students are smokers, with most (41.2%) having started between 15 and 20 years old.
- Smoking Frequency: 70.2% are daily smokers, while 4.6% smoke occasionally.
- Quitting Attempts: While 45.5% have attempted quitting frequently, 18.9% have never tried, and 2.2% do not wish to quit.
- Cigarette Consumption: 29.2% smoke 11–20 cigarettes per day, while 12.4% smoke over 31 cigarettes daily.
- Physical Activity Among Smokers: 42.3% engage in less than 30 minutes of daily exercise, while 32.5% engage in more than 30 minutes.
- Sleeping Patterns: 49% of smokers sleep more than 6 hours per night, while 26.2% sleep less than 6 hours.
- Health Issues: 18% report worse cold and flu symptoms, 8.5% experience shortness of breath, and 7.9% have frequent coughing spells. 27% report no smoking-related symptoms.

4. Discussion

Smoking tobacco represents a major public health burden, as it increases susceptibility to numerous health risks, including cancer and cardiovascular diseases (Sychareun et al., 2013). The findings of this study revealed that 74.8% of pharmacy students were classified as smokers, a prevalence higher than previously reported among healthcare providers in Jordan: 25% (Alkhatabeh et al., 2017) and 65% (El-Khushman et al., 2008). Moreover, 769 students (93.6%) reported receiving formal instruction on the dangers of smoking. This figure substantially exceeds earlier studies on pharmacy students, which found rates of 25% (Sychareun et al., 2013) and 29.7% (Parthasarathi et al., 2021).

In addition, most participants (79.4%) believed that assessing the effectiveness of cessation techniques through specialized smoking cessation clinics could facilitate quitting. However, prior research has shown that in many developing countries healthcare practitioners rarely discuss smoking cessation with their patients (Stead et al., 2013; Abdullah & Husten, 2004). In Jordan, the Ministry of Health has attempted to address this gap through sustained efforts to raise awareness of smoking hazards and to expand smoking cessation clinics across the country. The effectiveness of these initiatives could be further strengthened by enforcing stricter smoke-free regulations, such as banning tobacco sales to minors and prohibiting smoking in public places. These measures were strongly endorsed by students in this study: 88.7% supported restrictions on tobacco sales to adolescents, and 81.3% supported public smoking bans.

Despite these positive attitudes, many students demonstrated limited awareness of the significance and efficacy of cessation methods. While most had heard of smoking cessation (SC) programs, their knowledge of practical applications was incomplete. Many also expressed the belief that integrating SC instruction into the pharmacy curriculum would improve their understanding and equip them to support patients more effectively. Other policy measures, such as raising cigarette prices, were also highlighted as strategies to reduce smoking prevalence in Jordan and similar settings.

This study has certain limitations. First, it was conducted in a single university, which limits the generalizability of findings to all pharmacy students in Jordan. Second, while participants' attitudes and beliefs toward SC methods were assessed, their actual knowledge of these interventions was not directly measured.

From a methodological standpoint, the comparative analysis of predictive models yielded valuable insights. The Random Forest (RF) classifier, particularly when combined with SMOTE, achieved the highest performance with an overall accuracy of 92% and a macro-F1 score of 0.91, outperforming the neural network (NN), which achieved an accuracy of 88% and macro-F1 score of 0.88. These results are consistent with previous evidence indicating that ensemble-based methods such as RF perform robustly on moderately sized datasets, especially when interpretability and resistance to overfitting are critical.

Nevertheless, the NN showed distinct advantages for minority classes (e.g., Nicotine patch, Therapy, Nicotine spray), where it achieved relatively higher recall than RF. This finding underscores the NN's ability to detect subtle patterns in underrepresented categories. Such complementarity is methodologically significant: while RF excels in predicting majority and well-structured classes, NN contributes to identifying rare but clinically meaningful cases. In public health applications, where overlooking minority cases can compromise intervention effectiveness, this property of NN is particularly valuable [Filist et al., 2025a; 2025b].

Importantly, beyond success-oriented prediction, the introduction of a failure model added interpretability. Whereas the success model highlighted the most promising cessation methods, the failure model identified scenarios where relapse or treatment failure was more likely. For example, the failure model demonstrated relatively high recall for nicotine replacement therapy and group counseling, suggesting that while these methods may be effective, they are also vulnerable to dropout or relapse in certain populations.

These findings mirror clinical practice, where predicting unsuccessful outcomes is as critical as identifying likely successes. Anticipating failure allows healthcare providers to strengthen interventions preemptively, for instance by combining behavioral therapy with pharmacological aids or by extending follow-up support. Thus, the complementary application of both success and failure models enhances the robustness of predictive analytics, providing a more comprehensive understanding of smoking cessation dynamics.

4.1 Comparison with Previous Studies and the Role of Nicotine as a Chemical Hazard

The current investigation unveiled a smoking prevalence of 74.8% among pharmacy students, a figure that is notably greater in comparison to other geographical areas. As an illustration, Malaysia had a prevalence rate of 14.5%, whereas India had a rate of 29.7% among healthcare students. The higher occurrence of this condition emphasizes a heightened susceptibility to nicotine, a powerful chemical danger known for its addictive qualities and significant health risks. Nicotine induces the release of dopamine, which results in addiction and the subsequent risks of cardiovascular illnesses and other health complications [CDC, 2020; Mishra & Mishra, 2018]. The increased incidence among Jordanian students indicates that they are more likely to experience these negative health consequences. The current survey revealed that 79.4% of students held the idea that smoking cessation clinics are effective, which aligns with the findings in Saudi Arabia, where 76% of individuals had the same perspective. Having a positive perspective is essential, considering the addictive properties of nicotine, which can make it difficult to quit, and highlights the importance of seeking expert assistance. In contrast, a mere 62% of students in Pakistan considered smoking cessation as a component of their professional responsibilities. This discrepancy may indicate differing levels of knowledge regarding the dangers of nicotine and the significance of addressing addiction in healthcare environments [Sreeramareddy et al., 2015; Choudhury et al., 2004].

The survey revealed that a substantial majority of pupils, namely 93.6%, had received formal instruction on the hazards of smoking. This percentage is notably higher than the stated figure of 25% in Egypt. An enhanced level of consciousness is vital for comprehending the toxicological impacts of nicotine, including heightened blood pressure, heart rate, and its involvement in atherosclerosis. This comprehension can promote more robust anti-smoking attitudes and actions. In India, while 70% of students have received education on the hazards of smoking, there is a recognized requirement for more extensive teaching on the precise risks associated with nicotine, particularly its ability to cause cancer when mixed with other components of tobacco smoke [Laniado-Laborín, 2010; Reitsma, 2017].

In this work, 44.4% of respondent students acknowledged being aware of electronic cigarettes as a strategy for quitting smoking, while 38.8% of students stated that they had actually tried using them. Although e-cigarettes are often perceived as safer alternatives, they nonetheless administer nicotine, which sustains addiction and exposes users to other detrimental substances. In the United States, similar patterns may be observed, however in South Africa, just a quarter of students were knowledgeable of e-cigarettes as a means of quitting smoking, indicating a lower level of understanding regarding alternate methods that still entail the hazards associated with nicotine. It is crucial to treat nicotine dependency in a comprehensive manner, including the use of cessation aids such as e-cigarettes [Hartmann-Boyce et al., 2021; Goniewicz et al., 2014].

Finally, the survey unveiled that 81.3% of students expressed their endorsement for public smoking prohibitions, surpassing the recorded figure of 68% in Australia. The robust endorsement is probably associated with the recognition of the hazards of secondhand smoke, whereby nicotine and other detrimental substances provide substantial health perils to individuals who do not smoke. The presence of nicotine in secondhand smoke is a significant factor in the development of chronic public health concerns, such as respiratory disorders and an elevated risk of cancer. The strong endorsement of smoking prohibitions among Jordanian students demonstrates a proactive strategy in addressing and reducing these public health risks [Callinan, 2010; WHO, 2009].

5. Future Work

Further research holds significant potential to deepen our understanding of smoking patterns among pharmacy students. Longitudinal studies are particularly crucial for monitoring the progression of smoking behaviors, beliefs, and attitudes as students advance through their academic and professional trajectories. Such methodologies will allow for the assessment of the long-term effectiveness of smoking cessation education and interventions. Additionally, exploring the integration of structured smoking cessation programs into pharmacy curricula could prove highly beneficial, enabling evaluation of how educational interventions impact students' knowledge, attitudes, and behaviors regarding quitting smoking.

Comparative research conducted across multiple settings—both within Jordan and internationally—may provide valuable insights into the prevalence, beliefs, and attitudes toward smoking among pharmacy students across different cultural and geographical contexts. This could highlight important variations in smoking patterns and in the effectiveness of cessation strategies. Furthermore, investigating the barriers that prevent pharmacy students from quitting could facilitate the design of more tailored and effective interventions, ensuring programs address the specific needs of this demographic.

Future investigations should also prioritize examining the relationship between smoking and academic performance, including potential impacts on cognitive function, concentration, and overall academic achievement. Moreover, assessing the role of pharmacy students and pharmacists in public health campaigns would help clarify their contributions to reducing smoking rates and their participation in community outreach initiatives. Research into gender-based disparities in smoking behavior and the utilization of modern technologies—such as mobile applications, telemedicine, and AI-powered health tools—could offer novel approaches to cessation. In addition, evaluating psychological and social determinants of smoking behavior, as well as the long-term implications of smoking on career progression, would provide a more comprehensive understanding of how smoking influences the future responsibilities of healthcare professionals and their capacity to effectively counsel patients.

From a methodological perspective, future studies should also explore hybrid modeling strategies that combine the interpretability and robustness of Random Forest (RF) with the sensitivity of neural networks (NN) in capturing underrepresented classes. One promising approach is a two-stage pipeline, where RF is first applied for feature selection and interpretability, followed by NN for fine-grained classification of minority outcomes. More advanced architectures, such as attention-based models or deep gradient boosting frameworks, combined with data-balancing methods (e.g., SMOTE, ADASYN, or generative oversampling), could further improve predictive performance.

Another important research direction involves examining how dataset size and quality influence the relative performance of different algorithms. While Random Forest demonstrated strong results on the current dataset, neural networks may surpass ensemble methods when trained on larger and more heterogeneous data. Finally, future work should incorporate explainable AI (XAI) techniques to enhance the transparency and clinical acceptability of neural network outputs, thereby facilitating their integration into health education and public health decision-making.

6. Conclusion

The present study demonstrates that Jordanian pharmacy students exhibit a considerably higher prevalence of smoking, leading to elevated exposure to nicotine—a toxic substance with serious health risks. Despite this challenge, the survey revealed a strong foundation of knowledge and positive attitudes toward smoking cessation among participants. However, the persistence of nicotine dependence highlights the urgent need for targeted educational interventions and sustained public health initiatives to reduce smoking prevalence and mitigate nicotine-related health consequences. Given that a substantial proportion of future pharmacists are themselves smokers, and considering their influential role as health professionals and behavioral role models, this study emphasizes the importance of explicitly integrating smoking cessation training into pharmacy education. Ongoing education and reinforcement of cessation strategies are essential to improve treatment uptake, increase quit rates, and ultimately achieve better public health outcomes. Accordingly, the findings strongly support the integration of structured cessation programs within academic curricula, equipping students with practical skills to apply in real-world clinical and community contexts.

From a methodological standpoint, the comparative evaluation of Random Forest (RF) and neural network (NN) models demonstrated complementary strengths. Ensemble approaches such as RF achieved superior overall predictive accuracy (macro-level performance), while neural networks provided distinct advantages in detecting rare and less frequent smoking cessation strategies. These results underscore the necessity of adopting a multi-model framework, where algorithm selection is guided not only by accuracy but also by sensitivity to minority classes and clinical relevance. Neural networks should therefore be viewed not as replacements for ensemble methods but as complementary tools, particularly valuable for identifying uncommon behavioral patterns that are critical for effective intervention [Filist et al., 2025a; 2025b].

Equally important, the incorporation of a failure model enhances the practical utility of predictive analytics. By identifying individuals at high risk of relapse or unsuccessful cessation, alongside predicting successful outcomes, this dual-model framework provides a more balanced and proactive basis for intervention. Effective public health strategies depend not only on maximizing success rates but also on minimizing the likelihood of treatment failure. In this context, the failure model emerges as a vital complementary tool, enabling the design of more personalized cessation programs and strengthening the resilience of smoking cessation initiatives among pharmacy students.

CRediT Author Contribution Statement

All authors must specify their roles using the CRediT taxonomy. Use clear role labels and multiple roles per author if applicable.
Example:
Etab.Taha AL Kasasbeh: Conceptualization, Supervision, Writing – Review & Editing
Wasan AL Maaitah: Investigation, Data Curation, Writing – Original Draft

Ruba T. AL Kasasbeh: Methodology, Validation
Ashraf Shaqadan: Statistical Analysis, Validation
Osama Al-Habahbeh: Statistical Analysis, Validation

Conflict of Interest Statement
The authors declare no conflicts of interest related to this study. The research was conducted independently, without any financial or commercial relationships that could be construed as a potential conflict of interest.

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