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Review article

Applications of machine learning in addiction studies: A systematic review

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ABSTRACT

This study aims to provide a systematic review of the applications of machine learning methods in addiction research. In this study, multiple searches on MEDLINE, Embase and the Cochrane Database of Systematic Reviews were performed. 23 full-text articles were assessed and 17 articles met the inclusion criteria for the final review. The selected studies covered mainly substance addiction (N = 14, 82.4%), including smoking (N = 4), alcohol drinking (N = 3), as well as uses of cocaine (N = 4), opioids (N = 1), and multiple substances (N = 2). Other studies were non-substance addiction (N = 3, 17.6%), including gambling (N = 2) and internet gaming (N = 1). There were eight cross-sectional, seven cohort, one non-randomized controlled, and one crossover trial studies. Majority of the studies employed supervised learning (N = 13), and others employed unsupervised learning (N = 2) and reinforcement learning (N = 2). Among the supervised learning studies, five studies used ensemble learning methods or multiple algorithm comparisons, six used regression, and two used classification. The two included reinforcement learning studies used the direct methods. These results suggest that machine learning methods, particularly supervised learning are increasingly used in addiction psychiatry for informing medical decisions.

1. Introduction

Applications of machine learning in computational psychiatry (Bzdok and Meyer-Lindenberg, 2018) and computational neurosciences (Yahata et al., 2017) are emerging. In clinical psychiatry, machine learning can facilitate the translation of neuroscience research to clinical practices (Huys et al., 2016), from prognosis (Fusar-Poli et al., 2018) to diagnosis of mental disorders, such as Alzheimer's disease (Eke et al., 2018), anxiety and depression (McGinnis et al., 2018), as well as autism (Kassraian-Fard et al., 2016; Soussia and Rekik, 2018).

Starting from the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), substance use disorder has been used, in lieu of substance abuse and substance dependence by the American Psychological Association (American Psychiatric Association, 2013). The World Health Organization has also included gaming disorder in the 11th edition of the International Classification of Diseases (ICD). In general, addictive behaviors are relatively less observable when compared with other health behaviors. Although traditional epidemiological methods such as follow-up surveys could identify onsets of substance uses (Sargent et al., 2010), those methods sometimes may be limited by manpower, non-responses, and social desires. At the same time, drug screening inventory in schools (Kirisci et al., 1995) and random drug tests at workplaces (DuPont et al., 1995) may not be effective. In addition to data collection, conventional approaches to data analysis are usually lacking of the capacity of feature extraction and selection. With the advancement of machine learning technologies, addiction researchers could better identify target groups for interventions (Ferreri et al., 2018).

There are three major machine learning methods available for behavioral analytics. The first two types are task-driven supervised learning and data-driven unsupervised learning. In supervised learning, dependent variables are predicted from independent variables by mapping functions. It has two major subtypes, namely classification and regression. Unlike supervised learning, unsupervised learning does not require a specific outcome variable. Unsupervised learning also has two major subtypes which are clustering and dimensionality reduction. In addition, ensemble learning methods are used to combine different learning methods in a homogenous (e.g. bagging, also known as bootstrap aggregating, and boosting) or heterogeneous (e.g. stacking and voting) way, for better predictive performance.

The third machine learning method is reinforcement learning which is relatively more technical for implementations than the former two machine learning methods. Reinforcement learning uses goal-oriented algorithms with emphases on the interactive environment for machine training through rigorous trial-and-error processes. The environment rewards the agents for correct actions as reinforcement signals. Positive

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rewards are accumulated, whereas negative rewards are avoided. These algorithms are also good matches with the reinforcement learning theory in psychology to understand the antecedent stimulus (Skinner, 1938). There are two major subtypes of reinforcement learning, being direct (model-free) and indirect methods (model-based).

Addiction psychiatry is an important subspecialty of psychiatry. While reviews of machine learning methods (Dwyer et al., 2018; Janssen et al., 2018) and big data analysis (Monteith et al., 2015) for general psychiatry exist, there is no systematic review of machine learning applications to addiction psychiatry. This systematic review aimed at providing an up-to-date summary of machine learning methods being employed in addiction studies.

2. Methods

In this systematic review, a comprehensive search strategy was developed to search for published articles from major databases, including MEDLINE, Embase, and Cochrane Database of Systematic Reviews. The databases were searched from the date of inception of the databases to December 2018. Keyword combinations of machine learning methods and outcome measures used for searching were: 1) Method 1: Supervised learning (support vector machine (SVM), linear discriminant analysis (LDA), Naïve Bayes (NB), k-nearest neighbors (KNN), learning vector quantization (LVQ), decision trees, random forests, chi-square automatic interaction detection (CHAID), iterative dichotomizer 3, least angle regression, ridge regression, least absolute shrinkage and selection operator (LASSO), elastic net); 2) Method 2: Unsupervised learning (k-means clustering, k-medians clustering, k-medoids clustering, hierarchical clustering, fuzzy clustering, hidden markov model); 3) Method 3: Reinforcement learning (model-based, model-free, direct, indirect); 4) Method 4: Ensemble learning (bagging, boosting, stacking, voting); and 5) Outcome Measures: Smoking, alcohol, drugs, cocaine, opioid, internet addiction, game addiction.

The inclusion criteria were: 1) Studies published in English or in other languages with English abstracts; 2) Studies used addictive behaviors as the major outcome measures; 3) Studies used machine learning for feature extraction and selection. The exclusion criteria were: 1) Studies used simulation of addictive behaviors; 2) Studies used regression models merely as statistical models, rather than extended regression models in machine learning; 3) Studies used factor analysis as statistical models, rather than dimensionality reduction models in machine learning; and 4) Review articles. Two researchers (KKM and KL) conducted the literature search and the article review independently. Disagreements were discussed with a third researcher for resolution in consensus meetings. The search results are shown in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram.

3. Results

3.1. Summary

In Fig. 1, a total of 31 records were identified via database searching and other resources. After removing one duplicated record, 30 records were included for screening and 7 were excluded after abstract reading. The full text of the selected 23 articles were assessed and 6 ineligible articles were further excluded. In Table 1, the final 17 eligible articles covered topics of substance ($N = 14$) and non-substance addiction ($N = 3$). The 14 substance addiction articles included cigarette smoking ($N = 4$), alcohol drinking ($N = 3$), cocaine use ($N = 4$), opioid use ($N = 1$), and multiple substance use ($N = 2$). The three non-substance addiction articles consisted of gambling ($N = 2$) and internet game addiction ($N = 1$). There were 8 cross-sectional studies, 7 cohort studies, and one non-randomized controlled study, and one cross-over trial. Majority of the subjects were sampled from North America ($N = 10$), followed by Europe ($N = 4$), Asia ($N = 1$), and more than one continent ($N = 2$). Most studies recruited adults ($N = 14$) and only few recruited adolescents ($N = 2$) (with one unknown). The sample sizes varied across studies and machine learning methods, ranging from 34 to 228,405 for supervised learning, 395 to 5390 for unsupervised learning, and 22 to 25 for reinforcement learning. All publications were published between 2012 and 2018. The selected studies employed supervised learning ($n = 13$), unsupervised learning ($n = 2$), and reinforcement learning ($n = 2$) to understand addictive behaviors via feature extraction and selection. Five studies used supervised ensemble methods or multiple method comparisons.

3.2. Supervised learning

3.2.1. Ensemble methods or multiple method comparisons

Five studies employed supervised ensemble methods or multiple method comparisons. In a USA cohort study, classification tree was found to be better than discriminant analysis or Naïve Bayes, with an accuracy of 86% for classifying 300 smoking cessation attempters with different levels of urges to smoke. Filter and wrapper methods were used for feature selection with 10-fold cross-validation; and bagging was chosen as the ensemble method (Dumortier et al., 2016).

An alcohol drinking cohort study conducted in Canada (3826 subjects) and Australia (2190 subjects) used seven supervised machine learning methods to predict mid-adolescence alcohol drinking by early-adolescence predictors (demographics, psychopathology, personality, risk, cognitive, drinking motives, alcohol attitudes, peer pressure). Elastic net was found to the best-performed algorithm among the seven tested algorithms, including elastic net, logistic regression, support vector machines, random forests, neural network, lasso regression, and ridge regression. The corresponding area under the curve (AUC), F1 prediction scores, and accuracy were 0.869, 0.885, and 0.852 for Canadian sample; and 0.855, 0,876, and 0.847 for Australian sample (Afzali et al., 2018).

In another alcohol drinking cohort study using ensemble method, hierarchical classification was used to define the stages of addictive alcohol drinking behaviors in a social media Twitter study in the USA. Currently drinking tweets were relatively more frequent in men than women. Moreover, stages shifts observed were from “looking to drink” (Tuesday to Friday) to “currently drinking” (Saturday to Sunday), to “reflection of drinking” (Monday to Wednesday). A total of 4,839,870 tweets were collected from 228,405 users. These tweets were then classified using logistic regression, support vector machine, and random forests, with 5-fold stratified cross-validation. Tweeted words extracted using term frequency-inverse document frequency (tf-idf) were found to be the best features. Based on the classifier ensemble results, user features such as twitter followers did not improve model performance (Liu et al., 2017).

In addition to alcohol drinking, a non-randomized controlled trial in the USA examined the effects of oral methylphenidate hydrochloride (MPH) treatments among 18 cocaine use disorder subjects and 16 matched controls. Filter method was used to select features of resting-state functional connectivity, which were measured by functional magnetic resonance imaging (fMRI). Low classification errors (0.10–0.20) were resulted from the seven algorithms, including nearest neighbors, support vector machine, decision trees, random forests, Naïve Bayes, logistic regression, and linear discriminant analysis, with leave-one-out cross-validation (Rish et al., 2016).

A substance use disorder cohort study used super learning to take a weighted average of all algorithms, including logistic regression, penalized regression, random forests, and artificial neural networks to predict treatment success among 99,013 patients in the USA. The 28 predictors included were patient characteristics, treatment characteristics, principal source of referral, types of problematic substance uses, and mental health problems. Multiple substances under investigations were alcohol, marijuana, cocaine, methamphetamine, opiates,

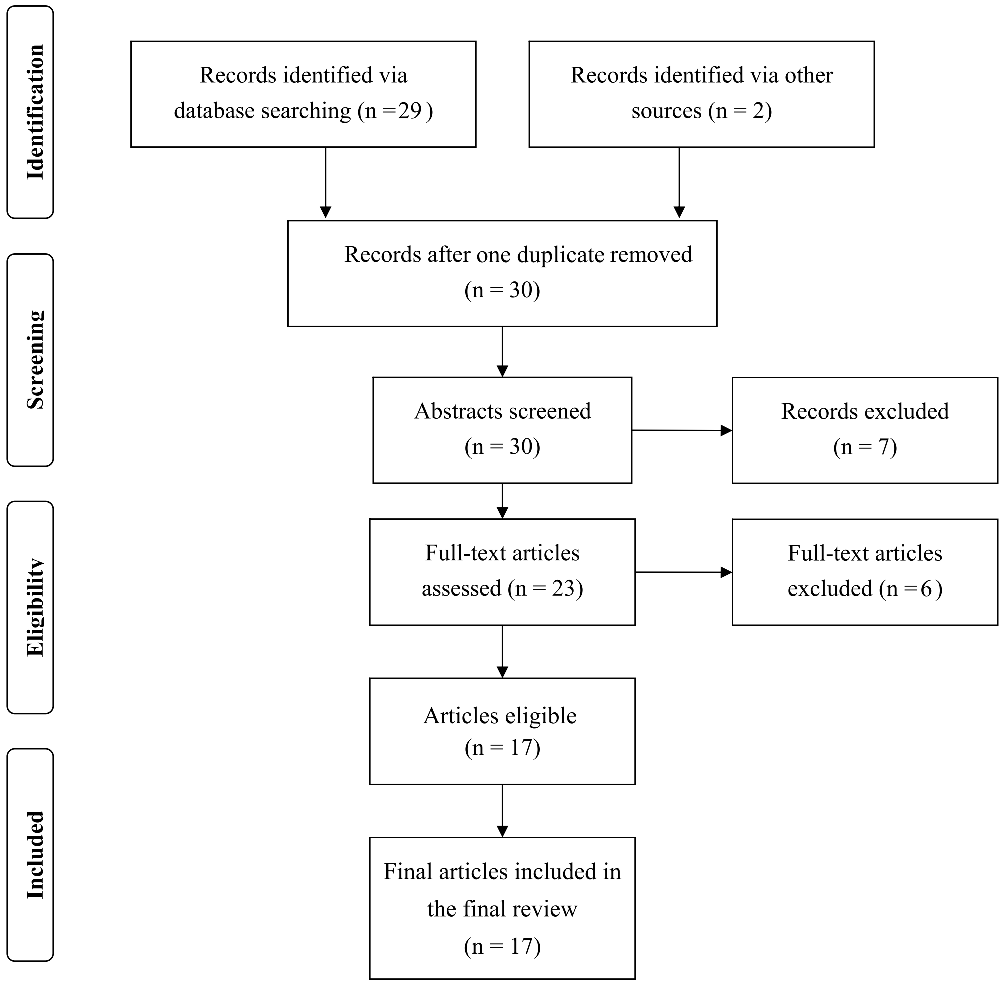

Fig. 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Flow Diagram.

hallucinogens, sedatives, and stimulants. With 2-fold cross-validation, the AUC values for all algorithms ranged from 0.793 to 0.820 (Acion et al., 2017).

3.2.2. Individual methods

There were eight studies which employed individual supervised learning methods to predict behavioral addiction. Among them, two studies investigated smoking behaviors. A recent 6-month follow-up study used classification and regression trees (CART) to understand the success of cognitive-behavioral therapy for smoking cessation among USA adults. The training cohort included 90 smokers and validation cohort included 71 smokers. The respective quit rates were 43.8% and 27.1%. Smoking status was validated by exhaled carbon monoxide and urine cotinine. Feature selection was conducted using generalized estimating equations (GEE) to predict abstinence in the training cohort by clinical (including Fagerstrom Test for Nicotine Dependence), and executive function and impulsivity measures (including Barratt Impulsiveness Scale). Abstinent and relapsed groups were classified using CART with an impurity criterion and chi-squared test for model evaluation. The prediction accuracy was 80% at baseline and 81% at follow-up (Coughlin et al., 2018).

A USA cross-sectional study used functional magnetic resonance imaging (fMRI) to classify 100 cigarette smokers from 100 matched non-smokers by resting-state features (local and network measures), using radial basis function-support vector machine classifier (RBF-SVM). Grid search was used for feature selection and 10-fold cross-validation was used for model evaluation. The accuracy was 75.5% for feature combination and classifier combination, and 73.0% for kernel combination (Ding et al., 2017). These results were consistent to the reported performance similarities between kernel combination and classifier combination in a series of computational experiments (Lee et al., 2007).

In a cohort study among 692 adolescents in Europe (UK, Ireland, Germany, France, Italy), demographics, fMRI, 14 single nucleotide polymorphisms (SNPs), personality, cognition, family history and life events were used to predict current (at 14 years) and future (at 16 years) alcohol drinking. Six features used at baseline were demographics, family history, genetics, brain images, personality, and cognition. Brain regions predicting future drinking were related to reward anticipation, reward outcome, inhibition failure, inhibition success, face processing, and grey matter volume. Elastic net results were validated with 10-fold cross-validation with three levels of nesting. Model evaluations with receiver operating characteristic (ROC) curves resulted in an area under curve of 0.80 (Whelan et al., 2014).

In addition to smoking and alcohol drinking, individual supervised machine learning methods were also employed to predict drug uses. For instance, elastic net regularization, as one of the penalized regression methods was used to identify drug-specific markers among 141 subjects with heroin dependence and amphetamine dependence, and 81 controls in Bulgaria. In this cross-sectional study, 54 predictors included were demographics, 11 psychiatry measures, including Fagerstrom Test for Nicotine Dependence (Heatherton et al., 1991), personality measures, and neurocognitve impulsivity measures. The area under curve (AUC) values generated from the ROC curve for heroin dependence were 0.946 and 0.863, respectively for the 1000 randomly selected training and test sets. The corresponding AUC values for amphetamine

Table 1
Summary of studies included in the systematic review.

No.	Authors (year)	Study design	Samples	Outcomes	Features	Machine learning method types	Machine learning method subtypes	Machine learning algorithms	Feature/ action selection algorithms	Model evaluation methods	Model performance measures (combined or highest values)
Supervised learning											
1	Acion et al. (2017)	Cohort	99,013 substance use disorder treatment patients in the USA (77.9% men, age range = 18 to > 55)	Substance use (alcohol, cocaine/crack, marijuana/hashish, prescription opiates/ synthetics, methamphetamine)	-Primary, secondary, and tertiary substance problems -Usual route of administration -Frequency of use -Age at first use	Supervised learning	Ensemble	-Logistic regression -Penalized regression -Artificial neural networks	-Random forests	-2-fold cross-validation	Area Under Curve: 0.820
2	Afzali et al. (2018)	Cohort	3826 adolescents in Canada (50.8% boys; mean age = 12.8) 2190 adolescents in Australia (56.3% boys; mean age = 13.3)	Alcohol drinking	-Demographics -Psychopathology -Personality -Risk -Cognitive -Drinking motives -Alcohol attitudes -Peer pressure	Supervised learning	Multiple-algorithm comparison	-Elastic-net -Logistic regression -Support vector machines -Random forests -Neural network -Lasso regression -Ridge regression	-Correlations	-Receiver operating characteristic (ROC) -K-fold cross-validation	Area under curve: 0.869 (Canada) Area under curve: 0.855 (Australian)
3	Ahn et al. (2016)	Cross-sectional	31 current cocaine dependent adults (64.5% men, mean age = 47.0 23 controls in Europe (UK, Ireland, Germany, France, Italy) (43.5% men, mean age = 35.4)	Cocaine dependence	Impulsivity (traits, actions, choices)	Supervised learning	Regression	-Least absolute shrinkage and selection operator (LASSO)	-Regression coefficients	-Receiver operating characteristic curve (ROC) -5-fold cross-validation	Area under curve: 0.912
4	Ahn & Vassileva (2016)	Cross-sectional	44 heroin dependent adults (75.0% men; mean age = 29.3) 39 amphetamine dependent adults (66.7% men; mean age = 23.4) 58 poly-substance dependent adults (84.5% men, mean age = 26.0) 81 non-substance dependent adults (72.8% men; mean age = 24.3) All samples in Bulgaria	Heroin and amphetamine dependence	-Demographic -Personality -Psychiatric problems -Neurocognitive impulsivity	Supervised learning	Regression	-Elastic net	-Analysis of variance (ANOVA)	-Receiver operating characteristic curve (ROC)	Area under curve: 0.863 (heroin) and 0.712 (amphetamine)
5	Braverman et al. (2013)	Cross-sectional	4056 internet adult gamblers in the UK (91.0% men; mean age = 28.9)	Internet gambling	-Demographics -Gaming behaviors	Supervised learning	Regression	-Chi-square automatic interaction detector (CHAID)	-Chi-squared test	-10-fold cross-validation	Specificity: 96.7% Sensitivity: 19.8%

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Table 1 (*continued*)

No.	Authors (year)	Study design	Samples	Outcomes	Features	Machine learning method types	Machine learning method subtypes	Machine learning algorithms	Feature/ action selection algorithms	Model evaluation methods	Model performance measures (combined or highest values)
6	Coughlin et al. (2018)	Cohort	90 adult smokers in training cohort (53.8% men; mean age = 46.6) 71 adult smokers in validation cohort (59.3% men; mean age = 51.71) All samples in the USA	Cigarette smoking	-Clinical -Executive function -Impulsivity measures	Supervised learning	Classification	-Classification and regression trees (CART)	-Generalized estimating equations (GEE)	-Chi-squared test	Accuracy: 80% at baselines and 81% at follow-up
7	Ding et al. (2017)	Cross-sectional	100 adult smokers (53% men; mean age = 31.9 100 adult non-smokers (53% men, mean age = 32.6) All samples in the USA	Cigarette smoking	Resting-state fMRI	Supervised learning	Classification	-Support vector machine	-Grid search	-10-fold cross-validation	Accuracy: 75.5%
8	Dumortier et al. (2016)	Cohort	248 adult smokers in the USA (43% men; mean age = 44.1)	Cigarette smoking (urges)	-Day of the study -Tense level -Energy or arousal level -Restlessness level	Supervised learning	Ensemble	-Decision trees -Naïve Bayes -Discriminant analysis	-Filter method -Wrapper method	-10-fold cross-validation	Accuracy: 86%
9	Liu et al. (2017)	Cohort	228,405 twitter users in the USA (gender and age unknown)	Alcohol drinking	Twitter data	Supervised learning	Ensemble	-Logistic regression -Support vector machine -Random forests	-Grid search	-5-fold cross-validation	Area under curve: 0.87
10	Mete et al. (2016)	Cross-sectional	93 abstinent (2–4 week) cocaine-dependent adults (67% men; mean age = 40.0) 69 healthy controls (33% men; mean age = 34.6) All samples in the USA	Cocaine dependence	Brain regions relevant to -Cognitive control -Default mode network related self-referential thought -Behavioral inhibition -Contextual memories	Supervised learning	Classification	-Support vector machine	-Grid search -Information gain	-Leave-one-out 10-fold cross-validation	Accuracy: 0.89 for leave-one-out cross-validation and 0.88 for 10-fold cross-validation
11	Rho et al. (2016)	Cross-sectional	511 adults in Korea (59.9% men, age range = 20 to 49)	Problematic internet gaming	-Gaming costs -Average weekday gaming time -Offline internet gaming community meeting attendance -Average weekend and holiday gaming time -Marital status -Self-perceptions of	Supervised learning	Regression	-Decision trees	-Pearson's chi-squared test	N/A	Accuracy: 70.41 Specificity: 66.55% Sensitivity: 74.04%

(*continued on next page*)

Table 1 (*continued*)

No.	Authors (year)	Study design	Samples	Outcomes	Features	Machine learning method types	Machine learning method subtypes	Machine learning algorithms	Feature/ action selection algorithms	Model evaluation methods	Model performance measures (combined or highest values)
					addiction to internet game use						
12	Rish et al. (2016)	Non-randomized controlled trial	18 cocaine use disorder adults (88.9% men, mean age = 45.6) 16 controls (gender and age unknown) All samples in the USA	Cocaine use	Brain fMRI after methylphenidate treatment	Supervised learning	Multiple-algorithm comparison	-Nearest neighbors -Support vector machine -Decision trees -Random forests -Naive Bayes -Logistic regression -Linear discriminant analysis	-Filter method	-Leave-one-out cross-validation	Classification error = 0.10 to 0.20
13	Whelan et al. (2014)	Cohort	692 adolescents in Europe (UK, Ireland, Germany, France, Italy) (52.0% boys; mean age = 14.6)	Alcohol drinking	-Demographics, -fMRI -Single nucleotide polymorphisms -Personality, -Cognition -Family history -Life events -Smoking	Supervised learning	Regression	-Elastic net	-Voxel-wise regression	-Receiver operating characteristic (ROC) curve -10-fold cross-validation	Area under curve = 0.80
Unsupervised learning											
14	Gray et al. (2015)	Cross-sectional	217 adult casino employees in the USA (33% men; mean age = 36.5) 178 adult online gambling operators in Gibraltar (65% men; mean age = 31.3)	Gambling	-Gambling-related knowledge -Opinions prior to responsible gambling training	Unsupervised learning	Clustering	-K-means clustering	N/A	-Analysis of variance (ANOVA)	Cohen's Kappa = 0.913
15	Sun et al. (2012)	Cross-sectional	5390 adults in the USA (54.3% men; mean age = 40.3)	Opioid dependence	Genetic heritability	Unsupervised learning	Clustering	-K-medoids clustering	-Multiple correspondence Analysis (MCA)	-Analysis of variance (ANOVA)	N/A
Reinforcement learning											
16	Baker et al. (2018)	Cohort	25 moderate cigarette smoking university students in Canada (48.0% men; mean age = 21.1)	Cigarette smoking (learning rate)	Smoking states -As usual -Abstinence -Cigarette consumption -Approach -Avoidance	Reinforcement learning	Direct reinforcement learning	-Q-learning	-Softmax action selection	-Repeated measures analysis of variance (ANOVA)	Partial eta-squared = 0.13
17	Wang et al. (2018)	Crossover trial	22 adult cocaine dependent users in the USA (100.0% men; mean age = 45.7)	Cocaine use	Cocaine deprivation	Reinforcement learning	Direct reinforcement learning	-Q-learning	-Softmax action selection	-Leave-one-out validation -Multiple comparisons with Bonferroni correction	$r = 0.46$

dependence were 0.847 and 0.712 (Ahn and Vassileva, 2016).

A cross-sectional study in Europe (UK, Ireland, Germany, France, Italy) used least absolute shrinkage and selection operator (LASSO) to predict cocaine dependence among 31 users and 23 health controls, using impulsivity phenotypes. The impulsivity phenotypes assessed in the study were trait impulsivity (with Barratt Impulsiveness Scale-11), impulsive actions (Immediate Memory Task, Stop-Signal Task), and impulsive choice (Adjusting Delay-Discounting Task, Monetary Choice Questionnaire, Iowa Gambling Task, Probabilistic Reversal-Learning Task). Urine tests were conducted, in addition to Structured Clinical Interview for DSM-5 to confirm cocaine uses. The AUC found from the ROC analysis was 0.912 (Ahn et al., 2016).

In a USA cross-sectional study, support vector machine (SVM) were used to classify 93 2-4 week abstinent cocaine-dependent and 69 control groups, based on regional cerebral blood flow (rCBF) from the single photon emission computerized tomography (SPECT) and MRI brain images. 1500 spatially connected voxels in 30 distinct clusters were identified. When compared with controls, 27 clusters showed rCBF increases in cocaine-dependants and 3 showed rCBF decreases in cocaine-dependants. The accuracy was 0.89 (sensitivity: 0.90 and specificity: 0.89) for leave-one-out cross-validation; and accuracy was 0.88 (sensitivity: 0.83 and specificity: 0.83) for 10-fold cross-validation (Mete et al., 2016).

The included non-substance addiction studies mainly covered topics of gambling and internet game addiction. In a UK cross-sectional study, five gambling activities under investigations were sports betting with fixed-odds, sports betting with live-action, casino, poker, and games (e.g. backgammon). 23 variables from 48 variables were selected for the final model. Two risk groups were identified, players involving more than two gambling activities and with high variability of stakes in casinos; and players involving two gambling activities and with high variability of stakes in live-action sports betting. Chi-square automatic interaction detector (CHAID) with 10-fold cross-validation achieved a high specificity of 96.7%, but a low sensitivity of 19.8% for the combined models (Braverman et al., 2013).

In a cross-sectional online survey among 3881 internet game users in Korea, CHAID was used to predict the patterns of problematic users. The six predictors were gaming costs (predicted 50%), average weekday gaming time (predicted 23%), offline Internet gaming community meeting attendance (predicted 13%), average weekend and holiday gaming time (predicted 7%), marital status (predicted 4%), and self-perceptions of addiction to Internet game use (predicted 3%). Three patterns (cost-consuming, socializing, solitary player) of problematic internet gamers were identified based on six classification rules with an accuracy of 70.41 (Rho et al., 2016).

3.3. Unsupervised learning

Two studies have applied unsupervised learning to the investigations of substance and non-substance addictive behaviors. In a family-based genetic study in US, 5390 subjects were recruited to understand the heritable subtypes of opioid uses. In this cross-sectional study, Semi-Structured Assessment for Drug Dependence and Alcoholism (SSADDA) and computer-assisted interview were used to diagnose DSM-IV defined substance use disorders. Multiple correspondence analysis (MCA) was used to select features. Five homogenous inherited opioid user groups of different levels of uses, onset time, and comorbidity were identified with heritability ranging from 0.69 to 0.76, using k-medoids clustering and hierarchical clustering (Sun et al., 2012).

In a cross-sectional survey study, k-means clustering algorithms with two heuristics, elbow method and gap statistic, were used to identify subgroups of gamblers among 217 employees of a casino in Las Vagus (resulting in 4 natural groups) and 178 operators of an online gambling company in Gibraltar (resulting in 2 natural groups). Analysis of variance (ANOVA) with post hoc tests were conducted for model evaluation (Gray et al., 2015).

3.4. Reinforcement learning

Two studies have employed direct reinforcement learning to investigate smoking and cocaine use. A Canadian cohort study used a model-free reinforcement learning method to assess the relationships between cigarette smoking and reinforcement learning signals among 25 university students who were moderate dependent smokers. Smokers' trial-to-trial training choices were modeled using Q-learning algorithms. Softmax action selection was used to control the relative levels of exploration and exploitation, to optimize the selections of rewarded actions. Positive learning rate differences between smoking abstinence and cigarette consumption states were correlated with carbon monoxide differences ($r = 0.47$). Moreover, negative learning rate was significantly ($P < 0.05$) enhanced for smoking abstinence when compared with cigarette consumption. Partial eta-squared of repeated measures ANOVA was 0.13. These results suggested that smoking states (abstinence and cigarette consumption) may be related to positive probabilistic selection task signals, reinforcement learning, and decision making. The positive learning rates of smokers who relapsed after abstinence have restored to a rate level of current smokers (Baker et al., 2018).

A randomized cross-over study included 22 USA adults with cocaine use disorder who were non-treatment seekers. Cocaine use status was assessed by urine test. Participants performed probabilistic loss-learning tasks during functional magnetic resonance imaging (fMRI). Model-free reinforcement learning, Q-learning with softmax action selection was used to estimate the neural positive prediction error and negative prediction error. Path analysis has further shown a significant mediating effect of the neural positive prediction error signals during deprivation, between years of cocaine use and desire to use. These results suggested that the observed higher positive learning rates of cocaine dependent users may attribute to the neural dopamine dysregulation (Wang et al., 2018).

4. Discussion

This systematic review summarized the studies with machine learning applications in the investigations of addictive behaviors. Machine learning methods helped integrate results of assessment scales and medical tests for predictions of addictive behaviors. Most of the included studies used machine learning for predicting substance addiction, with majority being cigarette smoking, alcohol drinking, and cocaine use. All included studies were published in recent years, suggesting that development of machine learning has provided an opportunity of adopting new analytic approaches in addiction research. Methodologically, supervised learning is relatively more common than unsupervised learning in the included addiction studies. Supervised ensemble learning, meta-algorithms in other words, is also emerging to optimize prediction accuracy. The two unsupervised learning studies used k-means clustering and k-mediods clustering. Moreover, the two reinforcement learning studies used direct reinforcement learning (model-free algorithms) which could be less efficient than indirect reinforcement learning (model-based algorithms) for predictions (Dayan and Niv, 2008). These two direct reinforcement learning studies used Q-learning as the off-policy learning algorithm, and softmax action selection method as the exploration. The softmax selection has a relatively higher success rate than other methods such as epsilon-greedy action selection.

There are several limitations for this systematic review. First, machine learning applications in addiction research are yet to be popular, thus the small numbers of studies eligible for the final review may not well represent the potential applications of machine leaning methods in addiction psychiatry. Second, classifications of machine learning subtypes could be ambiguous. Semi-supervised learning methods using both labeled and unlabeled data exist between supervised and unsupervised methods. Third, several studies did not provide details of their feature selection and model evaluation. Last, the heterogeneity of the samples and study designs also made direct comparisons difficult. Not all sample sizes of the included studies were considered as sufficient (at least 75) for classification purposes (Beleites et al., 2013). Out-of-sample classification accuracy was used in some studies, due to their small sample sizes (Ahn et al., 2016; Ahn and Vassileva, 2016).

It is foreseeable that machine learning will play an important role in helping psychiatrists and neuroscientists to identify and profile behavioral addiction groups. A screening test of higher sensitivity and specificity to a certain population will promote earlier clinical diagnosis and treatments (Usher-Smith et al., 2016). These could be followed by stage-specific diagnostic tests such as neurological, neurobehavioral, and molecular biomarkers (Volkow et al., 2015). In future, applications of machine learning in the investigations of comorbidity of behavioral addiction such as depression and impulsivity should be examined. The potential use of temporal difference reinforcement learning (TDRL) model for understanding the relapses of addictive behaviors could also be studied (Redish et al., 2007). At the same time, traditional statistical methods should continue serving as a foundation and complement to machine learning methods in addiction research. Furthermore, related security (Varshney and Homa, 2017) and ethics issues (Galit, 2017) should also be considered and addressed.

In conclusion, this systematic review has provided an up-to-date overview of the available literature using machine learning for examining addictive behaviors. A wide variety of machine learning methods, in particular supervised learning have been demonstrated in the included studies for informing medical decisions. Further investigations of the potential applications of machine learning in precision psychiatry and neuroscience are warranted.

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