Predicting quantity of cannabis smoked in daily life:

An exploratory study using machine learning

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Abstract

Background: Cannabis use is prevalent in the United States and is associated with a host of negative consequences. Importantly, a robust indicator of negative consequences is the amount of cannabis consumed.

Methods: Data were obtained from fifty-two adult, regular cannabis flower smokers (3+ times per week) recruited from the community; participants completed multiple ecological momentary assessment (EMA) surveys each day for 14 days. In this exploratory study, we used various machine learning algorithms to build models to predict the amount of cannabis smoked since participants' last report including forty-three EMA measures of mood, impulsivity, pain, alcohol use, cigarette use, craving, cannabis potency, cannabis use motivation, subjective effects of cannabis, social context, and location in daily life.

Results: Our best-fitting model (Gradient Boosted Trees; 71.15% accuracy, 72.46% precision) identified that affects, subjective effects of cannabis, and cannabis use motives were among the best predictors of cannabis use amount in daily life. The social context of *being with others*, and particularly with a significant other or friend, were moderately weighted in the final prediction model, but contextual items reflecting *location* were not strongly weighted in the final prediction model, the one exception being *not at work*.

Conclusions: Machine learning approaches can assist researchers in identifying additional relevant environmental and psychological phenomena that may be clinically-relevant to cannabis use.

Keywords: mobile survey, machine learning, digital health, ecological momentary assessment, cannabis

1. Introduction

Cannabis use is prevalent in the United States and is associated with numerous clinically-relevant psychological processes such as affect, impulsivity, and pain (Hasin et al., 2020; Li et al., 2019; Trull et al., 2016; Volkow et al. 2014), as well as a host of negative consequences (e.g., driving while impaired; poor performance at work or school; Pearson, 2019). Importantly, a robust indicator of negative consequences is the amount of cannabis consumed (Callaghan et al., 2020). Therefore, research into the best predictors of the amount of cannabis consumed could inform future prevention and treatment efforts aimed at mitigating the risk for negative consequences.

Because individual motives for and subjective experiences of cannabis use may vary across time and contexts, researchers seeking to understand how these processes unfold in daily life often use methods such as *Ecological Momentary Assessment* (EMA; Wycoff et al., 2018). Using smartphones for data collection, EMA allows researchers to assess cannabis use and other psychological phenomena while participants are in their natural environments, increasing ecological validity. Furthermore, EMA involves repeatedly assessing participants throughout a given day, revealing the temporal dynamics of these psychological processes. This is especially important as patterns and predictors of cannabis use may vary both between and within episodes. EMA methods are particularly useful when studying substance use behaviors like cannabis use, as this approach mitigates retrospective recall bias by prompting participants to recall events over relatively shorter periods of time (e.g., in the past 15 minutes, past hour, and/or since the prior recording), thus reducing measurement error (Trull & Ebner-Priemer, 2013; Freeman et al., 2022; Mun et al., 2021; Solhan et al., 2009; Wray et al., 2016).

What do we know about correlates of increased cannabis use in daily life? EMA research demonstrates that *subjective experiences of cannabis intoxication* may vary withinperson based on method of cannabis consumption and various *qualities of the cannabis consumed* (e.g., potency, amount; Li et al., 2019; Okey et al., 2023; Trull et al., 2022). Furthermore, *motives for cannabis use* may differentially predict the subsequent quantity of cannabis one consumes (Bonar et al., 2017) as well as the *subjective experience* of cannabis use (Buckner et al., 2013, 2015; Comulada et al., 2016; Ross et al., 2018; Shrier & Scherer, 2014; Votaw & Witkiewitz, 2021). Additionally, *momentary affect* may predict subsequent cannabis use (Buckner et al., 2012a, 2013, 2015; Chakroun et al., 2010) and fluctuate following cannabis use (Buckner et al., 2015; Henquet et al., 2010; Tournier et al., 2003; Tyler et al., 2015), though the direction of association between cannabis use and affect across studies remains unclear. Although research is limited, studies examining the relationship between cannabis use and *impulsivity* demonstrate that individuals generally report elevated impulsivity on days they use cannabis (Ansell et al., 2015; Trull et al., 2016), but the temporal precedence involved in this association (i.e., whether impulsivity increases prior to or after cannabis use) is not currently known. Finally, even though *pain relief* is the most reported motive for medical cannabis use (Boehnke et al., 2019), the EMA literature addressing this topic is limited and inconclusive regarding whether elevated pain levels predict subsequent cannabis use and whether pain decreases following cannabis use (Kuerbis et al., 2019; Li et al., 2019).

The *context* of cannabis use in daily life has been relatively understudied (Denson et al., 2023). Most studies of context in the daily lives of cannabis users have sampled undergraduate or clinical participants in treatment for cannabis use disorder, have only examined who the participant is with at the time of cannabis use, and few have considered the location of the participant when using cannabis (Buckner et al., 2012a, 2015, 2016; Henquet et al., 2010; Phillips et al., 2018; Sznitman et al., 2022; Treloar Padavano & Miranda, 2018; Tyler et al., 2015). Therefore, a more comprehensive evaluation of the associations between contexts and cannabis use seems warranted.

Traditionally, researchers focus on a limited number of variables to predict important clinical outcomes. For example, researchers use a set of mood variables to predict substance use, but not include a number of other potentially relevant variables like motives, contexts, or impulsivity. Although this approach has the advantage of limiting the number of predictors used in models to those that are believed to be most theoretically relevant to the outcome, in some cases not enough is known about a range of potential predictors of the outcome. Furthermore, initial discovery or exploratory research is often needed to hone in on promising predictors of the outcome that can later be tested in replication studies (Rubin & Donkin, 2022; Yarkoni & Westfall, 2017). Therefore, to evaluate the relations between a range of putative predictors and cannabis use, we opted to use machine learning algorithms to identify those features most associated with using more versus less cannabis flower during a given smoking episode.

In summary, increased cannabis use is robustly associated with higher negative consequences, and a growing body of daily life studies suggest a range of possible predictors for higher levels of cannabis use. In the present study, we used various machine learning algorithms to build models to predict the amount of cannabis smoked since participants' last report from momentary measures of mood, impulsivity, pain, alcohol use, cigarette use, craving, cannabis potency, substance use motivation, and effects of cannabis. Because cannabis use and cannabis problems have been associated with social context, we also collected data on participants' social context as well as on their current location. Finally, we sampled adults in the community who were regular cannabis users, as these participants may be more representative of the general population of cannabis smokers.

2. Method

2.1 Participants

Fifty-two recreational cannabis users (mean age of 24.21 years old; 49.06% women, 47.17% men, 3.77% other gender; 81.13% European American/White, 15.09% African American/Black, 7.55% Asian American) from central Missouri participated in this study. Inclusion criteria for the study were being between 18 and 50 years old and reporting smoking cannabis flower three or more times per week. Exclusion criteria for the study included using cannabis *primarily* in any form other than combustible flower (e.g., vaping, edibles, concentrates), testing positive for using illicit substances other than cannabis (e.g., cocaine, opiates, amphetamines) during the study's initial visit, a history of head trauma involving sustained impairment in mood, attention, or concentration, having sought or intending to seek treatment for substance-related problems, or reporting active psychosis or suicidal ideation.

2.2 Procedure

Individuals interested in participating in the study were screened by phone for eligibility, and informed consent was obtained before study entry. Participants completed an initial visit, during which they were taught to use the smartphone data collection app (*TigerAware*; Morrison et al., 2018) and completed baseline questionnaires (and were paid $10 for completing the questionnaire). Following the baseline visit, participants completed 14 days (two weeks) of EMA, including morning reports upon wakeup, four random prompts scheduled at quasi-random times throughout the day (i.e., a random prompt within four, three-hour windows between 12 noon and 12 midnight), and self-initiated reports on their substance use when consuming cannabis. Participants were reimbursed at the end of the EMA phase up to $50 based on their survey compliance.

2.3 Measures

2.3.1 EMA-Affect

Participants reported on their affect in the past 15 minutes by responding to 17 items from in the Positive and Negative Affect Schedule Extended Form (PANAS-X). Items were rated on a Likert scale from 1 (*Very Slightly or Not at All*) to 5 (*Extremely*). Sample items include "excited," "active," "happy," and "alert," for the Positive Affect (PA) subscale and "downhearted", "alone," and "angry," and "sad," for the Negative Affect (NA) subscale (Watson & Clark, 1994)**.** The Positive and Negative Affect items were averaged, respectively, into two composite predictors (PA and NA).

2.3.2 EMA-Impulsivity

Participants reported on their impulsivity features within the last 15 minutes using four items adapted from the UPPS Impulsive Behavior Scale (Whiteside & Lynam, 2001). One item was selected from each subscale of the 44-item version of the UPPS, including Urgency (*acting on a strong impulse*), Lack of Premeditation (*doing something without really thinking it through*), Lack of Perseverance (*giving up easily*), and Sensation-seeking (*doing something for the thrill of it*). Participants rated how impulsive they felt on a Likert scale from 1 (*Very Slightly or Not at All*) to 5 (*Extremely*). These four impulsivity items were averaged into a composite predictor (IMP).

2.3.3 EMA-Alcohol and Tobacco Use

At each prompt, participants responded "yes" or "no" to questions asking whether they had consumed any alcohol or smoked any cigarettes since the last prompt.

2.3.4 EMA-Cannabis Use

Participants reported whether they consumed cannabis since the last survey they completed. If they endorsed cannabis use, follow-up questions were asked, such as how many times they consumed cannabis and *how much cannabis they consumed in grams since the last* *prompt*. Participants also reported when they finished using cannabis, with the options of "just now," "15 minutes ago," "30 minutes ago," "45 minutes ago," "1 hour ago," and "more than 1 hour ago." Finally, participants reported how they would rate the "strength or potency" of the cannabis they consumed since the last survey, with options of "less strong than," "similar in strength to," or "stronger than" what they typically consume.

2.3.5 EMA-Motives for Cannabis Use

When they endorsed cannabis use, participants were asked about their motives for consuming cannabis using 12 items from the Marijuana Motives Measure (MMM; Simons et al., 1998). Participants rated these items on a Likert scale from 1 (S*trongly Disagree*) to 4 (*Strongly Agree)*. Sample items include "To be liked by others," "Because it's fun," and "To expand my awareness."

2.3.6 EMA-Cravings for Cannabis Use

Participants rated (1) how much they craved cannabis and (2) how hard it was to stop thinking about using cannabis in the past 15 minutes using a Likert scale from 1 (*Very Slightly or Not at All*) to 5 (*Extremely*).

2.3.7 EMA-Subjective Effects of Cannabis

When they endorsed cannabis use, participants were asked about their subjective experience of intoxication and indicated the extent to which 14 options applied to them. Sample items include, "I have difficulty in remembering," "My mouth seems very dry," and "I am more suspicious of others (Chait et al., 1988). Items were rated on a Likert scale from 1 (*Very Slightly or Not at All)* to 5 (*Extremely*).

2.3.8 EMA-Pain

Participants reported how much pain they have felt in the past 15 minutes on a Likert scale from 1 (*No Pain*) to 10 (*The Worst Possible Pain*).

2.3.9 EMA-Location

Participants were asked to indicate whether their current location could be described as home, work, a bar/restaurant, outside, another public space, or another kind of location.

2.3.10 EMA-Social Contexts

Participants reported whether they were with anyone in the past 15 minutes. If they reported they were with someone, they specified whether they were with a significant other, a friend, or someone else.

3. Analytic Plan

For predictors, given the existing literature on correlates of cannabis use, we selected forty-three attributes from the Cannabis Use and Random Prompt survey data that focus on mood, impulsivity, pain, alcohol use, cigarette use, craving, cannabis potency, cannabis use motivations, effects of cannabis, and who participants were with and where they were (see Table 1). Based on an examination of cannabis quantity score distributions (0.2 grams or less [~50%] and greater than 0.2 grams [~50%]) for cannabis used by participants, two ordinal classes were defined. Our dependent variable represented whether reported cannabis quantity fell within the range of one ordinal class or the other.

The raw data set contained 852 rows and 43 attributes/predictors from 52 participants. These data were split into labeled data and unlabeled data; unlabeled data were those endorsements of cannabis use without information on the amount used (~5% of data rows). The labeled data contained 813 rows, while the unlabeled data contained 39 rows. Then, labeled data were divided into the training and validation sets in the ratio of 6:4. At this stage, we set a random seed to ensure that the data split according to this ratio were consistent in each run. The training set contained 467 rows, while the test set contained 346 rows.

The mean values for each attribute/predictor in the training and test set were calculated for each participant, and any missing values in both the training set and the test set were replaced with the mean values (i.e., mean imputation). For both the training set and the test set, each participant's rows were up-sampled, if necessary, to match the number of rows for the participant with the highest count, ensuring all users had an equal number of rows. This was done to make sure that some participants' data was not weighted more heavily than others. The participant with the highest number of rows in the training set had 35, while the participant with the highest count in the test set had 24 rows. A random seed was set to ensure that randomly selected rows were added for those participants with fewer rows of data. After up-sampling, the training set contained 52 participants multiplied by 35 rows (total of 1,820 rows), and the test set contained 52 participants multiplied by 24 rows (total of 1,248 rows).

3.1 Model Training Steps

All model building, training, and evaluation was implemented using the ***RapidMiner*** software platform (Mierswa & Klinkenberg, 2018). We chose five frequently used algorithms: *Decision Trees, Random Forest, Gradient Boosted Trees, Support Vector Machine, and H2O's Deep Learning*. For each of these models, the training process consisted of two phases. In the *first phase*, the optimal parameters were determined. In the second phase, during model learning, it was observed that most confidence values did not resemble probabilities and could sometimes be severely skewed. To address this, an improved Platt scaling method was used to rescale the confidence produced by the model (Platt, 1999). This required a labeled calibration dataset that the model had not been trained on. Hence, the training set was divided into a 9:1 ratio before training to create the calibration dataset. In the process of finding the optimal parameters, cross-validation with 10 folds was used. The cross-validation involved a training section and a testing section, and, the improved Platt scaling method was employed to rescale the confidence generated by the model. The trained model was subsequently utilized in the testing process to assess its performance. Notably, H2O's Deep Learning is based on multilayer feed-forward artificial neural networks trained by stochastic gradient descent using backpropagation. As there was no need for the process of finding the optimal parameters, the improved Platt scaling method was utilized in both the first and second phases.

To evaluate performance, we calculated the classification accuracy and produced the confusion matrix for each model. The next step was interpretation of the prediction results. After inputting the trained model, training data, and validation data, the explain operator yielded the explained prediction results and the weights of the attributes in the output. The explained prediction results were displayed as a table highlighting the attributes that most strongly support each prediction result, while the local attribute weights were identified by the correlation of a neighboring set of data points generated by the operator. Although the relationship between attributes and predictions may be highly nonlinear globally, the local linear relationship is sufficient to explain the prediction results. In addition, this operator could compute model-specific but model agnostic global attribute weights. If the true labels of the test data are known, then all supporting and contradictory local explanations positively affect the weights of correct and incorrect predictions, respectively. In contrast, if the true labels are unknown, the global weights use only the supporting local weights.

4. Results

Table 1 presents all 43 features that were included as well as each feature's correlation with the ordinal class of amount of cannabis used in parentheses. Negative associations suggested a feature was associated with cannabis use at lower quantities, while positive associations suggested a feature was associated with higher quantities of use. These results index both the strength of association of each feature with the ordinal class as well as the valence of the association. The five features with the ***highest, positive association*** with cannabis amount were: physical pain (0.19); felt high (0.175); with a significant other (0.172); PA (0.156); and with a friend (0.155). The five features with the ***highest, negative***

association with cannabis amount were: difficulty stopping thinking about cannabis (-0.176); difficulty in remembering (-0.154); at work (-0.153); feel a very pleasant emptiness (-0.127); and thoughts seem to come and go (-0.096).

Table 2 shows the test accuracy, true positive rate (sensitivity), false positive rate, false negative rate, true negative rate (specificity), recall, and precision for all five models. The test accuracy score is an index that measures the number of correct predictions made by a model in relation to the total number of predictions made (i.e., total number of correct predictions/total number of predictions), while precision refers to the likelihood that a positive prediction is indeed correct. In terms of performance, the highest test accuracy we obtained came from Gradient Boosted Trees at 71.15%. This was followed by Support Vector Machine at 70.27%. In general, test accuracy above 70% is considered good. The Gradient Boosted Trees algorithm also produced the highest precision (72.46%).

Figure 1 displays the top attributes that have the greatest impact on model predictions. The *top ten attributes* were: (1) I have difficulty in remembering (*ce.difficulty*); (2) pain; (3) negative affect (*NA*); (4) positive affect (*PA*); (5) Because it makes social gatherings more fun (*cm.social*); (6) Because I like the feeling (*cm.feeling*); (7) cannabis potency; (8) To be liked by others (*cm.liked*); (9) I feel as if something pleasant had just happened to me (*ce.pleasant*); and (10) I feel a very pleasant emptiness (*ce.emptiness*).

The *weakest ten attributes* were: (1) At Other location (*loc_otherYN*); (2) At a bar/restaurant (*loc_barYN*); (3) At Other public place (*loc_otherpubYN*); (4) My mouth seems very dry (*ce.dry*); (5) Outside (*loc_outsideYN*); (6) I am more suspicious of others (*ce.suspicious*); (7) Alcohol (*alcYN*); (8) Because it's fun (*cm.fun*); (9) Some parts of my body are tingling (*ce.tingling*); and (10) Cigarettes (*cigYN*).

5.0 Discussion

In this study, we sought to identify the strongest correlates of higher quantity of cannabis use in daily life among 52 regular cannabis smokers. Based on previous investigations concerning predictors of the amount of cannabis used, we pre-selected 43 attributes from our smartphone survey data that focused on affect, impulsivity, pain, alcohol use, cigarette use, craving, cannabis potency, substance use motivation, effects of cannabis, and context (who participants were with and where they were). We then trained five models on the dataset using ***RapidMiner***. Our best fitting model, Gradient Boosted Trees, correctly predicted the class of amount of cannabis smoked in approximately 71% of cases, which is appreciably better than classification by the baseline model (Decision Tree; ~53% accuracy).

As presented in **Figure 1**, among the attributes that had the greatest impact on model predictions were affective state (PA and NA), pain, endorsement of a range of cannabis effects (e.g., difficulty in remembering; feel as if something pleasant had just happened to me; and feel a very pleasant emptiness), and motivations to use cannabis (e.g., it makes social gatherings more fun; because I like the feeling; to be liked by others).

These features are somewhat consistent with existing understandings of the factors that influence cannabis use. Concerning affective state and pain, several motivational theories of substance use are relevant. For example, the *affective-motivational model of drug addiction* suggests that individuals may use more of a substance in order to deal with painful or aversive states (Baker, 2004). Ostensibly, by using more cannabis when these states are present, negative affect and pain may be reduced, serving to negatively reinforce higher amounts of use. On the other hand, cannabis may be used more to enhance positive affect, and there is evidence that positive affect may be elevated in anticipation of the effects of cannabis use (Buckner et al., 2015; Chakroun et al., 2010).

Concerning cannabis motives, our results converge with the evidence that cannabis use may be used to improve social interactions and to also conform to others using cannabis or increase the probability of fitting in. Regarding subjective effects, the most highly weighted predictor of use of higher cannabis amounts was *lower scores* on the item “I have difficulty in remembering.” This suggests the possibility individuals may be more likely to use greater amounts when their memory is not impaired as a result of cannabis use, whereas individuals who report some degree of memory problems with lower levels of cannabis use may be inclined to remain at a lower dose to avoid exacerbating its effects. Other subjective effect predictors were also related to *decreased amounts of cannabis used*, including pleasant subjective effects (I feel as if something pleasant had just happened to me; I feel a very pleasant emptiness), suggesting that individuals were more likely to report pleasant effects when using lower amounts of cannabis. This could be seen as evidence for moderating the use of larger amounts of cannabis if one is already in a relatively positive state.

Given previous studies, we anticipated that contextual factors might emerge as among the strongest predictors of cannabis consumed. On the one hand, items reflecting *being with others*, and particularly with a significant other or friend, were moderately weighted in the final prediction model. This finding is consistent with a number of previous studies that have found more cannabis use occurs when in the presence of others (e.g., Buckner at al., 2013; Phillips et al., 2018). However, contextual items reflecting *location* were not strongly weighted in the final prediction model, the one exception being *not at work*. Previous studies have suggested that being at home or at a friend/relative’s house was significantly associated with both craving and cannabis use (e.g., Gunn et al., 2021; Shrier et al., 2014). One possible interpretation for these results is that *being with others* is more important than *where you are with others* in terms of using more cannabis.

5.1 Limitations and Implications

As mentioned earlier, a machine learning approach to classifying individuals has the advantages of evaluating a range of predictors. These approaches not only allow researchers to evaluate predictors using more focal, hypothesis-driven approaches, but also enable the discovery of less-studied but, perhaps, important correlates. In addition, these approaches can analyze large data sets efficiently and can be improved over time to increase accuracy of classification. However, the results of these approaches are influenced by the representativeness of the training data and ultimately of the sample itself.

Although our results revealed the strongest predictors of amount of cannabis used in daily life, a number of limitations of our study are important to acknowledge. First, our sample was relatively small and consisted of regular cannabis smokers (i.e., 3+ times per week) from the community. It is possible that a different pattern of results would be obtained from either an undergraduate or clinical sample, from lighter cannabis smokers, or from those who use cannabis via different delivery methods (e.g., concentrates, edibles). Secondly, because we were focusing on the total amount of cannabis smoked in each smoking session, our analyses essentially focus on day-level associations between cannabis amounts and our predictors. This has several implications for the interpretation of the results. Most importantly, we are unable to determine the temporal precedence of cannabis smoking and these predictors/features. These relations are best interpreted as concurrent associations; we cannot assume that cannabis smoking led to changes in these features or that these features influenced the initiation of cannabis use.

Our best performing model did improve upon the baseline model; however about 29% of the smoking sessions were misclassified in terms of the amount of cannabis smoked. It is possible that the accuracy of models could be improved with additional predictors/features that were not included in this study. For example, while we did assess whether the participant was alone or with others, we did not assess whether anyone in the participants' presence was smoking cannabis. Another limitation is that we relied on participants' reports of how much cannabis they had smoked. However, research suggests that participants' estimates of the amount of cannabis used may be unreliable (e.g., Prince et al., 2018).

Despite these limitations, we briefly highlight several possible implications for reducing the amount of cannabis smoked per day. On average, more cannabis was consumed when participants reported relatively higher levels of NA and pain. Interventions might include training in better coping skills or the use of other medical interventions, as opposed to using cannabis to deal with negative affect and pain. Another set of significant predictors of increased cannabis use include motives, specifically using cannabis to make social gatherings more fun, to be liked by others, and because of the feeling. CBT skills aimed at identifying and avoiding triggering situations, problem solving, and refusal skills may be helpful in mitigating the influence of these motives for cannabis use.

5.2 Conclusions

In this study, our best-fitting model identified that affect, pain, subjective effects of cannabis, and cannabis use motives were among the best predictors of cannabis use in daily life. This is consistent with previous research finding that individuals may use cannabis for particular motives or reasons, such as experiencing a subjective or affective change. However, additional research is needed to understand how other individual and contextual differences may directly or indirectly influence the use of cannabis. Machine learning approaches can assist researchers in identifying additional relevant environmental and psychological phenomena that may be clinically-relevant to cannabis use.

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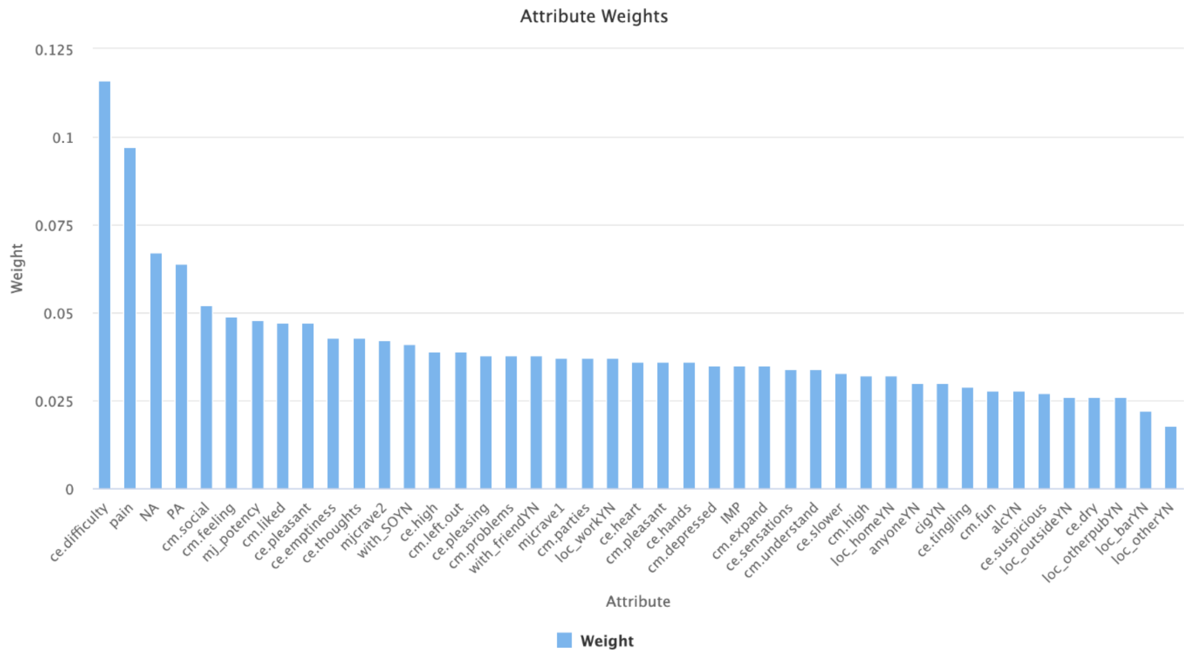
Figure 1

The attribute weights for Gradient Boosted Trees



Note: see Table 1 for definition of abbreviations.

Table 1

Forty-three attributes serving as predictors of the amount of cannabis smoked in daily life, and each attribute's correlation with amount of cannabis smoked (dichotomous; 0.2 grams or less and greater than 0.2 grams; **bolded**)

Affect, Pain, and Impulsivity (last 15 minutes)
Positive Affect (*PA; **0.156***); Negative Affect (*NA; **0.068***); Physical Pain (*Pain; **0.190***); Impulsivity (*IMP; **0.08***)

Cannabis craving (last 15 minutes)
How much did you crave cannabis? (*Craving1; **-0.095***); How hard was it to stop thinking about using cannabis? (*Craving2; **-0.176***)

Situation (last 15 minutes) (Yes/No)
Have you been with anyone? (*anyoneYN; **0.051***); Who have you been with--partner/spouse? (*with_SOYN; **0.172***); Who have you been with--friend/acquaintance? (*with_friend; **0.155***)

Location (current) (Yes/No)
Home (*loc_homeYN; **0.028***); Work (*loc_workYN; **-0.153***); bar/restaurant (*loc_barYN; **-0.01***); Outside (*loc_outsideYN; **0.030***); Other public place (*loc_otherpubYN; **0.013***); Other (*loc_otherYN; **0.030***)

Recent other substance use (Yes/No)
Alcohol (*alcYN; **0.031***); Cigarettes (*cigYN; **0.038***)

Potency of the cannabis you consumed
(*mj_potency*; **0.141**)
Less strong than what I typically consume (0); Similar in strength to what I typically consume (1); Stronger than what I typically consume (2).

Motivations for cannabis use (I used cannabis….) *[1=strongly disagree; 2=disagree; 3=agree; 4=strongly agree])*
Because I like the feeling (*cm.feeling; **0.020***); Because it makes social gatherings more fun (*cm.social; **0.140***); To be liked by others (*cm.liked; **0.030***); Because it helps me when I feel depressed or nervous (*cm.depressed; **0.017***); To understand things differently (*cm.understand; **0.036***); Because it's fun (*cm.fun; **-0.021***); Because it improves parties and celebrations (*cm.parties; **0.075***); So I won't feel left out (*cm.left.out; **0.073***); To forget about my problems (*cm.problems; **0.151***); To expand my awareness (*cm.expand; **0.056***); Because it gives me a pleasant feeling (*cm.pleasant; **0.022***); To get high (*cm.high; **0.084***)

Effect/Subjective response (Since using cannabis, how much have you felt….) *(1 = not at all, 5 = extremely)*
Things around me seem more pleasing than usual (*ce.pleasing; **0.054***); I feel as if something pleasant had just happened to me (*ce.pleasant; **-0.094***); I have difficulty in remembering (*ce.difficulty; **-0.154***); I feel a very pleasant emptiness (*ce.emptiness; **-0.127***); My mouth seems very dry (*ce.dry; **0.00***); Some parts of my body are tingling (*ce.tingling; **-0.020***); My movements seem slower than usual (*ce.slower; **-0.013***); I notice that my heart is beating faster (*ce.heart; **0.012***); My thoughts seem to come and go (*ce.thoughts; **-0.096***); I notice my hands are shaking (*ce.hands; **0.014***); I have an increasing awareness of my bodily sensations

(*ce.sensations;* ***0.038***); I am more suspicious of others (*ce.suspicious;* ***0.054***); high (*ce.high;* ***0.175***);

Table 2

Performance Comparison of Machine Learning Models in Predicting Larger Amount of Cannabis Smoked (i.e., > 0.20 grams)

MODEL	Accuracy	True Positive Rate (SENS)	False Positive Rate	False Negative Rate	True Negative Rate (SPEC)	Recall	Precision
Decision Tree	53.29%	83.05%	73.40%	16.95%	26.60%	83.05%	50.36%
Random Forest	61.10%	65.93%	37.54%	34.07%	62.46%	65.93%	61.16%
Deep Learning (H2O)	67.31%	65.08%	30.70%	35.42%	69.30%	65.08%	65.53%
Support Vector Machine	70.27%	71.19%	30.55%	28.81%	69.45%	71.19%	67.63%
Gradient Boosted Trees	71.15%	62.88%	21.43%	37.12%	78.57%	62.88%	72.46%