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Data-Driven Approaches to Smoking Cessation: Unraveling Predictors of Quitting Through Machine Learning

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Abstract:
In order to define the usefulness of machine learning in this domain and to pinpoint the machine learning techniques that have been used, a comprehensive review of the literature has been conducted. Multiple searches in MEDLINE, Science Citation Index, Social Science Citation Index, EMBASE, CINAHL Plus, APA PsycINFO, PubMed, Cochrane Central Register of Controlled Trials, and IEEE Xplore were conducted for the current study through December 9, 2022. Studies reporting cigarette smoking cessation results (smoking status and cigarette consumption) as well as a variety of experimental designs (such as cross-sectional and longitudinal) were considered as inclusion criteria. The effectiveness of behavioral markers, biomarkers, and other predictors was evaluated as a predictor of smoking cessation outcomes. Twelve papers were found in our systematic review that met our inclusion criteria. This review includes.

Keywords: Machine learning; Systematic review; Smoking cessation;

1. Introduction

Smoking causes about half a million deaths yearly, including nearly 30% of all cancer deaths in the US, making it the most preventable cause of death and disease [1–2]. These fatalities outnumber all deaths linked to alcohol, illegal drug use, violence, AIDS, and suicide put together [2]. Smoking cigarettes results in significant health and productivity costs that surpass $300 billion USD annually, which is not surprising. Reducing cigarette use can enhance public health by lowering mortality and morbidity. Fortunately, the majority of smokers want to stop, and there are effective smoking cessation treatments available. These medicines, such as bupropion, behavioral therapy, and nicotine replacement, lead to higher quitting rates than control or placebo treatments [3]. These therapies do, however, still have a great deal of space for development. For instance, smokers relapse at a rate of 70% within 6 months of finishing the most intensive evidence-based treatments under tightly monitored conditions [4, 5]. Consequently, identifying cessation predictors may make it easier to match patients with treatments and enhance treatment results.

Machine learning is one method for finding predictors of smoking cessation. A branch of artificial intelligence called machine learning "gives computers the ability to learn without explicitly being programmed"[6]. Machine learning techniques can be divided into two broad categories: supervised learning, which involves fitting a model to data that has been labeled through experimental

measurements or assignments, and unsupervised learning, which involves spotting patterns in unlabeled data. However, hybrid methods like semi-supervised learning aim to combine the advantages of both supervised and unsupervised learning (see Review [8] for more information).
Typically, these techniques develop and train a model using sample data sets before testing that model on new samples. While there have been more machine learning applications to health behaviors, as shown by various studies (e.g., [10, 11]), there haven't been many reviews of machine learning methods for tackling substance and cigarette use.

For instance, a review of machine learning in addiction research found significant variation in predicting current substance use [12] and identified the lack of data or inadequate validation measures as contributing factors. Another example reported that most research had a moderate to high risk of bias due to missing data or a lack of external validation [13] and conducted a systematic evaluation of machine learning approaches to alcohol use disorder. The scoping review of tobacco research, which is most pertinent to the present review, demonstrated the variety of applications of machine learning (e.g., content analysis of tobacco on social media, classification of smoking status, and prediction of tobacco-related outcomes) and came to the conclusion that it was a potent tool that could advance research and policy addressing tobacco control [14].

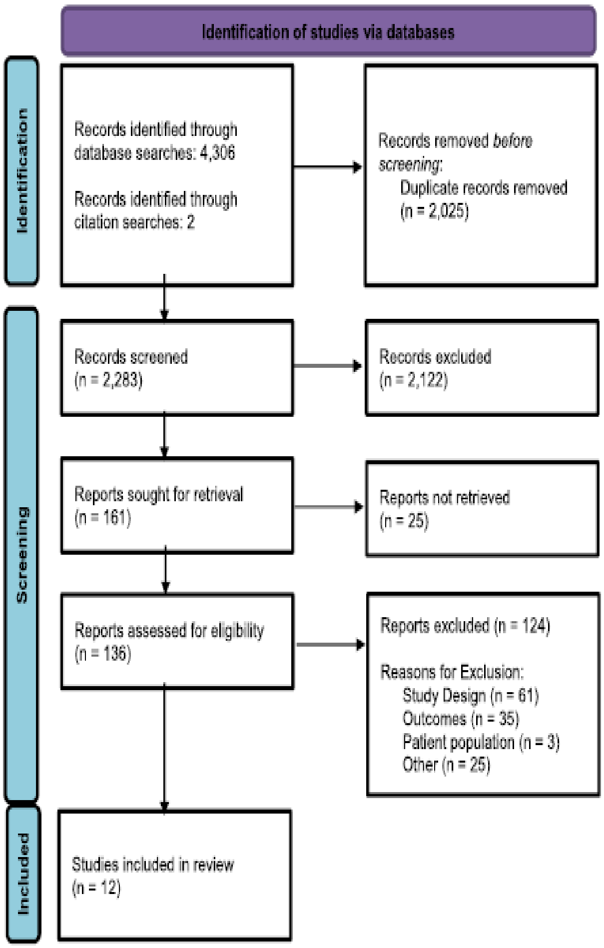

Fig. 1. PRISMA diagram.

The purpose of this systematic study is to describe how machine learning techniques are used and their capacity to find predictors of smoking cessation outcomes. We highlighted knowledge gaps and potential for innovation for machine learning research in the field of smoking cessation in this review.

2. Methods

Using Preferred Reporting Items for Systematic Reviews (PRISMA; Fig. 1), we report this systematic review. The systematic review protocol is listed in PROSPERO as (CRD42022323796).

2.1. Search strategies

PubMed MEDLINE, Science Citation Index, Social Science Citation Index, CINAHL Plus, APA PsycINFO, PubMed, Cochrane Central Register of Controlled Trials, and IEEE Xplore were among the databases that were searched for papers that were published before December 9, 2022. The search used full text, peer-reviewed, and English language filters to find publications on machine learning and smoking cessation. In particular, the following terms were looked up: (("machine learning "OR "reinforcement learning "OR "deep learning "OR "text mining ") AND (smoking OR tobacco OR nicotine OR cigarette OR e-cigarette OR "electronic nicotine delivery system "OR "smoking cessation "OR "smoking reduc "OR "tobacco reduc "OR cotinine OR "carbon monoxide " Studies have to be peer-reviewed, full-text, and available in English.

2.2. Criteria for inclusion and exclusion

The current review comprised observational studies (such as cross-sectional, longitudinal, and case series) and clinical trials (randomized or not) assessing smoking cessation results. Studies were also required to assess those results using machine learning. The participants in the study were smokers. Studies involving non-human subjects, studies on animals, and any gray literature were all disregarded.

2.3. Outcome measures

Machine learning meta-classes and methodologies that were employed to find predictors of smoking cessation results were our main metrics of interest.

2.4. Data collection and processing

L.N.A. and R.F.L. gathered the search results and put them into Covidence for further processing. The titles and abstracts were examined independently by two reviewers (C.L.D. and W.H.C.). Conflicts were settled by a third viewer (D.C.T.). Full-text screening was conducted independently by M.M. and Y.-H.Y., two reviewers. Disagreements were resolved in the full-text review by a third reviewer (D.C.T.). Full texts were excluded for the reasons that were noted and documented (Fig. 1). The data extraction and quality assessment for the included studies (D.C.T., L.N.A., M.M., R.F.L., Y.-H.Y.) were handled by the investigation team. Extracted data includes the following: study identifier, publication year, continent, study sample, study kind, intervention, participant count, demographics, smoking cessation outcome measure, assessed smoking cessation predictors, and machine learning technique.

2.5. Methodological quality assessment

The Mixed Method Appraisal Tool (MMAT; [9]) was used to evaluate the caliber of the studies that were included. The MMAT has 19 methodological quality criteria that are used to evaluate the quality of qualitative, quantitative, and mixed methods investigations. To determine an overall quality score for each included study, the 19 quality criterion domains are each given a score on a Yes/No/Can't Tell scale.

3. Results

3.1. Search results

4,306 citations were found in the initial database search. Through citation searching, two more studies were found and added. Duplicates (2,025) were excluded, leaving 2,283 titles and/or abstracts for screening. A total of 161 studies were sought for retrieval, and 136 full-text studies, including the two extra studies found through reference list searches, were evaluated (Fig. 1). Due to study design (n = 61), outcomes (n = 35), patient population (n = 3), and other (n = 25; for instance, text mining of tweets and examination of electronic medical records), we removed 124 studies. The review comprised 12 papers in total.

3.2. Study characteristics and quality assessment

Table 1 summarizes the general caliber of the studies that were included. Additionally, Supplementary Table 2 contains the results of the scoring of each MMAT item. A study with an MMAT score of 0% (no quality criteria met) received no points, a study with a score of 20% (one quality criteria met), a study with a score of 40% (two quality criteria met), a study with a score of 60% (three quality criteria met), a study with a score of 80% (four quality criteria met), and a study with a score of 100% (five quality criteria met).

3.3. Demographics

The characteristics of the included studies are shown in Table 1 and Supplementary Table 2. There were 40,208 individuals in all of the research, with the sizes of the studies varying from 39 [10] to 14,443 [11]. The studies that were incorporated were released between 2006 and 2022. The majority of the included studies—six out of twelve—were carried out in the United States, with additional research being carried out in the Netherlands, Canada, South Korea, China, and New Zealand. Smoking cessation in the included studies was assessed using self-report measures (such as point prevalence abstinence, reports of relapse, and daily cigarette consumption) and/or biochemical validation (such as carbon monoxide measurements). In Supplementary Table 2, demographic details given by each study are listed. A few research focused on more niche subgroups of smokers, including pregnant women and those from socioeconomically disadvantaged backgrounds [12, 11]. The majority of studies used non-specific samples. Participants in half of the trials (6/12) reported their baseline cigarette consumption, which ranged from at least 100 cigarettes in their lifetime to an average of 21 cigarettes per day.

3.4. Machine learning classes and techniques

Supervised machine learning techniques were used in each of the 12 included research. Table 1 lists certain machine learning techniques and their associated analysis of each study. The supervised machine learning techniques in particular comprise logistic regression, random forest, classification trees, and regression trees. Seven studies (n = 7) reported metrics for sensitivity and specificity, five studies utilized area under the curve (AUC), one study included both positive and negative predictive value, and three studies did not publish any pertinent machine learning metrics (Table 1).

3.5. Smoking cessation outcomes

Studies assessed the success of smoking cessation by self-report, biochemical evaluation, or both. Results of the biochemical validation included measurements of carbon monoxide using expired air (18) and coti-nine using saliva (27). Point-prevalence abstinence [21, 22], the number of cigarettes smoked [expired air; 18], Timeline Followback for use of patches and lozenges [24], re-lapse/lapse [16, 20], abstinence [17, 23], whether they were a current or former smoker [19], and reaching their daily substance use goal for the last seven days before discontinuing the intervention [26] were among the outcomes that were reported by participants themselves. It should be noted that only one study [expired air; 18] combined self-reported (cigarette smoking) and biochemical validation (expired carbon monoxide).

3.6. Predictors of smoking cessation evaluated

The 12 studies that were used made use of several smoking cessation predictors from seven different categories, including biomarkers, economic, environmental, and sociodemographic factors, engagement, neurocognitive factors, physical health-related factors, psychological factors, smoking severity and history, and other factors (Table 2). Exhaled carbon monoxide or neuroimaging (i.e., anatomical and functional imaging) were the predictors for biomarkers (n = 2 studies; [10, 15]). Economic, environmental, and sociodemographic factors (n = 9 studies; [11–19]) included elements including gender, race, household income, the number of smokers in the home, and the availability of cigarettes. User response rate and attendance predictors were included in the evaluation (n = 3 studies; [11, 16, 20]). Executive functioning (for example, delay discounting), memory, and attention were measured as part of neurocognitive (n = 1 study; [21]), which included them as predictors. Predictors for physical health included body mass index, alcohol consumption, sleep quality, and hypertension (n = 7 studies; [12-18]). Among the psychological predictors were motivation, self-efficacy, affect, and perceived stress (n = 9 studies; [11-15, 17-19, 21]). Indicators of nicotine dependency, such as the Fagerstrom Test for Cigarette dependency (formerly known as the Fagerstrom Test for Nicotine Dependence; [22]), age of smoking initiation, and quantity of intake were included in smoking severity and history (n = 8 studies; [11, 13, 15-19, 21]).

Table 1 Summary of studies evaluating smoking cessation outcomes with machine learning techniques.

Study ID	What country did the study take place?	What is the study design?	Where did the study take place? (i.e., setting)	What is the sample size of participants in the study?	Does the study have an intervention?	Describe the Machine learning methods used	Expand on the machine learning method used (i.e., neural network)	Was there training/testing and/or cross validation performed?	Did they test the predictions on an independently collected dataset?	What metrics were included?	Describe the smoking cessation outcome studied	When were the outcomes measured?	Quality
Coughlin 2020	United States	Observational study - Cohort	Other: This is a secondary data analysis. The parent study was conducted in-lab.	Two cohorts: training (n = 90), validation (71). Both cohorts received the same treatment. That is, six 60-minute closed-group CBT treatment sessions and a 6-month follow-up. Ths only difference: the training cohort was provided with 8 weeks of transdermal nicotine patches. The validation cohort was treated without nicotine patches.	Yes	Supervised	Classification and regression trees	Yes	Yes	Sensitivity; Specificity	Biochemical Validation - carbon monoxide (expired air); Biochemical Validation - cotinine (saliva)	Posttreatment and 6-month follow-up	***
Davagdorj 2020	Korea	Observational study - Cross-sectional	Other: public data reanalysis	Former smoker group: 951. Current smoker group: 2741. (Total: 3692)	No	Supervised	Logistic regression, multilayer perceptron, deep multilayer perceptron, random forest, gradient boosting trees, k nearest neighbors, support vector machine	Yes	No	Sensitivity; Specificity	Self Reports - point prevalence abstinence	Data collected from the national survey conducted in Korea	**
Fu 2022	Ontario, Canada	Observational study - Cross-sectional	Online	889	No	Supervised	Gradient boosting machine (GBM) model	Yes	No	Sensitivity; Specificity; Area under the ROC curve	Other: "develop a classification model to predict the status of successful vaping-assisted quitters"	In the survey asking about how vaping helped quiting in past 12months	***

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Table 1 (continued)

Study ID	What country did the study take place?	What is the study design?	Where did the study take place? (i.e., setting)	What is the sample size of participants in the study?	Does the study have an interven-tion?	Describe the Machine learning methods used	Expand on the machine learning method used (i.e., neural network)	Was there train-ing/testing and/or cross validation performed?	Did they test the predictions on an inde-pendently collected dataset?	What metrics were included?	Describe the smoking cessation outcome studied	When were the outcomes measured?	Quality
Hebert 2021	United States	Experimental study - Randomized control trial	In-lab	Analyses were restricted to the 74 participants with a directly identified lapse (n = 52, 70.3 %) or were verified as non-lapsed (n = 22, 29.7 %) at the 4-week post-quit visit.¬†	Yes	Supervised	Cox proportional hazards regression and Penalized cox proportional hazards regression	Yes	No		Other: Smoking status was self-reported at each EMA. Participants were asked if they had smoked any cigarettes (even a puff), and how long ago they last smoked a cigarette, with seven response options ranging from 15min ago to more than 8h ago. Temporally, data for each participant included all EMA observations up to the final measurement before the first lapse occurred. If the participant did not lapse, all of their observations were included and indicated as censored.	Post quit of 4 weeks	**
Kim 2019	Unites States	Experimental study - Randomized control trial	Other: In-person counseling sessions, phone counseling, automated calls	623 (315 for recommended usual care - RUC - and 308 for abstinence-optimized treatment - AOT)	Yes	Supervised	The Generalized, Unbiased, Interaction Detection and Estimation classification tree modeling program was used to identify predictors of patch use (in R-UC and A-OT) and mini-lozenge use in A-OT, and to distinguish subgroups of smokers based on medication use.	No	No	Sensitivity	Other: Self-Reports - TLFB for Patches and mini-lozenges	Patch use was assessed 4 weeks post-TQD (for both R-UCand A-OT) and 16 weeks post-TQD (for A-OT). Mini-lozenge. * TQD = Target quit date	**

Table 1 (continued)

Study ID	What country did the study take place?	What is the study design?	Where did the study take place? (i.e., setting)	What is the sample size of participants in the study?	Does the study have an interven-tion?	Describe the Machine learning methods used	Expand on the machine learning method used (i.e., neural network)	Was there train-ing/testing and/or cross validation performed?	Did they test the predictions on an inde-pendently collected dataset?	What metrics were included?	Describe the smoking cessation outcome studied	When were the outcomes measured?	Quality
Lai 2021	China	Observational study - Cohort	Chart review	4875	No	Supervised	ANN, SVM, random forest (RF), logistic regression (LoR), KNN, classification and regression tree (CART), and na√Øve Bayes (NB)	Yes	No	Sensitivity; Specificity; Area under the ROC curve	Self Reports - point prevalence abstinence	6 month follow up	*****
Medina 2022	New Zealand	Observational study - Cohort	Other: Quitline service	14,443 enrollments	No	Supervised	The study used four different tree-based models: Decision Trees, Random Forest, XGBoost and CatBoost.	Yes	No	Area under the ROC curve	Other: Self-report smoking cessation outcome	4-weeks follow-up assessment	**
Poynton 2006	United States	Observational study - Cross-sectional		Current smokers = 7,421; Former smokers = 6,995	No	Supervised	j48 - decision tree induction algorithm, logistic regression, and multi-layer perceptron - a backpropagation neural network algorithm	Yes	No	Area under the ROC curve	Other: Self report - current or former smoker	In a cross sectional survey	***
Ramos 2021	Netherlands	Observational study - Cohort	Online	32,398 participants enrolled from January 2016 to December 2020 in the Jellinek self-help intervention was available. Around 80% of the participants did not reach further than the first module of the intervention and were excluded from further analysis. 499 were included for the tobacco intervention (122 were successful in their goal and 377 were not)	Yes	Supervised	Logistic Regression and Random Forrest	Yes	No	Sensitivity; Specificity; Positive predictive value; Negative predictive value; Area under the ROC curve	Other: Self report - reaching the daily substance use goal for the last 7 days before discontinuing the intervention	7 days of consumption before discontinuation	*

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Table 2 Smoking cessation predictors.

Study	Biomarkers	Economic, Environmental, & Sociodemographic	Engagement	Neurocognitive	Physical Health-Related	Psychological	Smoking Severity & History	Best Predictor Identified (by machine learning technique)	Estimate/evidence of Predictive Ability
Coughlin 2020	N/A	N/A	N/A	- Delay discounting - MC Attention/mental control - MC Cognitive functioning - MC Cognitive proficiency - MC Information processing accuracy - MC Information processing speed - MC Reason-ing/calculation - MC Reaction time - MC Memory - MC Spatial processing	N/A	- BIS Cognitive - BIS Motor - BIS Nonplanning - EIS Impulsiveness - EIS Venturesomeness - EIS Empathy - FSBS Apathy - FSBS Executive dysfunction - FSBS Disinhibition - FSBS Total - Motivation - Self-efficacy - Perceived Stress Scale (PSS) - PANAS Positive affect - PANAS Negative affect - Rotter's Locus of Control Scale	- FTND	- Delay discounting	- The first split of each tree (i.e., delay discounting) on average correctly classified 74.3% of participants
Davagdorj 2020	N/A	- Age - Gender - Education - Household Income - Marital Status - Number of daily smokers at home* - Occupation - Second smoke at work*	- Attendance in smoking prevention (Psychoeducation)*	N/A	- Asthma - BMI - Diabetes - Exercise - Hypertension - Recent alcohol consumption frequency - Subjective Health Status	N/A	- Age of smoking initiation	- Synthetic Minority Over-Sampling Technique (SMOTE) with the Gradient Boosting Trees (GBT) model: Daily smokers at home - Synthetic Minority Over-Sampling Technique (SMOTE) with the Random Forest (RF) model: attendance in smoking cessation education	Feature importance scores: - Daily smokers at home = 0.089 - Attendance in smoking cessation education = 0.230

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Table 2 (continued)

Study	Biomarkers	Economic, Environmental, & Sociodemographic	Engagement	Neurocognitive	Physical Health-Related	Psychological	Smoking Severity & History	Best Predictor Identified (by machine learning technique)	Estimate/evidence of Predictive Ability
Fu 2022	N/A	- Age - Sex - Race - Education - Employment status - Marital status	N/A	N/A	- Perceived physical health status - History of or current diagnosis of asthma, chronic pain, other conditions	- Current stress level - Current substance use status - History of or current diagnosis of depression, anxiety, ADHD, other conditions - Perceived mental health status - Quitting motivation* - Set up a quit date*	- 18+ age of smoking initiation - 6+ lifetime quit attempts - Nicotine strength Vaping-Related: - 10+ times daily - Flavor - Number of lifetime attempts to quit smoking by vaping - Physical side effects - Puffs per vape - Started vaping to quit smoking - Time after waking up - Time since start of last attempt to quit smoking by vaping - Use of pod system - Vaped 100+ times in lifetime	- More positive experiences measured by the Vaping Experiences Score	- Relative importance score between 0 and 100; VES more positive experiences = 100
Hebert 2021	N/A	- Current physical location - Interacting with smokers* - Smoking bans* - Cigarettes are available to me*	N/A	N/A	- Past hour alcohol consumption	- Cigarette craving and urges* - Confidence (i.e., that I could do something other than smoke to improve my mood, smoking would improve my mood, ability to avoid smoking)* - Current feelings of stress - Mood (i.e., I feel: irritable, happy, frustrated/angry, sad, worried, miserable, restless, calm, bored, depressed, and anxious) - Motivation to avoid smoking*		- Higher odds of smoking today - Higher confidence in ability to avoid smoking	Univariate cox proportional hazards regression models: - Higher odds of smoking today was related to increased hazard of lapse (HR=1.37, 95 % CI =[1.23, 1.54]) - Higher confidence in ability to avoid smoking was related to reduced hazard (HR=0.67, 95 % CI =[0.56, 0.81])

3.7. Machine learning identified predictors

Table 2 is a list of the factors that each included study found to have the best predictive usefulness. Overall, delay discounting, the reduction in reward value as a function of delay to receipt [21], having people who smoke every day at home [16], attending smoking cessation education [16], having more positive experiences (measured by the Vaping Experiences Score) [17], higher perceived odds of smoking today [14], and an increase in risky behavior were the predictors with the highest predictive utility found in the 12 studies. (i.e., cognitive improvement, primary dependence, and taste/sensory properties) [18], parent ethnicity [11], smoking intervals [11], boredom [11], male sex [11], consumption when the intervention first started [20], engagement [20], irritability [12], cigarette availability [12], exposure to smokers [12], smoking restrictions [12], recent alcohol consumption [12] All seven of the aforementioned categories were included in the predictors this review found. A priori decisions, model reduction, and variable selection were all methods used in the included studies to evaluate which predictors to include (Supplementary Table 1). The included studies calculated the importance of these measures, odds ratios (probability that an individual will observe an outcome given an exposure compared to its absence [24]), univariate cox proportional hazards regression models (probability that an individual will experience a given event centered around a defined point in time [25], and Shapley additive exPlanations (SHAP) importance plots (quantify the prediction of an ins) as well as other methods. We acknowledge that some of the used algorithms have more obvious meanings in the feature space while others take a more "black box" approach, and that determining the relevance of a given feature is not an easy task. See [27] for a summary of these techniques.

4. Discussion

This is the first systematic review that we are aware of that assesses the use of machine learning techniques to forecast the success of smoking cessation. We examined the many kinds and subcategories of machine learning techniques employed in smoking cessation prediction. Then, we summarized the seven categories of currently used smoking cessation predictors and emphasized those with the most predictive power. We concluded by summarizing the smoking cessation outcome measures. Approaches to machine learning offer strong tools that can provide answers from a new paradigm. Many see machine learning as a mystifying phenomenon that excels in prediction but presents difficulties in interpretation. Some methods, such Support Vector Machines and Artificial Neural Networks, might support this viewpoint. However, certain machine learning techniques (such as classification and regression trees and decision trees) are based on trees and offer a very inter- pretable model. Several psychological factors, such as mood and self-efficacy, were found to be significant predictors of cessation by Medina et al. [11]. Additionally, Couglin et al. [21] examined a variety of psychological and neurocognitive parameters as predictors of smoking cessation in cognitive behavioral therapy (CBT) treatment. They did this by using classification and regression trees. The strongest predictor, delay discounting, which is the decrease in reward value as a function of delay to receipt, correctly identified post-treatment smoking for 80% of subjects. These findings show how tree-based machine learning might support therapeutic smoking cessation programs. Many of the most powerful predictors found using machine learning techniques are in agreement with those found using non-machine learning techniques earlier in the literature. For instance, systematic reviews and meta-analyses that looked at factors that influence smoking cessation have identified factors related to economics, the environment, and sociodemography (such as age, ethnicity, socioeconomic status, and environmental cigarette exposure); factors related to physical health (such as chronic conditions, alcohol consumption); and factors related to smoking severity and history (such as dependence measures, duration of smoking, and age of smoking initiation). Although predictors related to economic, environmental, and sociodemographic factors, physical health-related factors, smoking severity and history, and can help identify who may benefit from additional interventions, they are less informative on how to improve clinical interventions without understanding underlying mechanisms of behavior change. Neurocognitive [30] and psychological predictors of smoking cessation outcomes [24, 26, 29] have also been established in extant literature, despite the fact that several studies identified in this review focus on the predictive power of underlying psychological and neurocognitive mechanisms of behavior change. In the cognitive-behavioral model of relapse prevention, for instance, affective states and cognitive processes like self-efficacy and motivation have long been identified as drivers of relapse in substance use disorders [31–34]. Delay discounting is also strongly associated with smoking outcomes, differentiating smokers from controls [35-40], forecasting the intensity of use [36, 41–43], and predicting treatment outcomes [44, 45]. While several biomarkers for quitting smoking (such as cotinine and carbon monoxide) [22] have been discovered using non-machine learning techniques, machine learning has helped to uncover a brand-new biomarker in fMRI resting-state activity [10]. Two further studies that were thoroughly reviewed but ultimately disregarded worth consideration. When compared to traditional computer-tailored health communication (CTHC), the recommender system outperformed CTHC on measures related to self-perceived influence to quit, but did not lead to higher smoking cessation rates [46]. Sadasivam et al. (2016) investigated a "hybrid machine learning recommender system that selects and sends motivational messages using algorithms that learn from message rat- ings." Similar to this, Chen et al. (2021) found that strong user involvement predicted 6-month smoking cessation [47] when they examined smoking cessation using a recommender-based motivational message intervention. These studies, however, were not included in the current review due to their study design because they did not employ machine learning to assess the results of smoking cessation; instead, the intervention used machine learning. In a recent scoping review of machine learning in tobacco research by Fu et al. [48], four articles were discovered that, while they did not fit our inclusion criteria, merit discussion. The classification tree method was specifically employed by Dumortier et al. to forecast smoking desires in those who had started a stop attempt. Huda et al. used a cluster-based rule discovery model to predict intention to quit among smokers, finding that the decision forest is more accurate in predicting smokers' intention to quit than single decision trees [50]. These findings could be translated into improved clinical interventions for smoking cessation as predictors [49]. Singh & Katyan used decision trees to predict nicotine dependency in 9,190 smokers and 13,357 users of smokeless tobacco, and they discovered that duration of use was the best indicator of nicotine dependence [51]. Finally, one study was disqualified because it used machine learning techniques as its study intervention rather than techniques that were used to predict the success of smoking cessation interventions. In order to predict self-reported smoking cessation at three months after a smartphone intervention, Alsharif & Philip specifically examined multilayer perceptron, logistic regression, Bayes network, Nave Bayes, random subspace, and J48. They discovered that the Nave Bayes algorithm correctly identified 84.7% of people [52]. Although these studies used machine learning in cessation-related fields, they did not specifically address quitting smoking and were therefore excluded from this list.

4.1. Limitations and potential future directions

The sparse inclusion of the neurobehavioral mechanisms underlying smoking-related decision-making is a significant study area constraint. According to the conflicting neurobehavioral decision systems (CNDS) theory, an imbalance between the executive and impulsive decision-making processes contributes to addiction [53, 54]. Individuals with higher delay discounting rates show hyper-activation in impulsive brain systems (such limbic system parts) and hypoactivation of executive regions (like prefrontal cortex) [55]. Delay discounting has been established as an indication of CNDS balance. Delay discounting and possibly other neurocognitive decision-making variables could therefore be included in machine learning and smoking cessation research in the future, which may lead to the discovery of new treatment targets (c.f., [30]). The most effective smoking intervention treatment, according to research, changed delay discounting through rate-dependent effects, meaning that people with the highest baseline delay discounting rates experienced the biggest changes in discounting after treatment [56]. Interventions that lessen discounting simultaneously result in decreased cigarette demand [57, 58]. Delay discounting could therefore be usefully included into machine learning models for a more specialized treatment strategy. The apparent (1) reliance on self-reported measures, both as explanatory variables (e.g., FTND) and outcomes of smoking cessation (e.g., cigarettes per day), is another limitation in this field. The robustness of using machine learning would be improved by including clinical diagnoses and biochemical evidence of smoking cessation (e.g., CO levels). (2) Overfitting may occur when machine learning techniques are used to smaller, homogeneous data sets. By using big data sets (as done in [13]) and evaluating models using a different data set (as done in Coughlin et al., 2020 [21]), this restriction may be theoretically solved. (3) Supervised machine learning was used in every study mentioned here. Alternative approaches, such unsupervised and reinforcement learning, might provide more information on the prediction of smoking cessation. (4) Because two studies failed to identify the most reliable indicator of smoking cessation, they cannot be used to guide clinical interventions. By completely disclosing the predictors utilized and their individual predictive capacities, this barrier can be reduced. We are aware of a number of potential limitations in the approach used for this review in addition to the general constraints of the field mentioned above. While we acknowledged that the MeSH subheaders for machine learning may not be comprehensive, we relied on them to identify search phrases for smoking cessation and machine learning. For instance, some writers do not consider logistic regression to be a machine-learning strategy. We operationalized machine learning as a paper annotated with the relevant MeSh subheader in this review. Therefore, our search was potentially limited because we only considered studies that were found using specific search terms (see Section 2.1 for search terms), while we omitted papers that used comparable methodology. The MeSh subheaders for tobacco usage have similar constraints. Second, although finding two references for this review in a review of relevant publications, a formal snow-ball search process was not used.

5. Conclusions

In conclusion, machine learning technologies are only partially able to demonstrate therapeutic effects and have not yet significantly improved the smoking cessation paradigm. The topic is still in its infancy, and there remains a crucial knowledge gap on the brain mechanisms underlying decision-making and behavior change. When examining neural-based decision-making processes, using decision-tree-based machine learning techniques may offer the most illuminating and compareable models to enhance therapeutic results.

References

1. J Lortet-Tieulent, A Goding Sauer, RL Siegel, KD Miller, F Islami, SA Fedewa, et al., State-Level Cancer Mortality Attributable to Cigarette Smoking in the United States,JAMA Intern. Med. 176 (2016) 1792–1798 .
2. R. Courtney, The health consequences of smoking-50 years of progress: a report of the surgeon general, 2014Us department of health and human services Atlanta, GA: Department of health and human services, centers for disease control and prevention,national center for, Drug Alcohol Rev. 34 (2015) 694–695 .
3. CD Patnode, JT Henderson, EL Coppola, J Melnikow, S Durbin, RG. Thomas, Interventions for Tobacco Cessation in Adults, Including Pregnant Persons, JAMA 325(2021) 280, doi:10.1001/jama.2020.23541 .
4. Clinical Practice Guideline Treating Tobacco Use and Dependence 2008 Update Panel, Liaisons, and Staff. A clinical practice guideline for treating tobacco use and dependence: 2008 update. A U.S. Public Health Service report, Am. J. Prev. Med. 35 (2008) 158–176 .
5. MC Fiore, CR Jaén, TB Baker, WC Bailey, NL Benowitz, SJ Curry, et al., Treating tobacco use and dependence: 2008 update, US Department of Health and Human Services, Rockville, MD, 2008 .
6. AL. Samuel, Some studies in machine learning using the game of checkers, IBM J.Res. Dev. 44 (2000) 206–226 .
7. JG Greener, SM Kandathil, L Moffat, DT. Jones, A guide to machine learning for biologists, Nat. Rev. Mol. Cell Biol. 23 (2022) 40–55 .
8. YC Padmanabha Reddy, P Viswanath, B Eswara Reddy, Semi-supervised learning: a brief review, Int. J. Eng. Technol. 7(2018) 81–85 .
9. Hong, Pluye, Fàbregues, Bartlett. Mixed methods appraisal tool(MMAT), version 2018. Registration of 2018.
10. A Tahmassebi, AH Gandomi, MHJ Schulte, AE Goudriaan, SY Foo, A. Meyer-Baese, Optimized Naive-Bayes andDecision Tree Approaches for fMRI Smoking CessationClassification, Complexity 2018 (2018), doi:10.1155/2018/2740817 .
11. Medina IC, Mohaghegh M. Explainable Machine LearningModels for Prediction ofSmoking Cessation Outcome in New Zealand. 2022 14thInternational Conference on COMmunication Systems & NETworkS (COMSNETS), 2022, p. 764–8.
12. R Suchting, ET Hébert, P Ma, DE Kendzor, MS. Businelle, Using Elastic Net Penalized Cox Proportional Hazards Regression to Identify Predictors of Imminent SmokingLapse, Nicotine Tob. Res. 21 (2019) 173–179 .
13. MR Poynton, AM. McDaniel, Classification of smoking cessation status with a backpropagation neural network, J. Biomed. Inform. 39 (2006) 680–686 .
14. ET Hébert, R Suchting, CK Ra, AC Alexander, DE Kendzor, DJ Vidrine, et al., Predicting the first smoking lapse during a quit attempt: A machine learning approach,Drug AlcoholDepend. 218 (2021) 108340 .
15. C-C Lai, W-H Huang, BC-C Chang, L-C. Hwang,Development of machine learning models for prediction of smoking cessation outcome, Int. J. Environ. Res. Public Health 18 (2021), doi: 10.3390/ijerph18052584 .
16. Davagdorj, Lee, Pham, Ryu. A comparative analysis of machine learning methods for class imbalance in a smokingcessation intervention. NATO Adv. Sci. Inst. Ser. E Appl. Sci. n.d.

17. R Fu, R Schwartz, N Mitsakakis, LM Diemert, S O'Connor, JE Cohen, Predictors of perceived success in quittingsmoking by vaping: a machine learning approach, PLoS One17 (2022) e0262407 .
18. N Kim, DE McCarthy, W-Y Loh, JW Cook, ME Piper, TR Schlam, et al., Predictors of adherence to nicotine replacementtherapy: machine learning evidence that perceived need predicts medication use, Drug Alcohol Depend. 205 (2019) 107668 .
19. Y-Q Zhao, D Zeng, EB Laber, MR. Kosorok, New Statistical learning methods for estimating optimal dynamic treatment regimes, J. Am. Stat. Assoc. 110 (2015) 583–598 .
20. LA Ramos, M Blankers, G van Wingen, T de Bruijn, SCPauws, AE. Goudriaan, Predicting success of a digital self-help intervention for alcohol and substance use with machine learning, Front. Psychol. 12 (2021) 734633 .
21. LN Coughlin, AN Tegge, CE Sheffer, WK. Bickel, A machine-learning approach to predicting smoking cessationtreatment outcomes, Nicotine Tob. Res. 22 (2020) 415–422.
22. K. Fagerström, Determinants of tobacco use and renaming theFTND to the Fagerstrom Test for Cigarette Dependence, Nicotine Tob. Res. 14 (2012) 75–78 .
23. ME Piper, DE McCarthy, DM Bolt, SS Smith, C Lerman, N Benowitz, et al., Assessing dimensions of nicotine dependence: an evaluation of the Nicotine Dependence Syndrome Scale (NDSS) and the Wisconsin Inventory ofSmoking Dependence Motives (WISDM), Nicotine Tob. Res.10 (2008) 1009–1020 .
24. M Riaz, S Lewis, F Naughton, M. Ussher, Predictors ofsmoking cessation during pregnancy: a systematic review and meta-analysis, Addiction 113 (2018) 610–622 .
25. A Vallata, J O'Loughlin, S Cengelli, F Alla, Predictors of Cigarette Smoking Cessation in Adolescents: A Systematic Review, J. Adolesc. Health Care 68 (2021) 649–657 .
26. A Bricca, Z Swithenbank, N Scott, S Treweek, M Johnston, NBlack, et al., Predictors of recruitment and retention in randomized controlled trials of behavioural smoking cessation interventions: a systematic review and meta-regressionanalysis, Addiction 117 (2022) 299–311 .
27. JJ Noubiap, JL Fitzgerald, C Gallagher, G Thomas, ME Middeldorp, P. Sanders, Rates, predictors, and impact of smoking cessation after stroke or transient ischemic attack:a systematic review and meta-analysis, J. Stroke Cerebrovasc. Dis. 30 (2021) 106012 .
28. E Vangeli, J Stapleton, ES Smit, R Borland, R. West, Predictors of attempts to stop smoking and their success in adult general population samples: a systematicreview,Addiction 106 (2011) 2110–2121 .
29. S Cengelli, J O'Loughlin, B Lauzon, J. Cornuz, A systematic review of longitudinal population-based studies on the predictors of smoking cessation in adolescent and young adult smokers, Tob. Control 21 (2012) 355–362 .
30. SK Syan, A González-Roz, M Amlung, LH Sweet, J. MacKillop, Delayed Reward Discounting as a Prognostic Factor for Smoking Cessation Treatment Outcome: A Systematic Review, Nicotine Tob. Res. 23 (2021) 1636–1645 .[31] K Witkiewitz, GA. Marlatt, Relapse prevention for alcoholand drug problems: that was Zen, this is Tao, Am. Psychol. 59 (2004) 224–235 .
31. ME Larimer, RS Palmer, GA. Marlatt, Relapse prevention. Anoverview of Marlatt's cognitive-behavioral model, AlcoholRes. Health 23 (1999) 151–160 .
32. CS Hendershot, K Witkiewitz, WH George, GA. Marlatt,Relapse prevention for addictive behaviors, Subst. AbuseTreat. Prev. Policy 6 (2011) 17 .

33. GA Marlatt, WH. George, Relapse prevention: introductionand overview of the model, Br. J. Addict. 79 (1984) 261–273 .
34. WK Bickel, AL Odum, GJ. Madden, Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers,Psychopharmacology 146 (1999) 447–454 .
35. MW Johnson, WK Bickel, F. Baker, Moderate drug use anddelay discounting: a comparison of heavy, light, and never smokers, Exp. Clin. Psychopharmacol. 15 (2007) 187–194 .
36. F Baker, MW Johnson, WK. Bickel, Delay discounting in current and never-before cigarette smokers: similarities anddifferences across commodity, sign, and magnitude, J. Abnorm. Psychol. 112 (2003) 382–392 .
37. AL Odum, GJ Madden, WK. Bickel, Discounting of delayed health gains and losses by current, never- and ex-smokers of cigarettes, Nicotine Tob. Res. 4 (2002) 295–303 .
38. SH. Mitchell, Measures of impulsivity in cigarette smokers and non-smokers, Psychopharmacology 146 (1999) 455–464 .[40] M Rezvanfard, H Ekhtiari, A Mokri, GE Djavid, H. Kaviani, Psychological and behavioral traits in smokers and theirrelationship with nicotine dependence level, Arch. Iran Med.13 (2010) 395–405 .
39. J MacKillop, CW. Kahler, Delayed reward discountingpredicts treatment response for heavy drinkers receivingsmoking cessation treatment, Drug Alcohol Depend. 104 (2009) 197–203 .
40. Y Ohmura, T Takahashi, N. Kitamura, Discounting delayedand probabilistic monetary gains and losses by smokers ofcigarettes, Psychopharmacology 182 (2005) 508–515 .
41. B Reynolds, JB Richards, K Horn, K. Karraker, Delaydiscounting and probability discounting as related to cigarette smoking status in adults, Behav. Processes. 65 (2004) 35–42 .
42. JH Yoon, ST Higgins, SH Heil, RJ Sugarbaker, CS Thomas,GJ. Badger, Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women, Exp. Clin.Psychopharmacol. 15 (2007) 176–186 .
43. C Sheffer, J Mackillop, J McGeary, R Landes, L Carter, R Yi,et al., Delay discounting, locus of control, and cognitive impulsiveness independently predict tobacco dependence treatment outcomes in a highly dependent, lower socioeconomic group of smokers, Am. J. Addict. 21 (2012)221–232 .
44. RS Sadasivam, EM Borglund, R Adams, BM Marlin, TK. Houston, Impact of a Collective Intelligence Tailored Messaging System on Smoking Cessation: The Perspect Randomized Experiment, J. Med. Internet Res. 18 (2016) e285 .
45. J Chen, TK Houston, JM Faro, CS Nagawa, EA Orvek, AC Blok, et al., Evaluating the use of a recommender system for selecting optimal messages for smoking cessation: patterns and effects of user-system engagement, BMC Public Health 21 (2021) 1749 .
46. R Fu, A Kundu, N Mitsakakis, T Elton-Marshall, W Wang, S Hill, et al., Machine learning applications in tobacco research:a scoping review, Tob. Control (2021), doi: 10.1136/tobaccocontrol-2020-056438 .
47. A Dumortier, E Beckjord, S Shiffman, E. Sejdi ć, Classifying smoking urges via machine learning, Comput. Methods Programs Biomed. 137 (2016) 203–213 .
48. Huda S, Yearwood J, Borland R. Cluster based rule discoverymodel for enhancement of government's tobacco controlstrategy, 2010.
49. A Singh, H. Katyan, Classification of nicotine-dependent \ users in India: a decision- tree approach, J. Public Health 27(2019) 453–459 .

50. AH Alsharif, N. Philip, Classifying and predicting instances for smoking cessation management system (Smoke mind),2016 International Conference on Engineering & MIS (ICEMIS), IEEE, 2016, doi:10.1109/icemis.2016.7745360 .
51. WK Bickel, ML Miller, R Yi, BP Kowal, DM Lindquist, JA.Pitcock, Behavioral and neuroeconomics of drug addiction:competing neural systems and temporal discounting processes, Drug Alcohol Depend. 90 (Suppl 1) (2007) S85–S91 .
52. SM McClure, WK. Bickel, A dual-systems perspective onaddiction: contributions from neuroimaging and cognitivetraining, Ann. N Y Acad. Sci. 1327 (2014) 62–78 .
53. SM McClure, DI Laibson, G Loewenstein, JD. Cohen,Separate neural systems value immediate and delayedmonetary rewards, Science 306 (2004) 503–507 .
54. WK Bickel, RD Landes, Z Kurth-Nelson, AD. Redish, Aquantitative signature of self- -control repair: rate-dependent effects of successful addiction treatment, Clin. Psychol.Sci. 2 (2014) 685–695
55. JS Stein, AG Wilson, MN Koffarnus, TO Daniel, LH Epstein, WK. Bickel, Unstuck in time: episodic future thinking reduces delay discounting and cigarette smoking, Psychopharmacology 233 (2016) 3771–3778 .
56. JS Stein, AN Tegge, JK Turner, WK. Bickel, Episodic future thinking reduces delay discounting and cigarette demand: an investigation of the good-subject effect, J.Behav. Med. 41 (2018) 269–276 . 16