Drug Consumption

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Contents

1 Introduction

Drug use is a significant risk behavior with serious health consequences for individuals and society. Multiple factors contribute to initial drug use, including psychological, social, individual, environmental, and economic elements, as well as personality traits. While legal substances like sugar, alcohol, and tobacco cause more premature deaths, illegal recreational drugs still create substantial social and personal problems.

In this data science project, we aim to identify factors and patterns potentially explaining drug use behaviors through machine learning techniques. By analyzing demographic, psychological, and social variables in our dataset, we'll aim to uncover potential predictors, use machine learning methods to understand the complex relationships surrounding drug consumption, demonstrating how machine learning can reveal insights into behavioral patterns. While our findings won't directly inform interventions, this project showcases how data-driven approaches can enhance our understanding of complex social phenomena and provide valuable practice in applying machine learning to real-world datasets.

The database contains records for 1,885 respondents with 12 attributes including personality measurements (NEO-FFI-R, BIS-11, ImpSS), demographics (education, age, gender, country, ethnicity), and self-reported usage of 18 drugs plus one fictitious drug (Semeron). Drug use is classified into seven categories ranging from "Never Used" to "Used in Last Day." All input attributes are quantified as real values, creating 18 distinct classification problems corresponding to each drug. A detailed description of the variables can be found in the Column Decsription text file.

2 Cleaning and Formatting the Dataset

2.1 Fomatting the Dataset

The original data set had all the values for most of the variables set to a random floating number representing a specific categorical value, we believe this was done in order to remove bias from the dataset. As the requirements of this project is different form the data set's original intention we had to replace these values with the original values in order to complete all the required steps for our project.

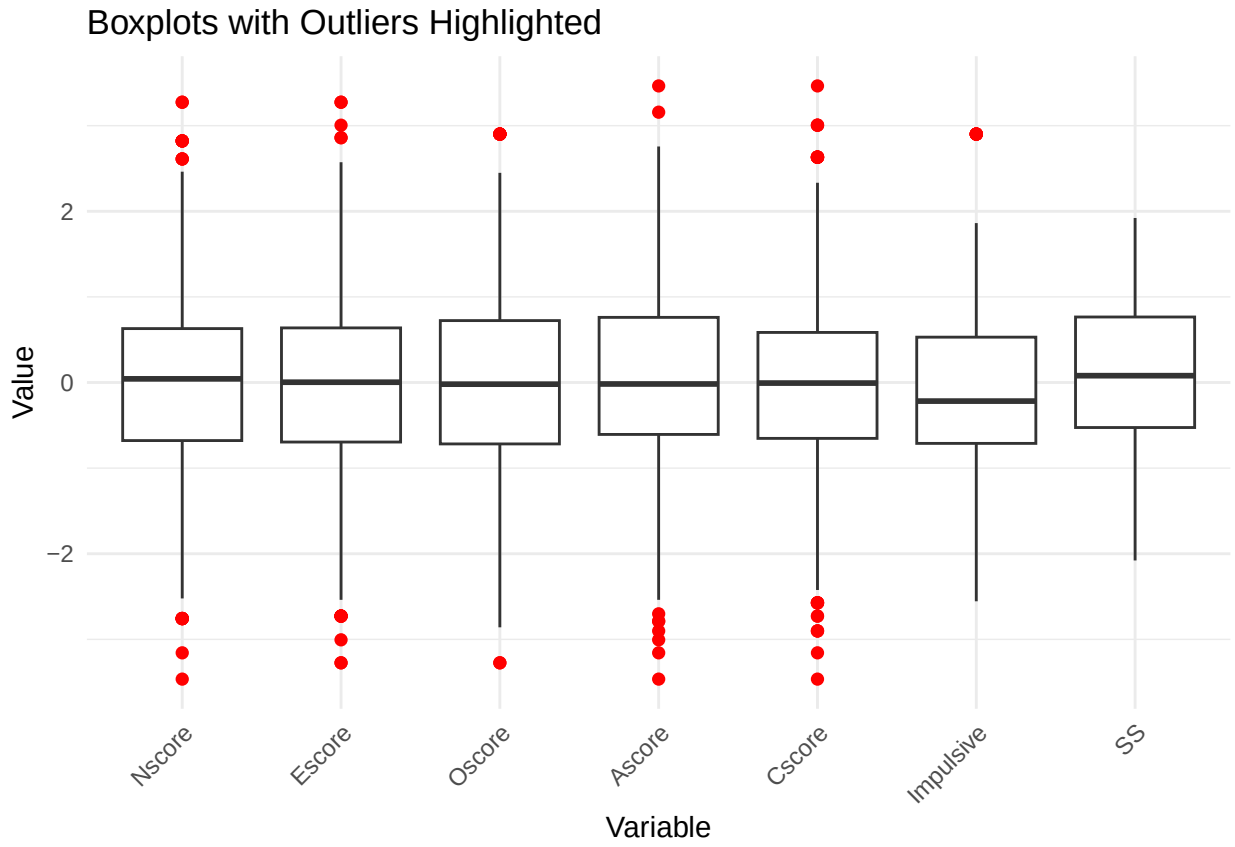
2.2 Investigating Missing Values

```
## NA values by column:

## Education Ethnicity
##        99        83
```

Only two columns contain missing values, affecting approximately 5% of the 1885 observations. Given the nature of these variables and the completeness of the rest of the data, we assume participants deliberately withheld this information. Therefore, we replaced the missing values with "Not Provided", allowing us to treat these instances as a distinct category.

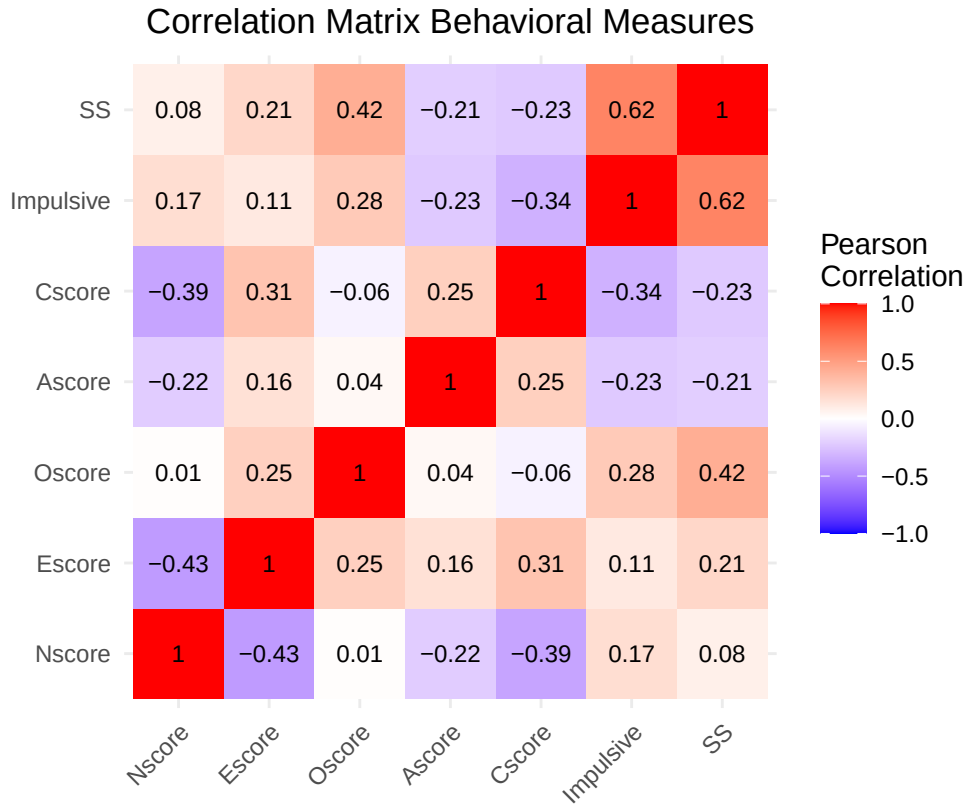
2.3 Investigating Outliers



As can be seen from the box plots our data set has some values that are outside of the upper and lower bounds. All thought these values are technically outliers they are not extreme, still fall inside of the range of our expected values and conforms to a normal distribution.

3 Exploratory Data Analysis

3.1 Correlation between Behavioral Measures



The correlation matrix shows that certain personality traits tend to cluster thougher for example SS (Sensation Seeking) has a positive correlation with Escore (Extraversion), Oscore (Openness) and Impulsive while they in turn also have positive correlations which other and a negative correlation to Cscore (Conscientiousness) and Ascore (Agreeableness) while they have a positive correlation with each other.

3.2 Comparing Behavioral Measure for Gender

The mean of all the Behavioral Measures is 0, the chart show the mean score broken down by gender for each Behavioral Measures. That chart shows that males tend to be more sensation seeking and impulsive but also more open, where females tend to be more impulsive but also more agreeable and conscientious.

3.3 Comparing Education Level with Behavioral Measures

It is not very clear at first glance but when you study the table closely it becomes clear that traits that can be precived as bad like Neuroticism, Impulsivity and Sensation Seeking is more prevelent with lower education levels inccluding Not Provided and steadily decrease as the level of education increases.

3.4 Analysis of Seremon Usage

Table 1: Semeron Usage Categories

Usage Category	Count	Percentage
Never Used	1877	99.58%
Used in Last Decade	3	0.16%
Used in Last Year	2	0.11%
Used over a Decade Ago	2	0.11%
Used in Last Month	1	0.05%

Semeron is a non exsisting drug that was introduced to the questonaire. With only 0.42% of resopndents reporting usage of Semeron. This would indicate that the survey data is likely of good quality, with most respondents providing attentive and truthful answers regarding their substance use.

4 Prepraring the Dataset for Machine Learning

Since the main focus of the project is implementing machine learning models we decided to prepare our data for this purpose. Just like we converted our original dataset to be more human readable for data exploration we have changed our dataset dataset to be more machine readable. The sex column was changed to binary data and for all the Drug columns, Education and Age we converted the data to ordinal data.

For the Ethnicity and Country columns we used a technique called One-Hot Encoding, where we transforms a categorical variable with multiple possible values into multiple binary (0 or 1) columns. Each new column represents one possible category from the original variable, and for each observation, exactly one of these new columns will have the value 1 (hence "one-hot") while all others will be 0.

It prevents the machine learning algorithm from assuming an arbitrary numerical relationship between categories. For example, if you simply encoded "USA"=1, "UK"=2, "Canada"=3, the algorithm might incorrectly assume that "Canada" is somehow "greater than" or "three times more important than" "USA".

5 Machine Learning Models

5.1 Linear Model

As linear regression is not the ideal model for our dataset when making predictions we decided to use linear regression to better understand what factors influences drug use and focus in the better suited models on making predictions.

5.1.1 Personality Traits as Predictors of Substance Use

Based on the comprehensive statistical analysis of the drug consumption dataset, several significant patterns emerged in the relationship between personality traits and substance use. Linear regression models were developed for various substances including Cannabis, Alcohol, Nicotine, Cocaine, and Ecstasy, with the most robust predictive model being developed for Cannabis (highest adjusted R^2 value). The analysis revealed that Sensation Seeking (SS) and Impulsivity consistently showed strong positive correlations with substance use across multiple drugs, while Conscientiousness and Agreeableness demonstrated significant negative relationships. Demographic factors also played important roles, with Age showing a generally negative association with drug use, particularly for Cannabis and Ecstasy. Gender differences were observed across several substances, with males showing higher consumption patterns for certain drugs. The regression diagnostics indicated reasonably well-fitting models, particularly for Cannabis, where personality traits explained a substantial portion of the variance in usage patterns. These findings support existing literature

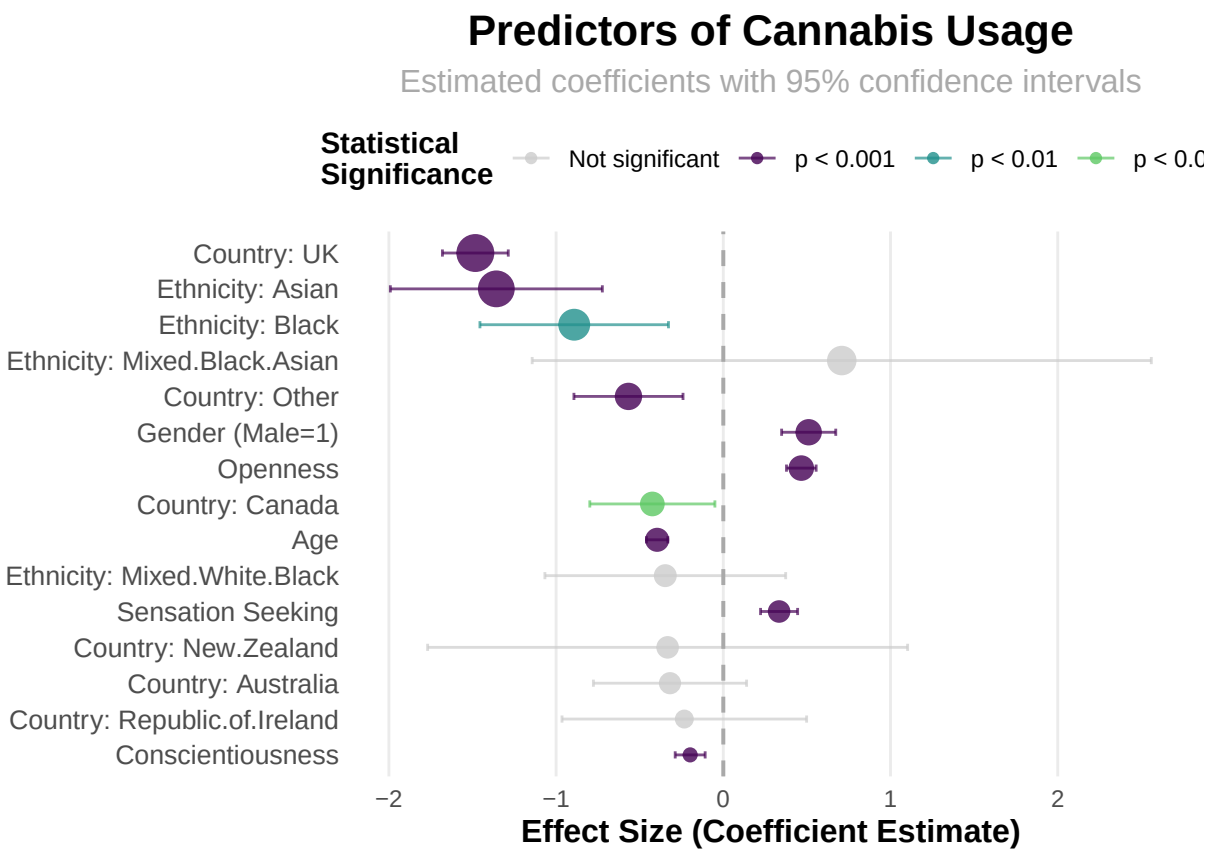
suggesting that certain personality profiles may predispose individuals to higher substance use behaviors, with Sensation Seeking emerging as the strongest personality predictor across multiple substances.

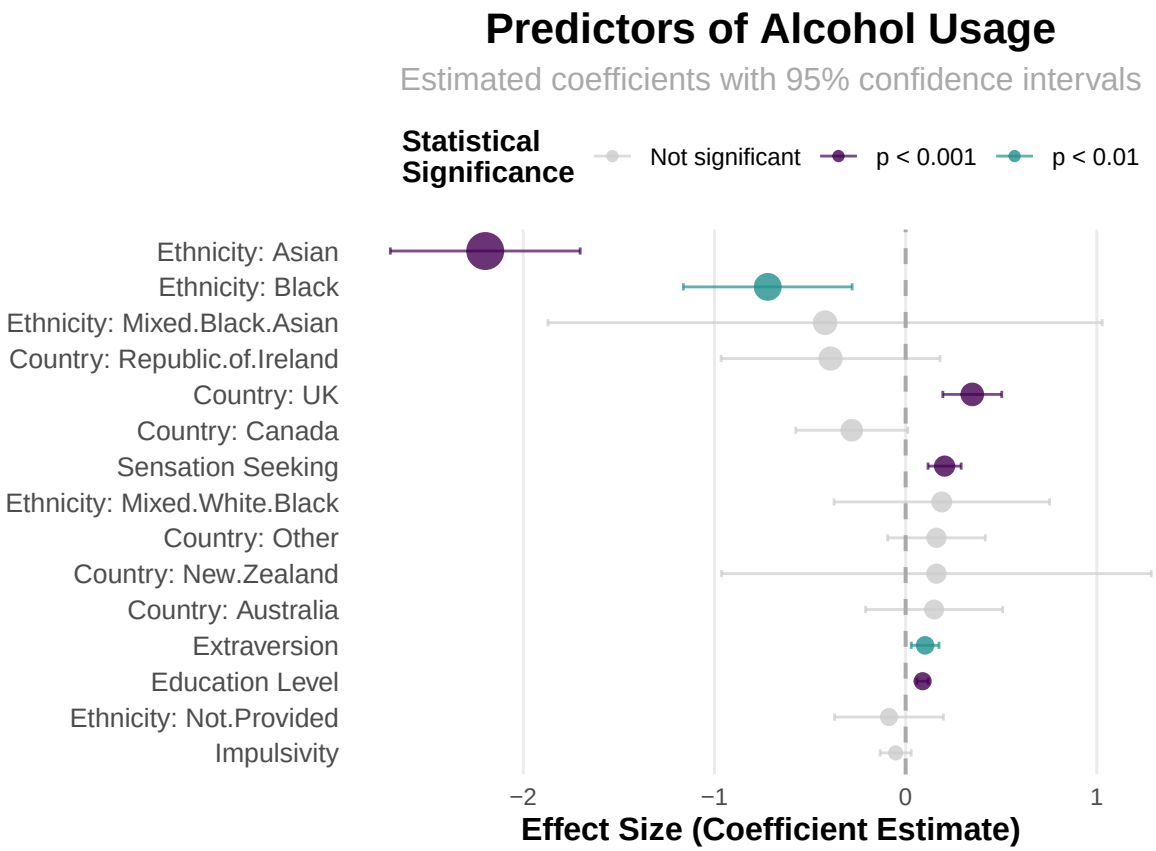
5.1.2 A graphical analysis of Cannibis

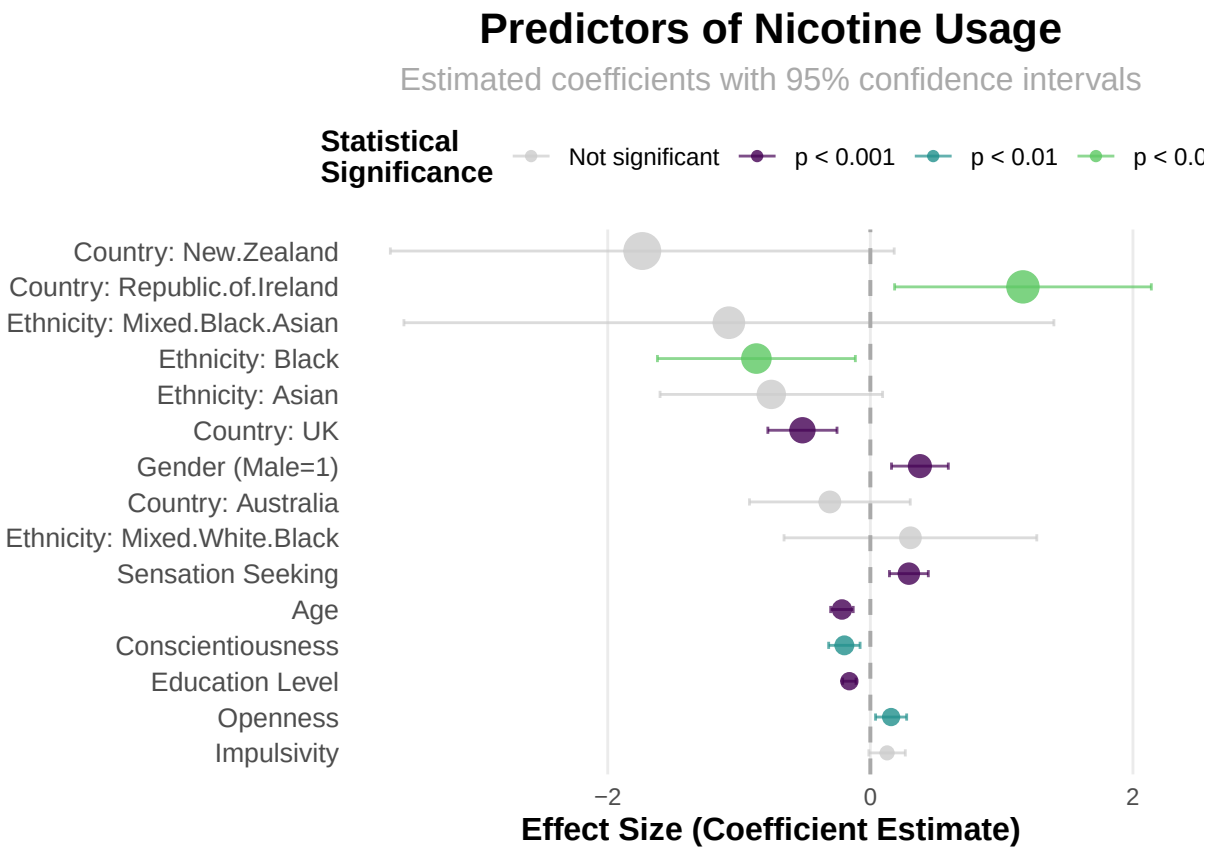
Table 2: Linear Regression Models for Drug Usage (Usage Level 0-6)

	Drug Models				
Variable	Cannabis	Alcohol	Nicotine	Coke	Ecstasy
Intercept	5.387***	3.929***	4.925***	1.588***	2.295***
Age	-0.396***	-0.031	-0.216***	-0.095***	-0.307***
Gender (Male=1)	0.511***	0.043	0.377***	0.216**	0.344***
Education Level	-0.116***	0.089***	-0.160***	-0.005	-0.026
Neuroticism	-0.112*	0.049	0.109	0.123**	-0.002
Extraversion	-0.098*	0.102**	0.009	0.113**	0.113**
Openness	0.467***	-0.040	0.158**	0.029	0.175***
Agreeableness	-0.037	-0.031	0.010	-0.144***	-0.026
Conscientiousness	-0.198***	-0.031	-0.198**	-0.095*	-0.169***
Impulsivity	0.017	-0.052	0.128	0.035	-0.003
Sensation Seeking	0.334***	0.204***	0.293***	0.272***	0.257***
N	1885	1885	1885	1885	1885
R^2	0.499	0.094	0.197	0.195	0.291
Adjusted R^2	0.494	0.083	0.188	0.186	0.283
F-statistic	88.484	9.151	21.715	21.454	36.412

Significance levels: * * p<0.05; ** p<0.01; *** p<0.001


Predictors of Cannabis Usage
Estimated coefficients with 95% confidence intervals
Statistical Significance
Not significant
p < 0.001
p < 0.01
p < 0.0
Country: UK
Ethnicity: Asian
Ethnicity: Black
Ethnicity: Mixed.Black.Asian
Country: Other
Gender (Male=1)
Openness
Country: Canada
Age
Ethnicity: Mixed.White.Black
Sensation Seeking
Country: New.Zealand
Country: Australia
Country: Republic.of.Ireland
Conscientiousness
−2
−1
0
1
2
Effect Size (Coefficient Estimate)


Predictors of Alcohol Usage
Estimated coefficients with 95% confidence intervals
Statistical Significance
Not significant
p < 0.001
p < 0.01
Ethnicity: Asian
Ethnicity: Black
Ethnicity: Mixed.Black.Asian
Country: Republic.of.Ireland
Country: UK
Country: Canada
Sensation Seeking
Ethnicity: Mixed.White.Black
Country: Other
Country: New.Zealand
Country: Australia
Extraversion
Education Level
Ethnicity: Not.Provided
Impulsivity
−2
−1
0
1
Effect Size (Coefficient Estimate)




```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
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```
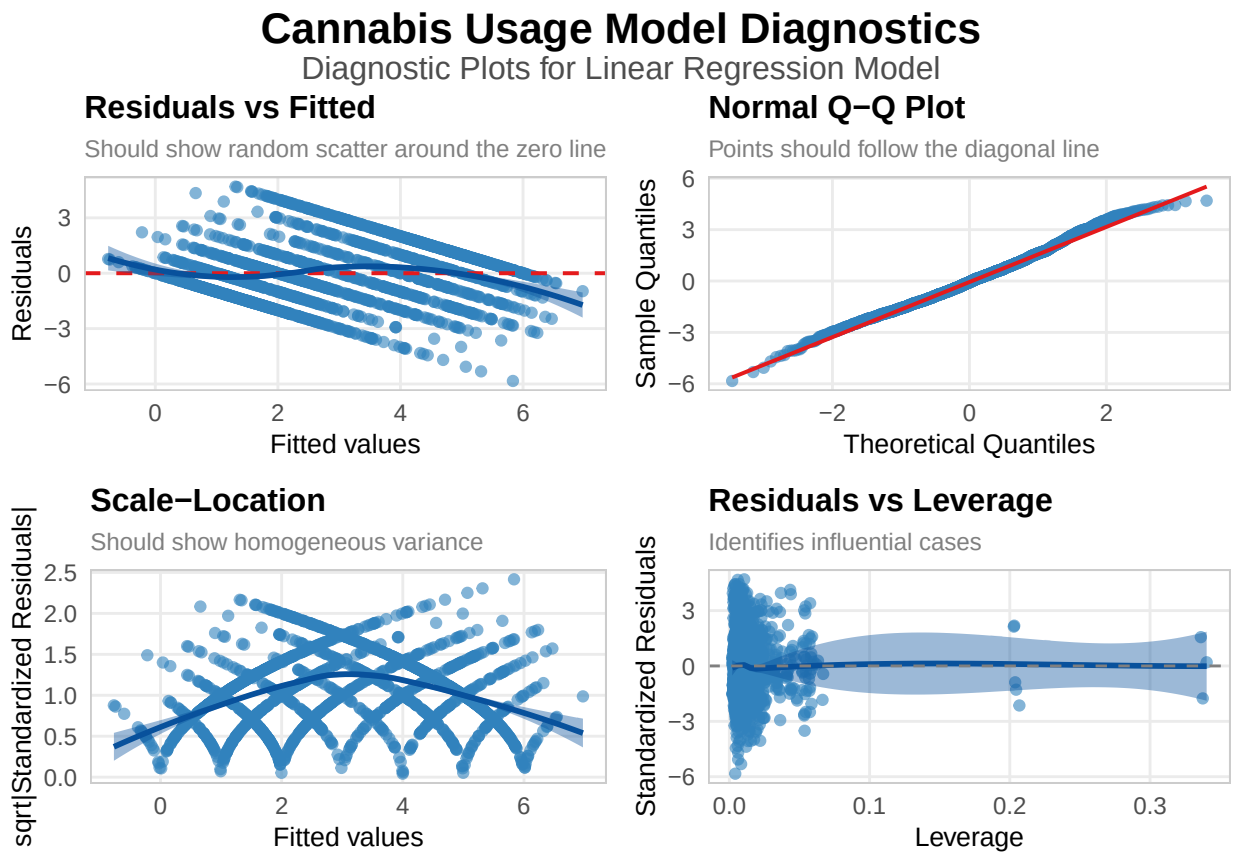




```
## TableGrob (2 x 1) "arrange": 2 grobs
##   z     cells    name           grob
## 1 1 (1-1,1-1) arrange gtable[arrange]
## 2 2 (2-2,1-1) arrange gtable[arrange]
```

5.1.3 Cannabis Usage Linear Regression Model: Diagnostic Analysis

1. Residuals vs Fitted Plot Analysis

The Residuals vs Fitted plot examines the relationship between model predictions and their errors. In an ideal linear regression model, residuals should display random scatter around the zero line with no discernible pattern. The Cannabis model exhibits some systematic patterning in the residual distribution rather than purely random dispersion. This non-random pattern suggests the presence of unexplained structure in the data that the current linear specification fails to capture. The deviation of the smoothed blue line from horizontal indicates potential non-linear relationships between predictors and cannabis usage that warrant further investigation. Such patterns may suggest the need for polynomial terms, interaction effects, or transformation of variables to improve model specification.

2. Normal Q-Q Plot Analysis

The Normal Q-Q plot evaluates whether model residuals conform to a normal distribution, a key assumption in linear regression. Points should ideally follow the diagonal reference line throughout the distribution. The Cannabis model shows reasonable conformity in the central region but notable departures at both extremes of the distribution. These deviations, particularly visible in the tails, indicate that the residuals exhibit

heavier tails than expected under normality. This pattern suggests that the model may produce less reliable predictions for individuals with very high or very low cannabis usage levels. The non-normality could affect the validity of confidence intervals and hypothesis tests, though the regression coefficients themselves remain unbiased estimators.

3. Scale-Location Plot Analysis

The Scale-Location plot assesses homoscedasticity—whether residual variance remains constant across all fitted values. The square root transformation of absolute standardized residuals helps visualize variance patterns. In the Cannabis model, the non-horizontal trend in the smoothed line indicates heteroscedasticity, with residual variance appearing to change across the range of predicted values. This uneven spread suggests that model precision varies depending on the level of cannabis use being predicted. The presence of heteroscedasticity does not bias coefficient estimates but may affect their efficiency and the validity of standard errors. Potential remedies include robust standard errors, weighted least squares, or variable transformations to stabilize variance.

4. Residuals vs Leverage Plot Analysis

The Residuals vs Leverage plot identifies observations that disproportionately influence model parameters. Points with both high leverage (ability to influence) and large residuals (poor fit) warrant careful examination. Cook's distance contours (red dashed lines) demarcate thresholds for highly influential points. The Cannabis model demonstrates relatively favorable characteristics in this regard, with most observations exhibiting moderate leverage and no extreme outliers beyond the Cook's distance boundaries. This indicates that the regression results are not unduly influenced by a small number of anomalous data points, enhancing confidence in the overall stability of the model findings.

Conclusion

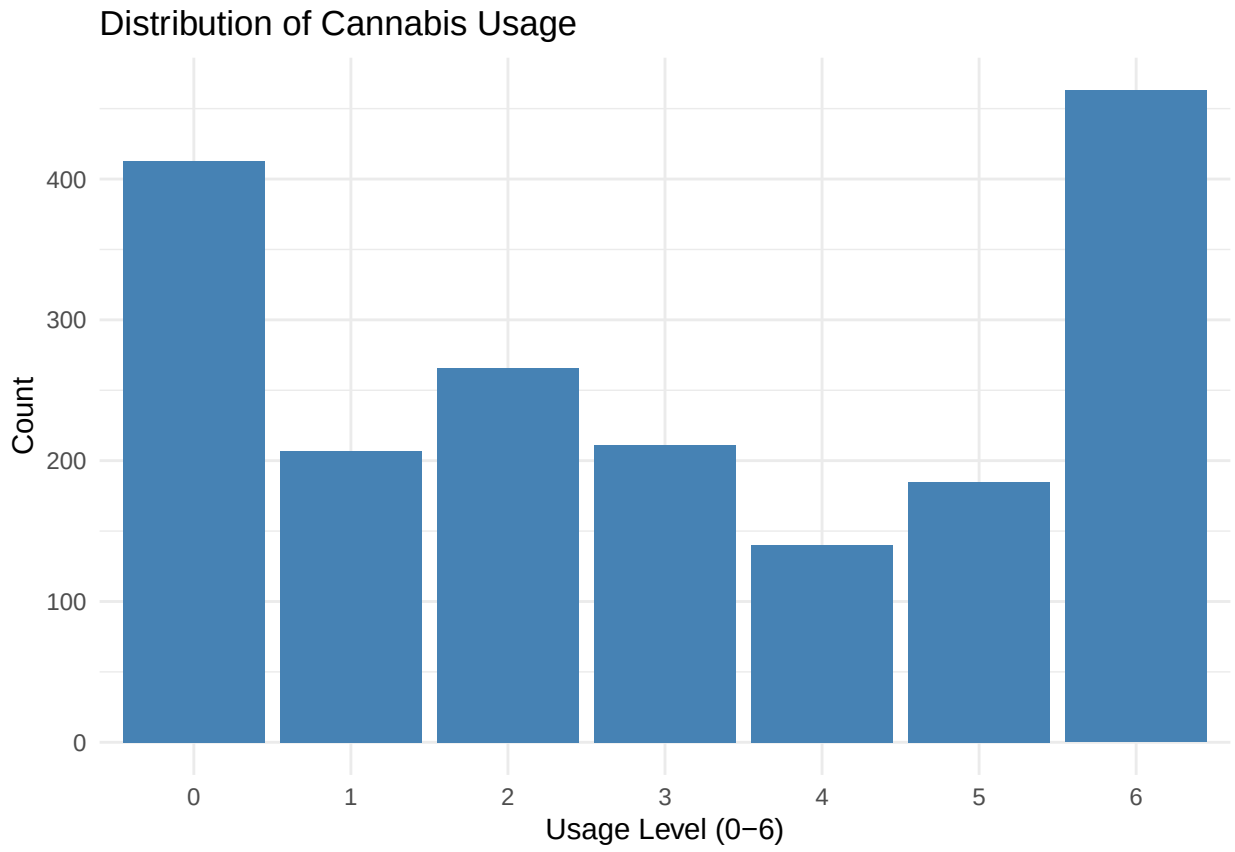
The diagnostic analysis reveals several limitations in the linear regression model for cannabis usage. The presence of non-random residual patterns, departures from normality, and heteroscedasticity suggest that while the model provides valuable insights into factors associated with cannabis consumption, it does not capture all relevant structures in the data. These limitations should be considered when interpreting the model's findings. Despite these limitations, the model maintains utility for its primary purpose—identifying significant predictors and their relative importance. The diagnostic results do not invalidate the substantive findings but rather contextualize their interpretation and highlight opportunities for model refinement. Future modeling efforts might benefit from exploring non-linear specifications, variable transformations, or alternative estimation methods to address the issues identified in this diagnostic assessment.

6 Generalised Linear Model with family set to Poisson

```
## 'data.frame':    1885 obs. of  41 variables:
##  $ Age                       : int  3 2 3 1 3 6 4 3 3 5 ...
##  $ Gender                    : int  0 1 1 0 0 0 1 1 0 1 ...
##  $ Education                 : int  7 10 7 9 10 5 9 1 7 9 ...
##  $ Nscore                    : num  0.313 -0.678 -0.467 -0.149 0.735 ...
##  $ Escore                    : num  -0.575 1.939 0.805 -0.806 -1.633 ...
##  $ Oscore                    : num  -0.5833 1.4353 -0.8473 -0.0193 -0.4517 ...
##  $ Ascore                    : num  -0.917 0.761 -1.621 0.59 -0.302 ...
##  $ Cscore                    : num  -0.00665 -0.14277 -1.0145 0.58489 1.30612 ...
##  $ Impulsive                 : num  -0.217 -0.711 -1.38 -1.38 -0.217 ...
##  $ SS                        : num  -1.181 -0.216 0.401 -1.181 -0.216 ...
##  $ Alcohol                   : int  5 5 6 4 4 2 6 5 4 6 ...
```

```
##  $ Amphet                    : int  2 2 0 0 1 0 0 0 0 1 ...
##  $ Amyl                      : int  0 2 0 0 1 0 0 0 0 0 ...
##  $ Benzos                    : int  2 0 0 3 0 0 0 0 0 1 ...
##  $ Caff                      : int  6 6 6 5 6 6 6 6 6 6 ...
##  $ Cannabis                  : int  0 4 3 2 3 0 1 0 0 1 ...
##  $ Choc                      : int  5 6 4 4 6 4 5 4 6 6 ...
##  $ Coke                      : int  0 3 0 2 0 0 0 0 0 0 ...
##  $ Crack                     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Ecstasy                   : int  0 4 0 0 1 0 0 0 0 0 ...
##  $ Heroin                    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Ketamine                  : int  0 2 0 2 0 0 0 0 0 0 ...
##  $ Legalh                    : int  0 0 0 0 1 0 0 0 0 0 ...
##  $ LSD                       : int  0 2 0 0 0 0 0 0 0 0 ...
##  $ Meth                      : int  0 3 0 0 0 0 0 0 0 0 ...
##  $ Mushrooms                 : int  0 0 1 0 2 0 0 0 0 0 ...
##  $ Nicotine                  : int  2 4 0 2 2 6 6 0 6 6 ...
##  $ VSA                       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ CountryAustralia          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ CountryCanada             : int  0 0 0 0 0 1 0 0 1 0 ...
##  $ CountryNew.Zealand        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ CountryOther              : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ CountryRepublic.of.Ireland: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ CountryUK                 : int  1 1 1 1 1 0 0 1 0 1 ...
##  $ CountryUSA                : int  0 0 0 0 0 0 1 0 0 0 ...
##  $ EthnicityAsian            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ EthnicityBlack            : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ EthnicityMixed.Black.Asian: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ EthnicityMixed.White.Black: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ EthnicityNot.Provided     : int  1 0 0 0 0 0 0 0 0 0 ...
##  $ EthnicityWhite            : int  0 1 1 1 1 1 1 1 1 1 ...
```

```
##
##   0   1   2   3   4   5   6
## 413 207 266 211 140 185 463
```




```
## Model fitted for Cannabis
## Model fitted for Alcohol
## Model fitted for Nicotine
## Model fitted for Coke
```

```
##                Variable      Estimate   Std_Error      z_value       p_value
## (Intercept) (Intercept)  1.6042654142 0.059330762  27.03935302 5.095951e-161
## Age                Age -0.1818878288 0.012651873 -14.37635636  7.282912e-47
## Gender          Gender  0.2112874708 0.029533515   7.15415938  8.418721e-13
## Education    Education -0.0462187160 0.007074931  -6.53274465  6.457519e-11
## Nscore          Nscore -0.0293297839 0.015863011  -1.84894180  6.446622e-02
## Escore          Escore -0.0768125072 0.015663886  -4.90379641  9.400192e-07
## Oscore          Oscore  0.2128848997 0.015417664  13.80785736  2.285282e-43
## Ascore          Ascore -0.0308928770 0.014230945  -2.17082399  2.994448e-02
## Cscore          Cscore -0.0668525744 0.015822675  -4.22511207  2.388219e-05
## Impulsive    Impulsive  0.0001830244 0.018718998   0.00977747  9.921988e-01
## SS                  SS  0.1700336576 0.019877189   8.55421065  1.186780e-17
##             exp_Estimate significance percent_change
## (Intercept)    4.9742043          ***           <NA>
## Age            0.8336949          ***        -16.63%
## Gender         1.2352674          ***        +23.53%
## Education      0.9548331          ***         -4.52%
## Nscore         0.9710962            .         -2.89%
## Escore         0.9260635          ***         -7.39%
## Oscore         1.2372422          ***        +23.72%
```

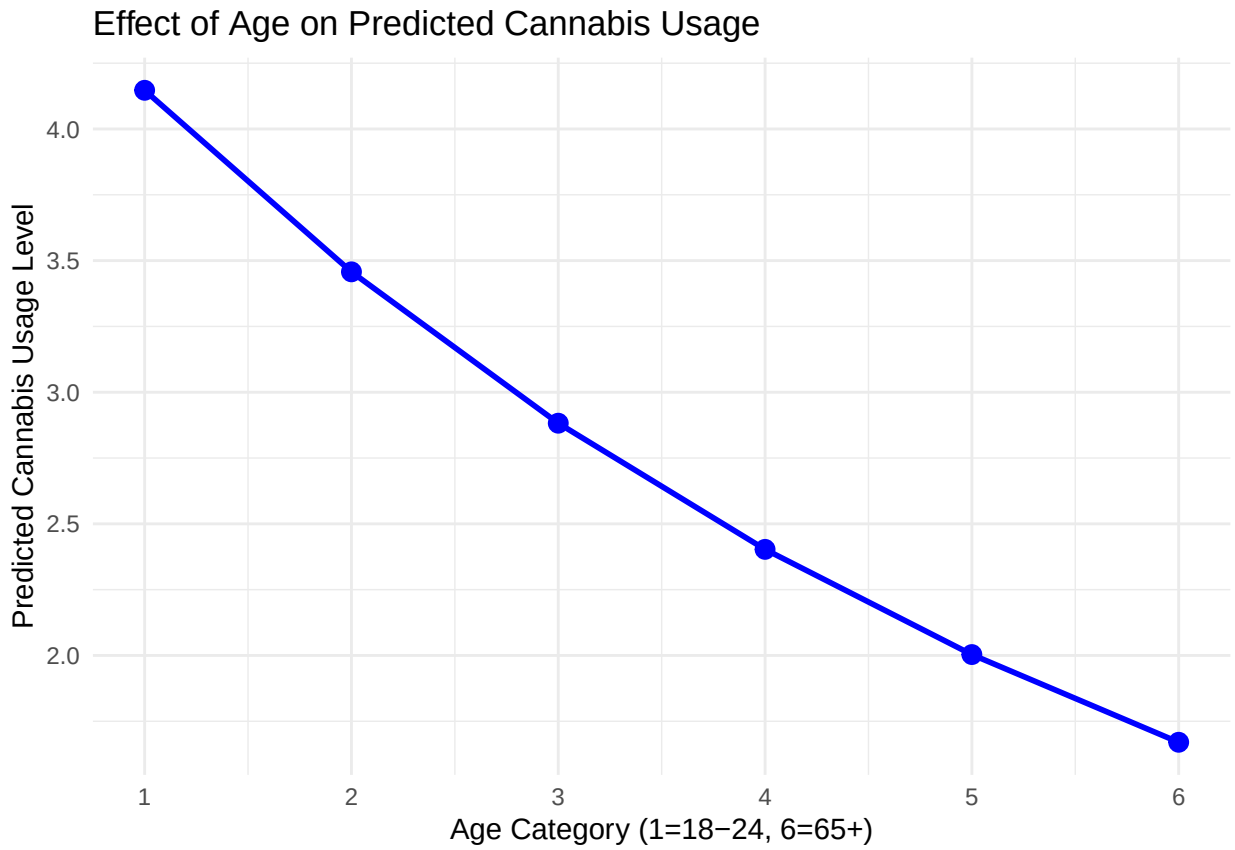
```
## Ascore         0.9695794            *         -3.04%
## Cscore         0.9353331          ***         -6.47%
## Impulsive      1.0001830                      +0.02%
## SS             1.1853447          ***        +18.53%
```

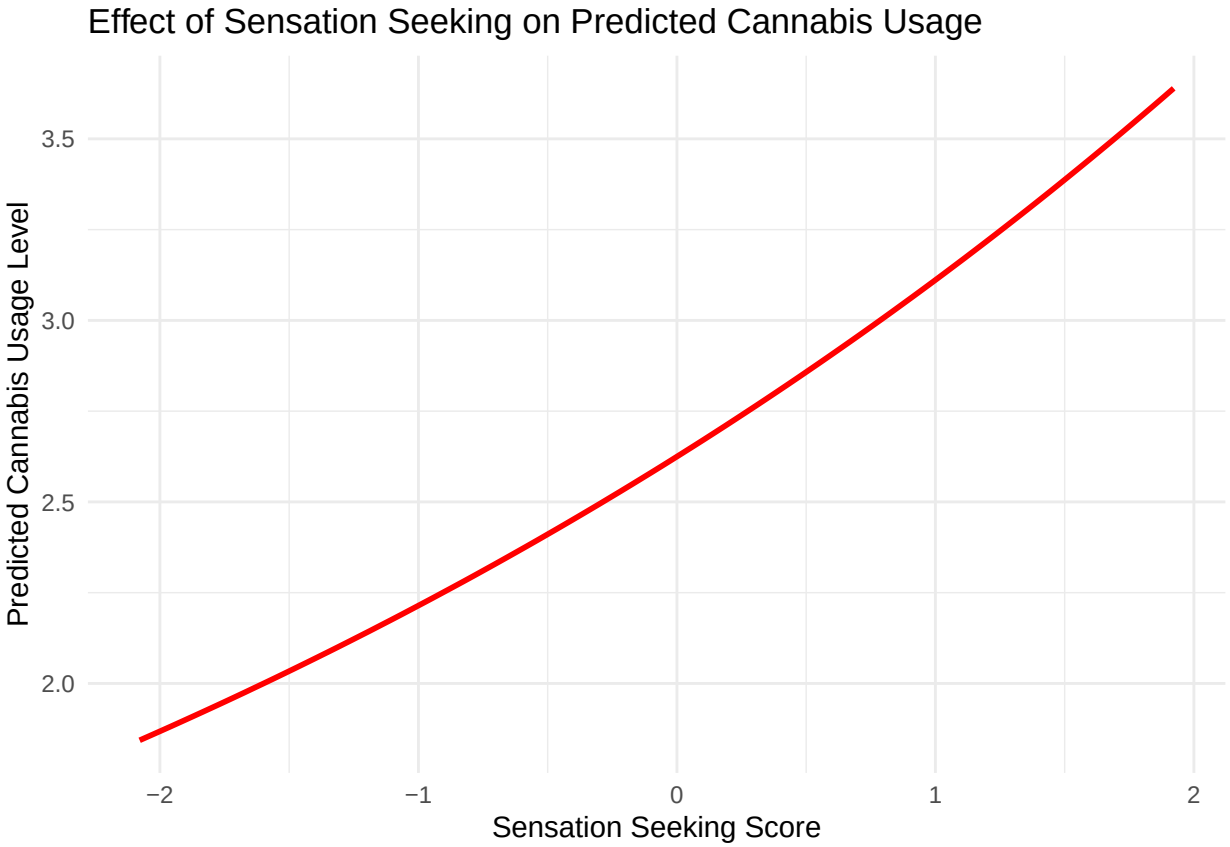
```
##       Drug      AIC      BIC    LogLik  Deviance    PseudoR2
## 1 Cannabis 7404.737 7465.695 -3691.368 2847.7237 0.161725061
## 2  Alcohol 7211.182 7272.140 -3594.591  925.0331 0.003668884
## 3 Nicotine 8599.435 8660.394 -4288.718 3974.5846 0.066817606
## 4     Coke 5672.902 5733.860 -2825.451 3317.8003 0.102191039
```

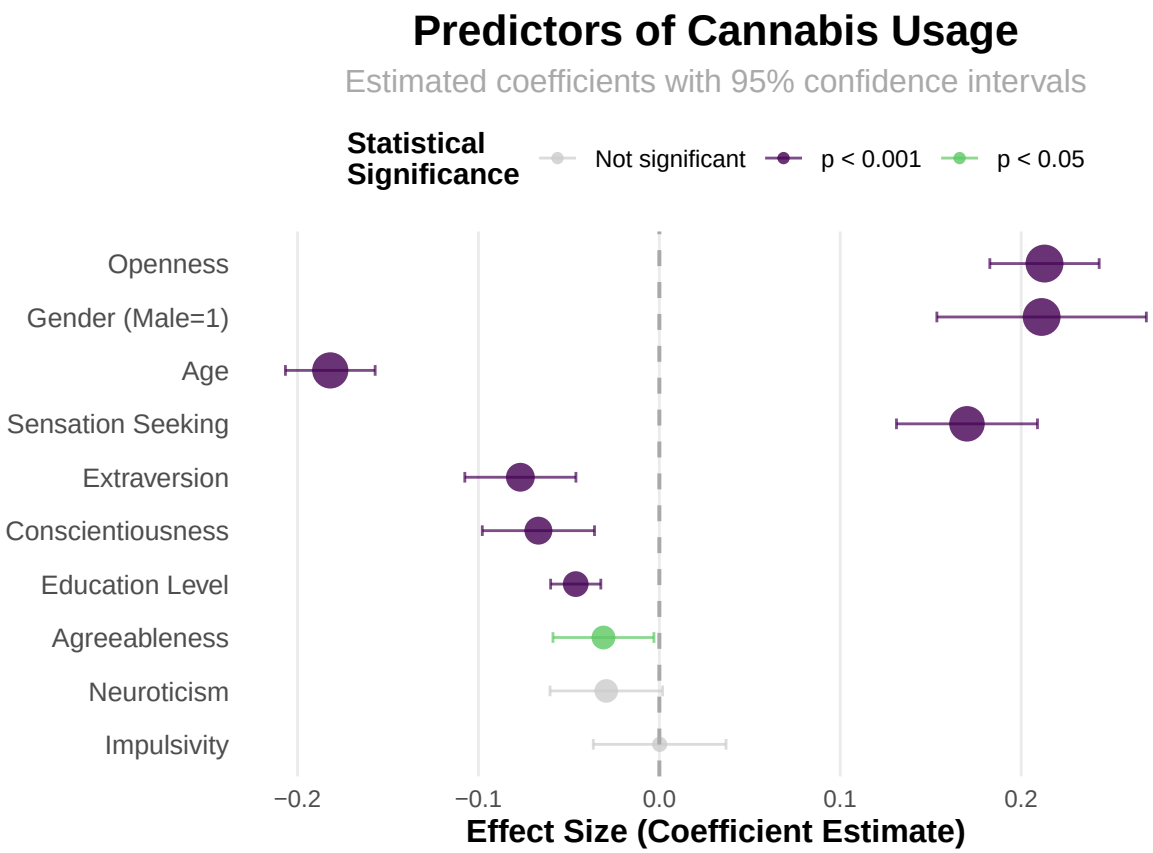
```
## Dispersion parameter for Cannabis model: 1.3211
```

```
## No strong evidence of overdispersion. Poisson model appears appropriate.
```

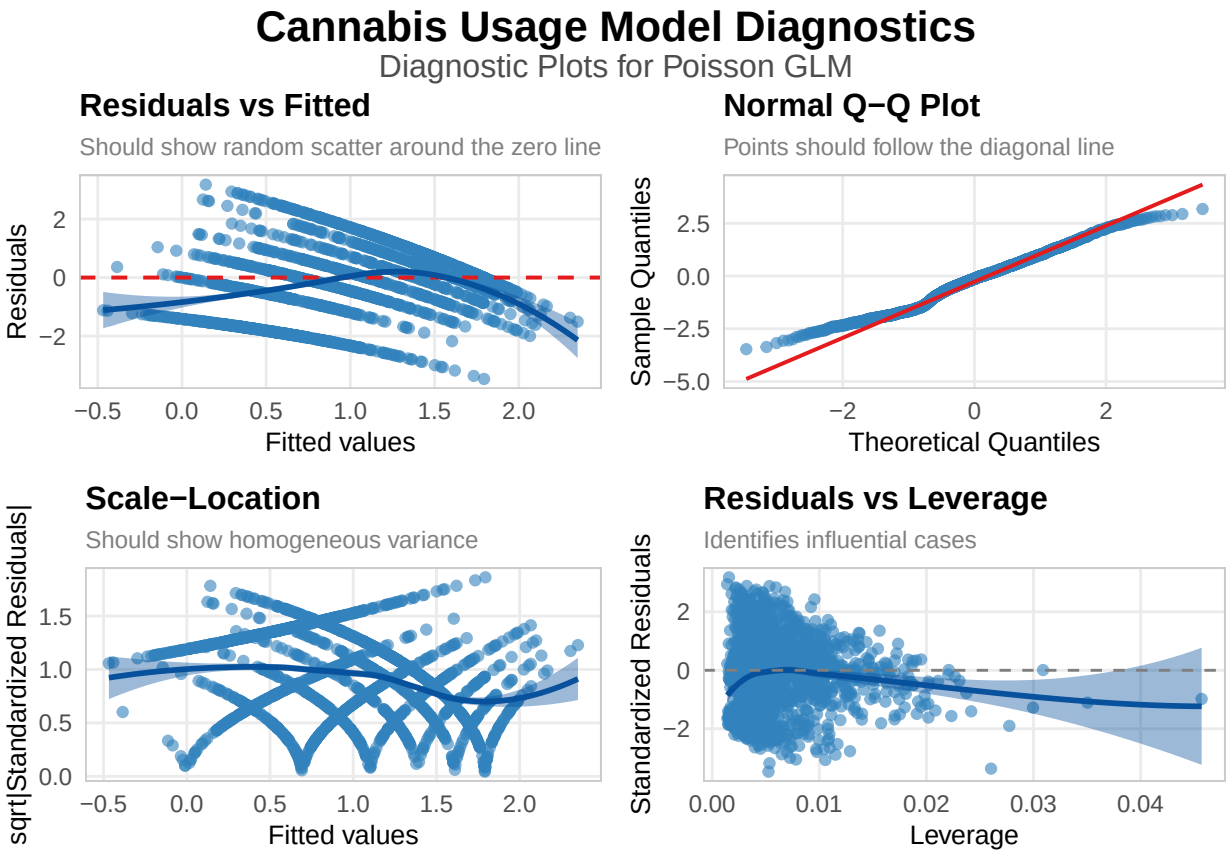
```
##
## Model comparison - Cannabis:
## Poisson AIC: 7404.737
## Negative Binomial AIC: 7395.353
## Theta value in NB model: 20.69155
```




Effect of Sensation Seeking on Predicted Cannabis Usage
Predicted Cannabis Usage Level
3.5
3.0
2.5
2.0
−2
−1
0
1
2
Sensation Seeking Score




```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```




```
## TableGrob (2 x 1) "arrange": 2 grobs
##   z     cells    name           grob
## 1 1 (1-1,1-1) arrange gtable[arrange]
## 2 2 (2-2,1-1) arrange gtable[arrange]
```

```
##       Age    Gender Education    Nscore    Escore    Oscore    Ascore    Cscore
##  1.165454  1.163059  1.096390  1.471590  1.514198  1.308782  1.174058  1.428603
## Impulsive        SS
##  1.746986  1.901863
```

```
##
## === Cannabis Model Analysis ===
## Number of observations: 1885
## Null deviance: 4272.046 on 1884 degrees of freedom
## Residual deviance: 2847.724 on 1874 degrees of freedom
## AIC: 7404.737
## McFadden's Pseudo R²: 0.1617
## Dispersion parameter: 1.3211
##
## Significant predictors (in order of effect size):
## 1. Oscore: positive effect (23.72% increase, p=0)
## 2. Gender: positive effect (23.53% increase, p=0)
## 3. Age: negative effect (16.63% decrease, p=0)
## 4. SS: positive effect (18.53% increase, p=0)
## 5. Escore: negative effect (7.39% decrease, p=0)
```

```
## 6. Cscore: negative effect (6.47% decrease, p=0)
## 7. Education: negative effect (4.52% decrease, p=0)
## 8. Ascore: negative effect (3.04% decrease, p=0.0299)
##
## Potential outliers (observations with |Pearson residual| > 2):
##      Observation Residual Actual Predicted
## 475          475 4.516734      6  1.152043
## 597          597 4.019779      6  1.342474
## 1187        1187 3.910567      6  1.389815
## 1036        1036 3.902408      6  1.393440
## 1000        1000 3.809559      6  1.435568
##
## Possible model improvements:
## - Consider using a negative binomial model to address overdispersion
## - Consider interaction terms (e.g., Age × Education, Gender × SS)
## - Consider polynomial terms for continuous predictors if relationship is non-linear

## Analysis of Deviance Table
##
## Model 1: Cannabis ~ Age + Gender + Education + Nscore + Escore + Oscore +
##     Ascore + Cscore + Impulsive + SS
## Model 2: Cannabis ~ Age + Gender + Education + Nscore + Escore + Oscore +
##     Ascore + Cscore + Impulsive + SS + Age:Education + Gender:SS
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1      1874     2847.7
## 2      1872     2826.9  2   20.801 3.042e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

7 Source

https://archive.ics.uci.edu/dataset/373/drug+consumption+quantified