Factors Affecting the use of Legal and Illicit Drugs

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***Abstract*— This paper aims to evaluate what variables can cause someone to become a user of an illicit or non-illicit drug. It was shown that for non-illicit drugs it is extremely hard to determine. This is because these drugs are openly available in various different countries and hence its (large amount of) users will exhibit a huge variety of characteristics. For illicit drugs, weak correlations are drawn to determine why someone is a "User". Classification models are then built for each respective drug variable and it is shown that for non-illicit drugs, classification is largely due to chance compared to illicit ones. While more research is needed into a larger variety of drugs and larger population size, it can be shown that there is some common themes as to why people consume illicit drugs.**

I. Introduction

Studies surrounding drug use have been around for decades. Much has been said about the reasoning of why people consume drugs and what are the characteristic traits exhibited in human behaviour that lead to the consumption of a particular drug. This paper not only aims to analyse characteristics such as age and gender but go further and look at things such as impulsiveness, sensation seeking and levels of education.

First, the background of the current research surrounding this topic will be evaluated as well as a background on the drugs and variables in question. Following from this, various hypotheses will be tested by building a classification model for each drug in question.

These models are then analysed in terms of robustness and accuracy. The results obtained are then used to gain further insight into the overall research goals. Finally, the limitations of this analysis will be observed as well as potential areas for further research.

II. Background

A. Drug Research

Drug abuse or addiction can be described as a chronic disease [1] like many other well known diseases. Addiction is described as *"not having control over doing, taking or using something to the point where it could be harmful to you" [2]*. Many modern day societies frown upon the use of drugs without being aware of the dependencies people have on them or what led them to consume these drugs in the first place.

Many drugs alter states in our mind causing euphoria and altering our "reward circuit" [1]. These are desired affects that usually relate to things such as eating and being around loved ones. It is this desire to recreate these effect on a continuous, unnatural, basis that can lead to addiction.

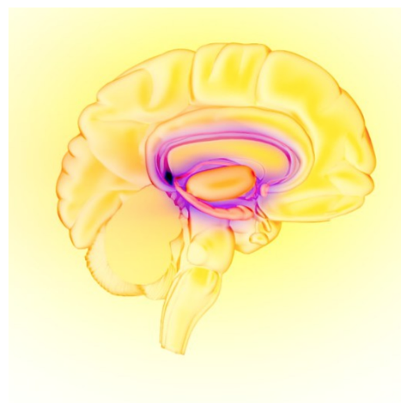

Fig. 1. The reward circuit within our brains [1]

Much has been discussed about the treatment of such addictions. These include behavioural counselling, medication and long-term follow-ups to prevent relapse [3]. However, this issue is described as a chronic disease and as such there is no such thing as a one treatment that will cure it. Hence, the focus on this paper is to see what attributes play a role in an individual taking these drugs in the first place. From there measures can be taken to prevent the use of such drugs.

B. Alcohol

Alcohol is one of the most used legal drugs in the world [4]. It is a mood changing drug which classifies under the "depressants". This essentially means that it slows down your central nervous system [5].

It is hugely popular worldwide due to its reasonable age limit (dependent on country) and the ease of access to it.

As a result, it exhibits some of the worst health statistics compared to nearly all other drugs. Taking Scotland as an example, alcohol contributed to 6.5% of all Scottish deaths in 2015, currently the cost of alcohol-related crime is estimated at £727 million a year and there were 35,499 alcohol-related hospital stays in 2017/18 [6].

C. Cannabis

Cannabis is the most widely used illicit drug in the world [14]. It is derived from the Cannabis sativa (hemp) plant and exhibits over 120 different compounds. Of these compounds THC is regarded as the most influential as to why it is consumed. THC is the key mind-altering (psychoactive) substance [14] and induces a variety of feelings such as excessive laughter, happiness, depression, anxiety or laziness.

D. Cocaine

Cocaine is one of the most popular illicit drugs and is an extremely powerful addictive stimulant. It affects the brain by producing dopamine which affects the reward circuits in our brains [8]. It can be extremely dangerous to use due to it not being sold in pure form in most cases. Instead, it is usually mixed or "cut" with other drugs such as amphetamine, or synthetic opioids, including fentanyl [8]. This can result in adverse side effects such as overdosing.

Cocaine ranks as the second most trafficked drug in the world and has a market value of over $28 Bn in the US alone [9].

E. Heroin

Heroin, like Cocaine, is a widely known illicit drug however is not as popular or readily available as the other drugs mentioned. It is an opiod drug that is made via morphine.

It is estimated some 9.2 Mn people take Heroin worldwide [10]. Interestingly, it is also estimated that heroin accounts for 18% of the admissions for drug and alcohol treatment in the US [10].

F. Dangers

Figure 2 highlights the dangers that each drug possess (based in the US). Although Heroin is not as commonly used it still has severe dangers due to the nature of the drug.

Popular non illicit drugs such as caffeine does not feature. This is due to the limited consequences it has on severe health outcomes. However, since it still possess adverse effects and can be accessible to the younger generation it should still be regarded in a serious manner.

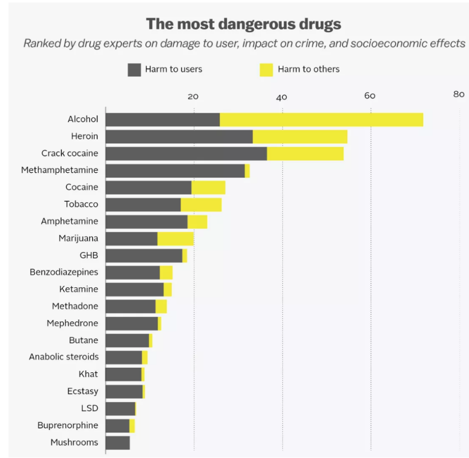

Fig. 2. The most dangerous drugs in the US [11]

III. THE DATA

The data used to analyse the attributes which affect drug consumption was sourced via *UCI, Machine Learning Repository, Centre for Machine Learning and Intelligent Systems*. The data set used was *Drug consumption (quantified) [12]* and contains 1885 instances and 32 attributes. These instances represent responses received and the 32 attributes include 19 drugs in question (of which we are looking at 4) and 13 known attributes (one of which is a simple ID reference which we are not particularly interested in).

These known attributes include age, sex, level of education, ethnicity, country and personality measures which include NEO-FFI-R (neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness), BIS-11 (impulsiveness), and ImpSS (sensation seeking).

Revised NEO Personality Inventory N(EO-FFI-R) is a *personality inventory that examines a person's Big Five personality traits [13]*. In a general sense, Neuroticism is the measure of how moody, anxious or worried someones is, extraversion is an indication of how outgoing someone is, agreeableness is an indication of kindness or warmth, conscientiousness is an indication of a desire to do one's work to a very good standard and finally openness indicates imagination or aesthetic sensitivity.

BIS-11 referred to how impulsive someone was and ImpSS was a measure of the levels of sensation a person was wishing to seek.

This data set was provided in quantified manner which meant that all 12 known attributes (excluding ID) were real valued. In terms of scales and meaning, the first five attributes can be seen in the following figures;

Value	Meaning	Cases	Fraction
-0.95197	18 - 24	643	34.11%
-0.07854	25 - 34	481	25.52%
0.49788	35 - 44	356	18.89%
1.09449	45 - 54	294	15.60%
1.82213	55 - 64	93	4.93%
2.59171	65+	18	0.95%

Fig. 3. Age

Value	Meaning	Cases	Fraction
0.48246	Female	942	49.97%
-0.48246	Male	943	50.03%

Fig. 4. Gender

Value	Meaning	Cases	Fraction
-2.43591	Left School Before 16 years	28	1.49%
-1.73790	Left School at 16 years	99	5.25%
-1.43719	Left School at 17 years	30	1.59%
-1.22751	Left School at 18 years	100	5.31%
-0.61113	Some College,No Certificate Or Degree	506	26.84%
-0.05921	Professional Certificate/ Diploma	270	14.32%
0.45468	University Degree	480	25.46%
1.16365	Masters Degree	283	15.01%
1.98437	Doctorate Degree	89	4.72%

Fig. 5. Education Level

Value	Meaning	Cases	Fraction
-0.09765	Australia	54	2.86%
0.24923	Canada	87	4.62%
-0.46841	New Zealand	5	0.27%
-0.28519	Other	118	6.26%
0.21128	Republic of Ireland	20	1.06%
0.96082	UK	1044	55.38%
-0.57009	USA	557	29.55%

Fig. 6. Country

The other personality trait attributes were also scaled in an ascending order fashion. The N-Score (used to measure Neuroticism) was quantified into values where a higher value indicated a person who was more likely to be moody. A higher Escore (used to measure Extraversion) meant a person was more outgoing and social. A higher Oscore (used to measure Openness to experience) meant that the person was more willing to try new things. A higher Ascore (used for Agreeableness) meant that the person is more likely to be friendly. A higher Cscore (used to measure Conscientiousness) indicates that a person is more likely to exhibit high

Value	Meaning	Cases	Fraction
-0.50212	Asian	26	1.38%
-1.10702	Black	33	1.75%
1.90725	Mixed-Black/Asian	3	0.16%
0.12600	Mixed-White/Asian	20	1.06%
-0.22166	Mixed-White/Black	20	1.06%
0.11440	Other	63	3.34%
-0.31685	White	1720	91.25%

Fig. 7. Ethnicity

discipline. A higher Impulsive value meant that the person was more likely to be impulsive about their decisions and SS (Sensation) is a measure of the physiological basis of perception, with a higher value indicating a higher sensation reward.
Finally all 19 drug attributes have 7 levels: "Never Used", "Used over a Decade Ago", "Used in Last Decade", "Used in Last Year", "Used in Last Month", "Used in Last Week", and "Used in Last Day".

IV. Hypothesis

Having looked at the data set and the different explanatory variables available, there could in fact be strong relationships between these attributes and drug consumption. As a result, the following hypotheses have been put forward:

1) Education levels have an effect on what drugs a user consumes
2) Higher sensation seekers will more likely be a "User" to an illicit drug
3) It is harder to determine characteristics that influence the use of non-illicit drugs than illicit ones due to the larger populations of consumption

V. Data Handling

The data set obtained had all of its attributes (apart from the drugs themselves) quantified. This meant that categorical variables (such as Education Level and Ethnicity) were converted into real values along with the discrete variables (such as the NEO Personality Inventory variables). This was useful as it meant that these variables did not have to be transformed.
In order to tailor the data to evaluate the hypotheses in question and help with classification, the drug levels were converted into two levels: "Non-user" and "User". All instances which were in "Never Used" and "Used over a Decade Ago" originally, were now converted to "Non-user" and the instances in the remaining levels were converted to "User". Figure 8 highlights a visual

distribution of the classes for alcohol.

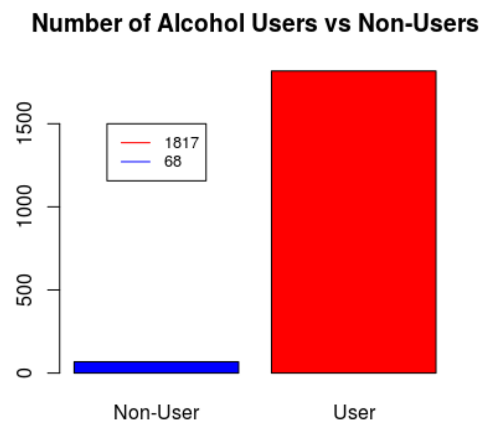

Fig. 8. Alcohol class distribution

Every drug which wasn't in question was also removed from the data set (i.e. if alcohol was being examined then it would be the only drug present in the data set). We can also see from *Figure 7* that "White" heavily dominates this variable as it amounts to 91.25% of the entire variable. As a result this attribute will also be removed from the data set due to the likelihood that it will nearly always come up as a dominant feature in classifying a drug (i.e. being White will almost certainly determine the outcome of drug use). The "ID" variable was also removed from the data set as it did not add any value to the analyses.

A. *Correlation*

To begin with, the correlation between alcohol and all remaining attributes were calculated individually. Correlation defines the statistical relationship between two variables whether it be positive, negative or casual. In order to calculate these correlations the statistical package "R" was used. "R" is a statistical programming language used mainly for statistical computing and graphics. It is a very useful tool as it contains multiple in-built functions that carry out statistics based problems (such as calculating correlation).
The *Pearson Correlation* was calculated via the R in built function *cor()*. This is based off the *Pearson Correlation Formula*:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

- x and y are the vectors of the two variables in question of length n
- $\bar{x}$ and $\bar{y}$ corresponds to the means of x and y, respectively.

This formula will calculate the linear dependence between two variables. The more highly correlated two variables are, the closer the absolute value of *r* will be to 1. On top of this, a correlation test was also carried out to evaluate the significance level of the correlation. This significance level is based off of a p-value which is the probability of obtaining an observed result given that the Null Hypothesis is correct. The lower the p-value, the more significant the correlation is and hence gives more reason to reject the Null Hypothesis (there is no correlation between the two variables). An example of an output for this test can be shown between Alcohol Consumption and Gender:

```
	Pearson's product-moment correlation

data:  alcohol and alcohol_data$Gender
t = 0.48938, df = 1883, p-value = 0.6246
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.03388871  0.05639675
sample estimates:
      cor
0.011277
```

The resulting p-value is very high and there is a very weak positive correlation present (r = 0.011277). This tells us that Gender has little effect on being a "User" or "Non-User" of alcohol.
Performing the same test on the remaining variables, the following were deemed to be significant (p-value < 0.05) or highly significant (p-value « 0.05): A-score (significant), C-Score (significant), Impulsive (highly significant), Sensation (highly significant) and Age (highly significant). These produced the following linear models:

$$y = -0.021127x_0 + 0.964657, R^2 = 0.009898$$

$$y = 0.018374x_1 + 0.963986, R^2 = 0.009012$$

$$y = 0.013320x_2 + 0.963830, R^2 = 0.004646$$

$$y = -0.012143x_3 + 0.963921, R^2 = 0.004217$$

$$y = -0.008965x_4 + 0.963924, R^2 = 0.002298$$

Where y = Alcohol consumption, x_0 = Age, x_1 = Sensation, x_2 = Impulsive, x_3 = C-Score and x_4 = Sensation. R^2 represents coefficient of determination and is a measure of how close the data is to the fitted regression line. It essentially shows how much of the variation of the response variable (y) is explained by the model.

The coefficient of determination values (and the corresponding Pearson correlation values which are next to the respective x variables) are all low and seem to contradict the p-value results of significance. This is due to the sample size in question. The p-value (significance level) is based on the t-value:

$$t = \frac{r}{\sqrt{1-r^2}}\sqrt{n-2}$$

This t-value is then applied to a t distribution table on $n-2$ degrees of freedom to determine the p-value. The larger the sample size, the larger the t-value and hence the more significant the p-value will become (whilst r stays fairly constant). This basically means that the significant p value refers to the fact that, given the sample size (n), the error measurement associated with these variables is small enough so the correlation is reliable.

Therefore, the following (although very weak) inferences can be made:

- A person who is younger is more likely to be an alcohol "User"
- A higher sensation feeling regarding the consumption of alcohol results in a person more likely to become a "User"
- The more impulsive some one is the more likely they are to become a "User"
- The less disciplined someone is (lower Cscore) the more likely they are to become a "User"
- A person who is less friendly or warm (lower Ascore) will more likely become a "User"

VI. Classifier

In order to determine whether or not a person is a user of alcohol, a statistical classifier was built using WEKA software. WEKA posses a comprehensive collection of data preprocessing and modeling techniques which is useful for classification. The 5 attributes included in classifying the Alcohol class are mentioned previously as the ones which tested significantly. A K-Nearest Neighbours (KNN) method was implemented to classify the Alcohol class. This approach works by looking out how closely an out-of-sample data point resembles a training data point based on how close it is to its neighbour (distance from its neighbour is determined by the k value). Here a k value of 5 was selected. This produced the following results (on a 66% training split):

```
=== Summary ===

Correctly Classified Instances         622               97.0359 %
Incorrectly Classified Instances        19                2.9641 %
Kappa statistic                          0
Mean absolute error                      0.0594
Root mean squared error                  0.1805
Relative absolute error                 88.1779 %
Root relative squared error            106.2138 %
Total Number of Instances              641
```

Fig. 9. Summary K-Nearest Neighbour Classifier

This shows a 97% accuracy in terms of classification which is very good. However, it can be suggested that this is extremely accurate due to the fact that the number of "Users" dominates the number of "Non-Users" (hence misclassification is difficult regarding "Users" and classification is difficult regarding "Non-Users"). A confusion matrix can be seen in *Figure 10*, which shows which correct and incorrect classifications were made.

```
=== Confusion Matrix ===

 a   b   <-- classified as
 0  19 |   a = Non-User
 0 622 |   b = User
```

Fig. 10. Confusion Matrix

From the confusion matrix it is clear that classification for "Non-Users" is difficult. It is also clear that the robustness of this model is weak. This can be seen with the Kappa Statistic value of 0. This statistic takes into account chance agreement. When the attributes used to build the classification model only agree on "chance" then the Kappa Statistic Value is 0 and when when they are in complete agreement the value is 1. A more detailed look at the accuracy can be seen in *Figure 11*.

```
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.000    0.000    ?          0.000    ?          ?        0.635     0.050     Non-User
                 1.000    1.000    0.970      1.000    0.985      ?        0.635     0.978     User
Weighted Avg.    0.970    0.970    ?          0.970    ?          ?        0.635     0.951
```

Fig. 11. Accuracy breakdown of classifier

This classifier produces a ROC (Receiver Operating Characteristic) of 0.635. This statistic analyses the True Positive rate against the False Positive Rate. A value of 0.5 would indicate that the classified classes were all down to chance and a value of 1 would indicate that chance does not play a part in classification and it is indeed a very good classifier. A value of 0.635 indicated that it tends towards chance.

VII. Different Drug Attributes

The same techniques discussed in the previous sections were applied to other drug attributes with results shown in *Table 1*. Note, a NaiveBayes classifier was used instead of a KNN classifier for "Heroin". This was because it produced a classification model with similar accuracy's to KNN, however more robust. The NaiveBayes classifier is based on applying Bayes Theorem with strong naive independence assumptions about the variables. It essentially works by predicting the probability of a certain classification given the prior knowledge (training data) it has access to.
It can be seen that the correlations between these drugs and the various other attributes are much greater (although still relatively weak) than those compared to alcohol.

A. Analysis of Table 1

Although nearly all of the correlations remain fairly weak between the drug attributes and the explanatory variables, the following inferences were made about each of the respective drugs:

- Cocaine - A person who exhibits any of the following attributes is more likely to become a "User"; Seeks a higher sensation fulfillment (x_{10}), is inherently more impulsive (x_9), has lower self-discipline (x_8), is less friendly/warm (x_7), is more open to trying new things (x_6), is from the USA (x_3), is male (x_1) and is generally younger (x_0).
- Heroin - A person who exhibits any of the following attributes is more likely to become a "User"; Seeks a higher sensation fulfillment (x_{10}), is inherently more impulsive (x_9), has lower self-discipline (x_8), is less friendly/warm (x_7), is more open to trying new things (x_6), is more anxious/moody/worried (x_4) and is from the USA (x_3).
- Cannabis - A person who exhibits any of the following attributes is more likely to become a "User"; Seeks a higher sensation fulfillment (x_{10}), is inherently more impulsive (x_9), has lower self-discipline (x_8), is more open to trying new things (x_6), is from the USA (x_3), is male (x_1) and is generally younger (x_0).

All these attributes contributed to classifiers that at least produced reasonable fits in classifying a "User" and a "Non-User". This, coupled with the fact that these classifiers (generally) tended away from chance meant that they were informative in showing what can affect someone being a "User" of the respective drug.
A general trend can also be seen from being a "User" of each drug. They tend to be higher sensation seekers, more impulsive, have lower self-discipline, are more open to new experiences and are from the USA. Interestingly the last point of the USA is consistent across all three drug variables. This is due to the fact that the USA holds a huge (biggest in some cases) market for each of the respective drugs compared to other countries, hence more users will originate from here.
Compared to alcohol, these classification models were far less down to chance and the correlations were far stronger. This may be due to the fact that Alcohol is far more widely available to the populations in each respective country. This means that there will be a huge amount of people who are a "User" (*Figure 8*) and hence within the population of these users, there will be a large variety of characteristics to examine. This then makes it difficult to identify a single attribute (or even multiple) that determine why a person will be a "User".
Once the numbers of "User" and "Non-User" even out, certain explanatory variables exhibit stronger correlations. But it should also be noted that no single attribute held a significantly strong correlation. This indicates that although some explanatory variables are useful in indicating why someone will be a "User" along with other variables, they are not very useful in this classification by themselves.

VIII. Conclusions

It was originally hypothesised that Education levels would have an influence on determining a "User" from a "Non-User". The thought behind this was that increased levels of education would generally mean people are more aware and capable of understanding the adverse effects of drugs, hence being deterred from using them. However this was not the case and did not become an influential variable for any of the drugs examined.
However, people who sought higher sensation fulfillment's were clearly more inclined to take illicit drugs. This is due to the fact that illicit drugs generally tend to produce more powerful and immediate effects regarding the sensation we feel from taking them.
It was also true that determining why someone is a "User" for non-illicit drugs was far more difficult with a lot of it being down to chance. This was because of the variety and size of the "User" populations. But what can also be seen from our results is that it is still difficult to underline a significant reason as to why someone would

TABLE I

$x_0 = Age, x_1 = Gender, x_2 = Education, x_3 = Country, x_4 = Nscore, x_5 = Escore, x_6 = Oscore, x_7 = Ascore, x_8 = Cscore, x_9 = Impulsive, x_{10} = Sensation$

Classification of Drug Attributes			
Drug Attribute	Attributes with Significant P-Values in relation to Pearsons Correlation (r)	Classifier used (trained on 66% split) and Accuracy	K-Means Classifier Robustness
Cocaine (Number of "Non-Users" = 1198, "Users" = 687)	$x_{10}(r = 0.3313977), x_9(r = 0.2516973), x_8(r = -0.1954631), x_7(r = -0.1724028), x_6(r = 0.1962896), x_3(r = -0.2694225), x_1(r = -0.1616339), x_0(r = -0.2322048)$	KNN; 67.5507% (k = 3) - Reasonable Fit	Kappa Statistic = 0.2824, ROC statistic = 0.674 - Classification tends towards chance
Heroin (Number of "Non-Users" = 1673, "Users" = 212)	$x_{10}(r = 0.2193746), x_9(r = 0.2020055), x_8(r = -0.1449864), x_7(r = -0.153676), x_6(r = 0.151081), x_4(r = 0.1565782), x_3(r = -0.3036575)$	NaiveBayes; 85.9416% - Very Good Fit	Kappa Statistic = 0.3798, ROC statistic = 0.832 - Classification shows fairly good robustness and a strong ROC value (indicating classifications aren't entirely based on chance)
Cannabis (Number of "Non-Users" = 620, "Users" = 1265)	$x_{10}(r = 0.4098043), x_9(r = 0.2952435), x_8(r = -0.2719424), x_6(r = 0.3502168), x_3(r = -0.4586584), x_1(r = -0.2374969), x_0(r = -0.4363857)$	KNN; 79.8752% (k = 6) - Good Fit	Kappa Statistic = 0.5573, ROC statistic = 0.839 - Classification shows good robustness with a strong ROC value (indicating classifications aren't entirely based on chance)

become a "User" of an illicit drug. There are so many external influences in the world that people are affected by and cause them to take these drugs. This means that there needs to be attention payed to multiple factors. It also shines light on the fact that people may consume these drugs for multiple different reasons which may be affecting their lives and hence understanding and supporting them is key.

A. Limitations

This data set only contained 1885 respondents (people who answered) and hence does not represent large populations in an accurate manner. It was also shown that "white" ethnicity severely dominated the respondents, meaning that other racial background were underrepresented. Due to this fact, the "Ethnicity" variable had to be removed and was not considered.
This study also considered only three illicit drugs and one non-illicit drug so the findings cannot accurately represent the wider drug variables available. On top of this, the assumption was made that anyone who "Used in Last Decade", "Used in Last Year", "Used in Last Month", "Used in Last Week", and "Used in Last Day" were classed as a "User". However, this does not take into account the frequency of use and hence does not clearly represent a typical "User" so to say.

B. Recommendations

More research should be done on a wider range of drugs (both illicit and non-illicit) to fully asses the Hypotheses in question. These studies should also be carried out on audiences of a larger magnitude and more diverse backgrounds. It would also be beneficial to obtain feedback from an equal number of users and non-users in order to clearly distinguish what are the key factors attributing to drug consumption.
Following from this, it would be recommend that action should be put in place to help people who exhibit the characteristics included in the classification models. This could help prevent them from consuming these drugs as well as supporting them in rehabilitation (if needed).

C. Applications

Drugs can have a damaging impact on people, families, communities and governments. On a regular basis they contribute to a large number of social, economic and health issues. This has led to increase in research to help combat drug use.
This paper analysed what influences a person to be a user in the first place. The results of this paper allow for more action to be taken on drug prevention and "User" identification. This can help with combating drug use before it has even begun and also allowing for support networks to be more efficiently established.

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