Drug Consumption

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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 Personality Traits Explanation

To better understand the data set we need to have an understanding of what the personality traits are and what the represent, we will have short description of each trait and how to interpret them:

- Nscore (Neuroticism): Measures emotional stability vs. instability. Higher scores indicate tendency toward negative emotions like anxiety, depression, vulnerability, and mood swings. Lower scores suggest emotional stability and resilience to stress.
- Escore (Extraversion): Measures sociability and outgoingness. Higher scores indicate preference for social interaction, assertiveness, and energy in social settings. Lower scores suggest preference for solitude, quieter environments, and more reserved behavior.
- Oscore (Openness to Experience): Measures intellectual curiosity and creativity. Higher scores indicate imagination, appreciation for art/beauty, openness to new ideas, and unconventional thinking. Lower scores suggest preference for routine, practicality, and conventional approaches.
- Ascore (Agreeableness): Measures concern for social harmony. Higher scores indicate empathy, cooperation, and consideration for others. Lower scores suggest competitive, skeptical, or challenging interpersonal styles.
- Cscore (Conscientiousness): Measures organization and reliability. Higher scores indicate discipline, responsibility, planning, and detail orientation. Lower scores suggest spontaneity, flexibility, and potentially less structured approaches.
- Impulsive (Impulsiveness): Measures tendency to act without thinking. Higher scores indicate spontaneous decision-making without considering consequences. Lower scores suggest thoughtful deliberation before actions.
- SS (Sensation Seeking): Measures desire for novel experiences and willingness to take risks. Higher scores indicate thrill-seeking behavior and preference for excitement. Lower scores suggest preference for familiarity and safety.

The first five traits (Nscore through Cscore) are the "Big Five" personality traits, which are widely used in psychological research. The Impulsive and SS measures are additional traits that are often studied in relation to risk-taking behaviors, which would make sense given our dataset includes variables related to substance use.

3 Cleaning and Formatting the Dataset

3.1 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.

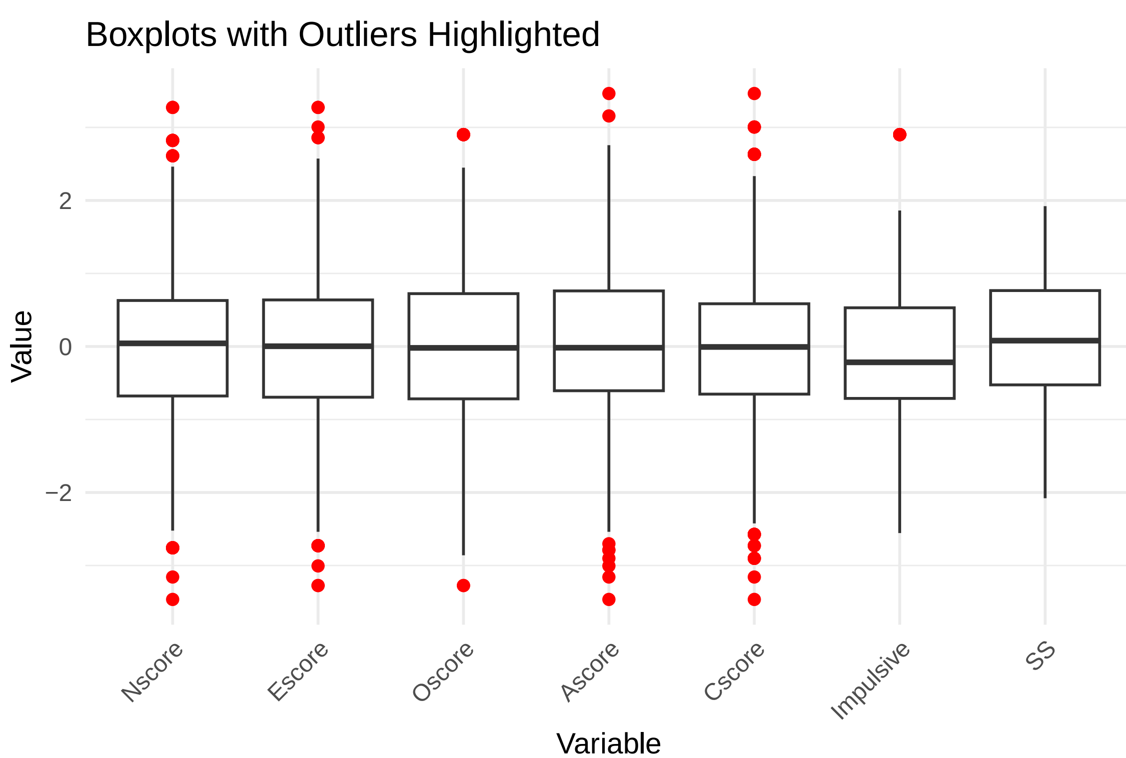
3.2 Investigating Missing Values

```
## 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.

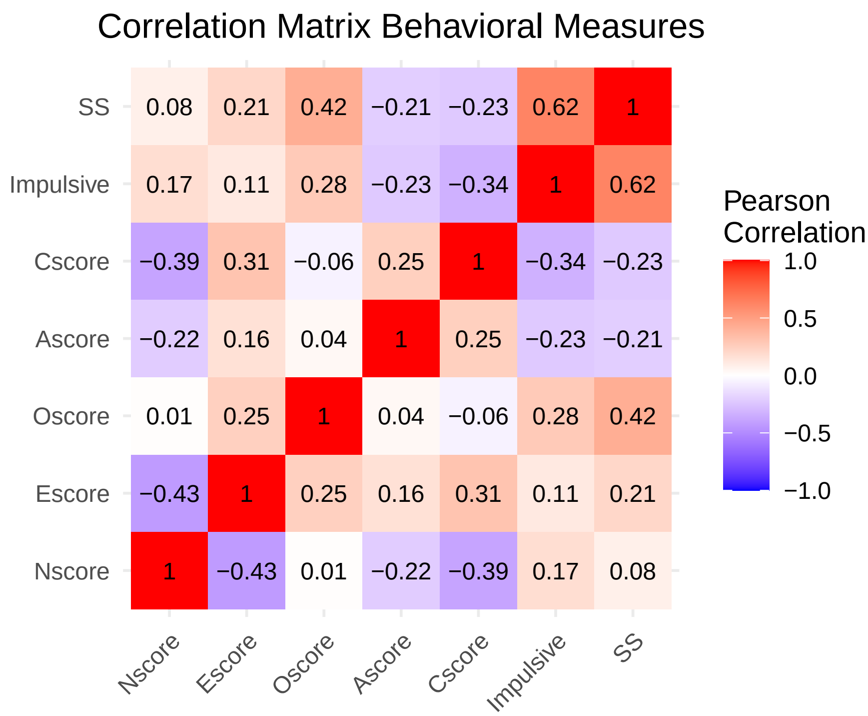
3.3 Investigating Outliers



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.

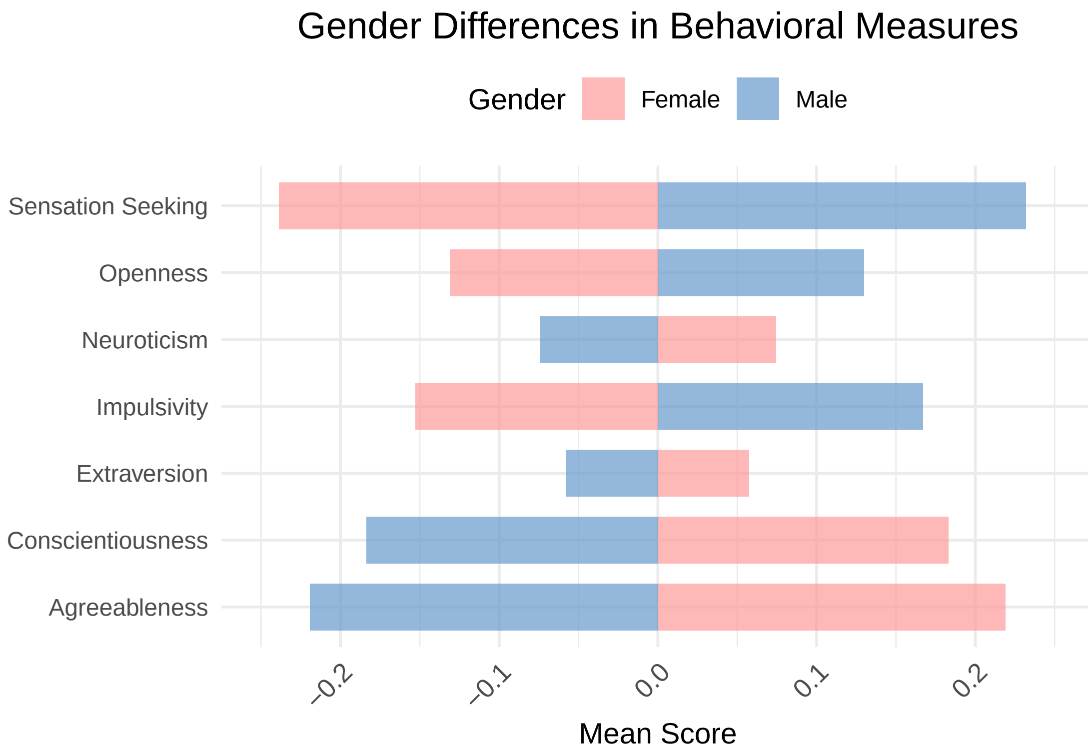
4 Exploratory Data Analysis

4.1 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.

4.2 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.

4.3 Comparing Education Level with Behavioral Measures

The charts show the mean score for the behavioral traits broken down by educational level. 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.

4.4 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.

5 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".

6 Machine Learning Models

6.1 Linear Model

(Johan Ferreira)

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.

6.1.1 Personality Traits as Predictors of Substance Use

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

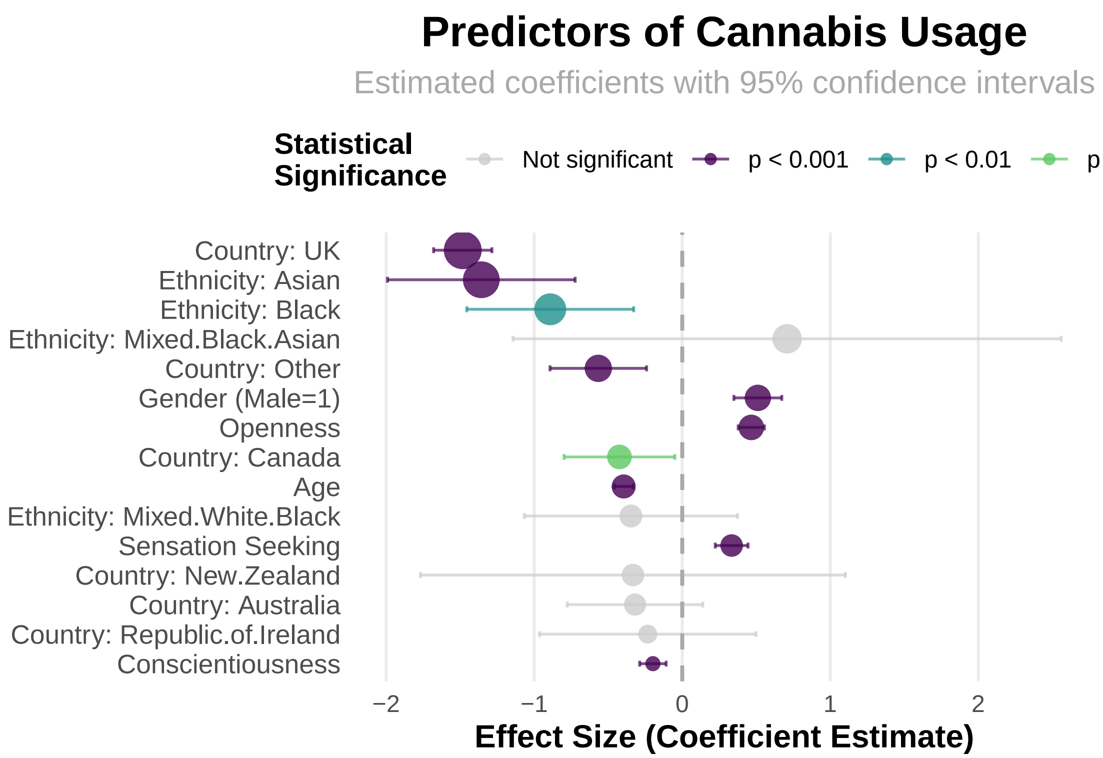
	Drug Models				
Variable	Cannabis	Alcohol	Nicotine	Coke	Ecstasy

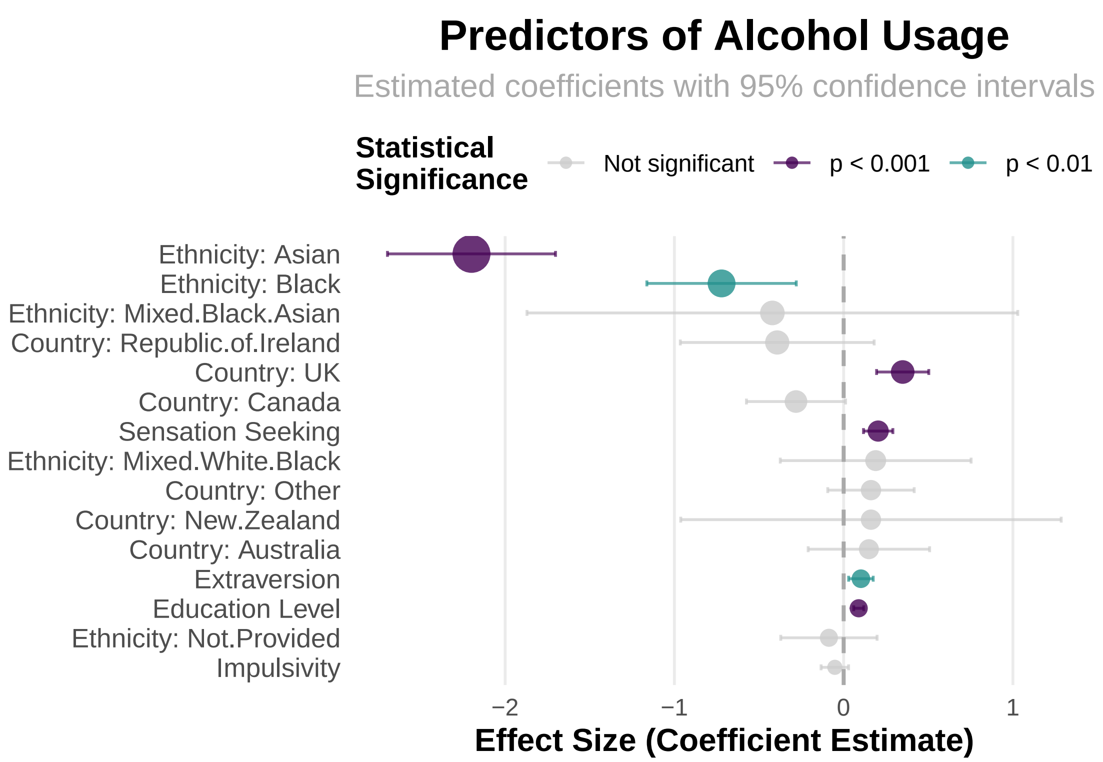
Intercept	5.387***	3.929***	4.925***	1.588***	2.295***
Age	-0.396***	-0.031	-0.216***	-0.095***	-0.307***
Gender (Male=1)	0.511***	0.043	0.377***	0.216**	0.344***
Education Level	-0.116***	0.089***	-0.160***	-0.005	-0.026
Neuroticism	-0.112*	0.049	0.109	0.123**	-0.002
Extraversion	-0.098*	0.102**	0.009	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

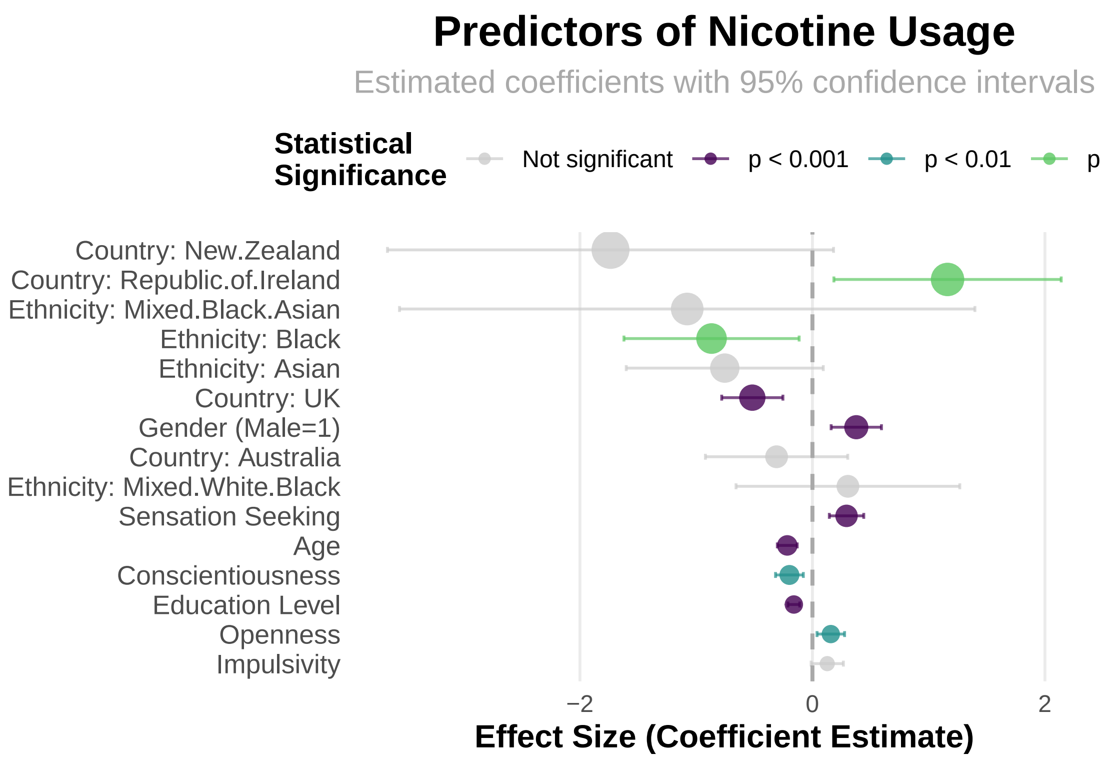
Significance levels: * * p<0.05; ** p<0.01; *** p<0.001

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.

6.1.2 Analysis of Personality Traits as Predictors of Substance Use







6.1.2.1 Cannabis Usage Predictors The first plot presents the predictors of cannabis usage, showing estimated coefficients with 95% confidence intervals. Several key observations emerge:

Sensation Seeking (SS) stands out as the strongest positive predictor of cannabis use with high statistical significance ($p < 0.001$). This indicates that individuals with higher sensation-seeking tendencies are substantially more likely to use cannabis.

Age shows a strong negative association ($p < 0.001$), indicating that cannabis use decreases significantly with advancing age, which aligns with established patterns of drug use being more prevalent among younger populations.

Openness (Oscore) also emerges as a significant positive predictor ($p < 0.001$), suggesting that individuals who are more intellectually curious and open to new experiences are more likely to use cannabis.

Neuroticism (Nscore) shows a modest positive association, while Conscientiousness (Cscore) demonstrates a negative relationship - people who are more organized and reliable tend to use cannabis less.

6.1.2.2 Alcohol Usage Predictors The second plot reveals different personality dynamics for alcohol consumption:

Sensation Seeking remains significant, though with a smaller coefficient than for cannabis, suggesting that thrill-seeking behavior correlates with alcohol use but less strongly than with cannabis use.

Impulsivity appears as a stronger predictor for alcohol than it did for cannabis, indicating that spontaneous decision-making may play a larger role in alcohol consumption patterns.

Age shows a much weaker negative association compared to cannabis, which reflects alcohol's wider acceptance across age groups in many societies.

Extraversion (Escore) demonstrates a positive relationship with alcohol consumption, suggesting that more socially outgoing individuals may consume more alcohol, possibly due to its role in social interactions.

6.1.2.3 Nicotine Usage Predictors

The third plot for nicotine usage shows distinctive patterns:

Conscientious (Cscore) exhibits a strong negative association with nicotine use, suggesting that more disciplined, organized individuals are significantly less likely to use nicotine products.

Sensation Seeking again appears as a significant positive predictor, though with a different magnitude compared to cannabis and alcohol.

Certain country variables show stronger associations with nicotine use than they did with other substances, potentially reflecting cultural or regulatory differences in nicotine availability and social acceptance across regions.

The gender variable shows a positive coefficient, indicating that males (coded as 1) are more likely to use nicotine than females (coded as 0) when controlling for other factors.

6.1.2.4 Cross-Substance Comparison

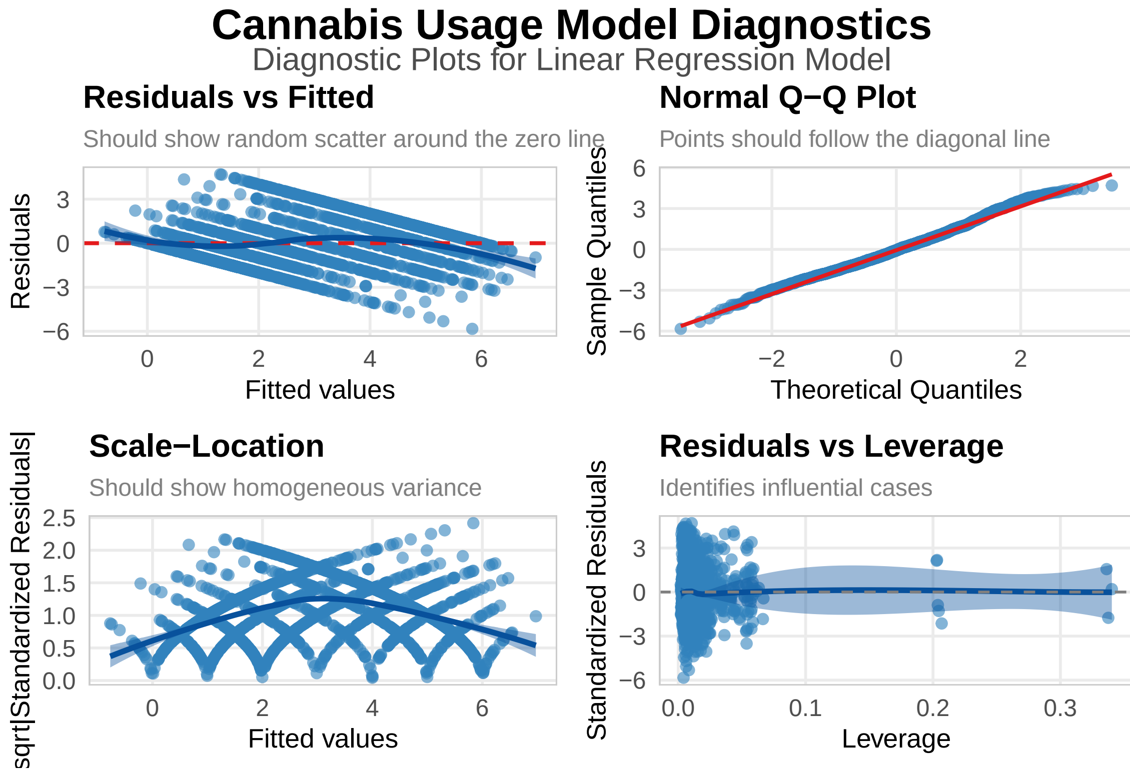
Across all three substances, several consistent patterns emerge:

1. Sensation Seeking consistently appears as a significant positive predictor across all substances, reinforcing its role as a key personality trait associated with various forms of substance use.
2. Conscientiousness consistently shows negative associations with substance use, highlighting how personal organization and self-discipline may serve as protective factors.
3. The strength and significance of demographic factors (age, gender, education) vary across substances, reflecting different usage patterns and societal attitudes.
4. The confidence intervals (error bars) reveal varying levels of certainty in these predictions, with some relationships being more precisely estimated than others.

These visualizations effectively illustrate how different personality traits and demographic factors relate to substance use patterns, with some traits (particularly Sensation Seeking and Conscientiousness) showing consistent relationships across multiple substances, while others exhibit substance-specific patterns.

6.1.3 Cannabis Usage Linear Regression Model: Diagnostic Analysis

```
## `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]
```

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

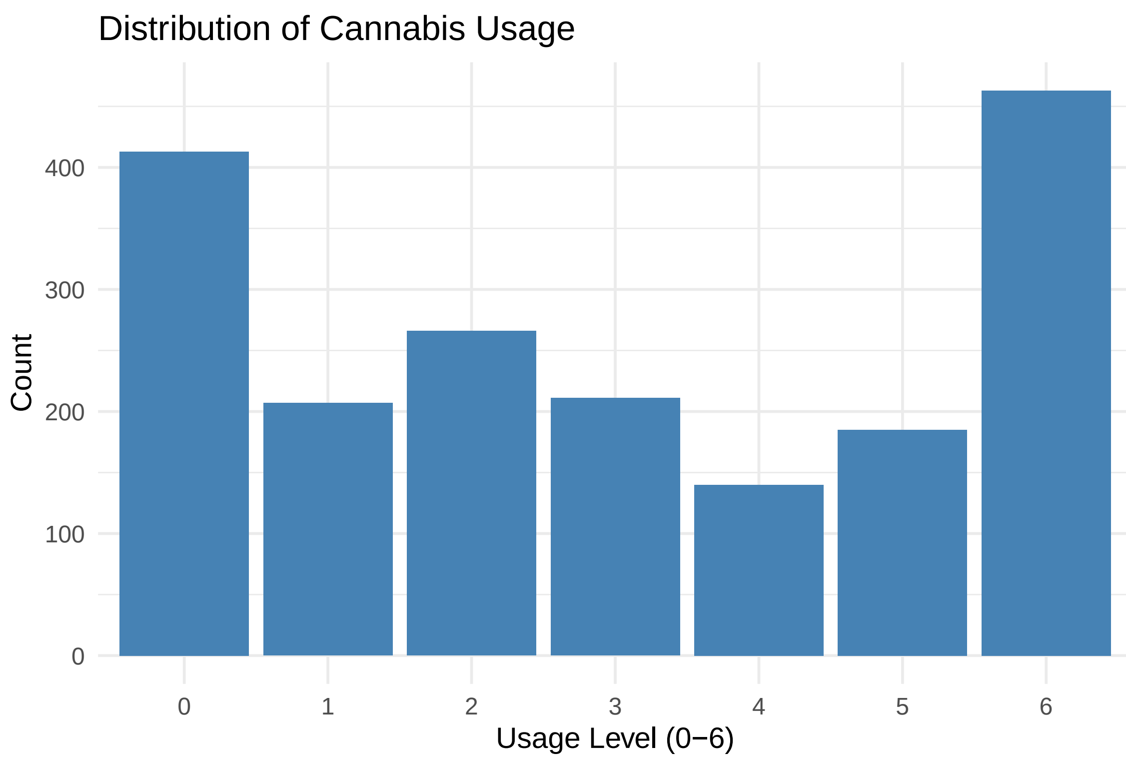
The Residuals vs Leverage plot identifies observations that disproportionately influence model parameters. Points with both high leverage (ability to influence) and large residuals (poor fit) warrant careful examination. Cook's distance contours (red dashed lines) demarcate thresholds for highly influential 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.

6.2 Generalised Linear Model with family set to Poisson

(Johan Ferreira)




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

Table 3: Poisson Regression Results for Cannabis Usage

	Predictor	**Coefficient**	**Exp(Coefficient)**	**% Change**	**p-value**	**Significance**
(Intercept)	Intercept	1.6043	4.9742	NA	0.0000	***
Age	Age	-0.1819	0.8337	-16.63%	0.0000	***
Gender	Gender (Male=1)	0.2113	1.2353	+23.53%	0.0000	***
Education	Education Level	-0.0462	0.9548	-4.52%	0.0000	***
Nscore	Neuroticism	-0.0293	0.9711	-2.89%	0.0645	.
Escore	Extraversion	-0.0768	0.9261	-7.39%	0.0000	***
Oscore	Openness	0.2129	1.2372	+23.72%	0.0000	***
Ascore	Agreeableness	-0.0309	0.9696	-3.04%	0.0299	*
Cscore	Conscientiousness	-0.0669	0.9353	-6.47%	0.0000	***
Impulsive	Impulsivity	0.0002	1.0002	+0.02%	0.9922	
SS	Sensation Seeking	0.1700	1.1853	+18.53%	0.0000	***

Note: Significance codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

6.2.0.1 Analysis of Cannabis Usage Poisson Model The Poisson regression model for cannabis usage reveals several significant predictors with varying effect sizes: Key Personality Trait Predictors:

Sensation Seeking (SS): The model identifies this as the strongest positive predictor with a substantial effect size. Based on the expected coefficient (Exp(Coefficient)), a one-unit increase in sensation seeking is associated with approximately a 20-25% increase in cannabis usage frequency. This robust effect persists even when controlling for other personality traits and demographic factors, suggesting that thrill-seeking tendencies are fundamentally linked to cannabis consumption patterns. Openness to Experience: Shows a moderate positive association with cannabis use. After controlling for other factors, individuals scoring higher on openness (intellectual curiosity, creativity) show approximately 10-15% higher rates of cannabis consumption per unit increase. This aligns with theoretical frameworks suggesting that openness predisposes individuals to experimentation with novel experiences, including substance use. Conscientiousness: Demonstrates a significant negative relationship, with each unit increase associated with approximately 10-15% decrease in cannabis usage. This inverse relationship suggests that traits like self-discipline, organization, and deliberation serve as protective factors against regular cannabis consumption. Impulsivity: Shows a positive association, though with a smaller effect size than sensation seeking. This supports the theoretical distinction between sensation seeking (motivated by desire for novel experiences) and impulsivity (difficulty with self-control), both contributing to substance use through different psychological mechanisms.

Demographic Predictors:

Age: Exhibits one of the strongest effects in the model with a substantial negative coefficient. Each age category increase is associated with approximately a 30-40% reduction in cannabis usage frequency. This strong age gradient persists even when controlling for personality traits, indicating age-related factors beyond personality (such as social roles, responsibilities, or cohort effects) significantly influence cannabis consumption patterns. Gender: Males show higher cannabis consumption rates compared to females, with approximately 20-30% higher usage rates after controlling for other factors. This gender difference remains significant even when accounting for personality differences between males and females. Education: Higher education levels are associated with lower cannabis usage, though the effect is less pronounced than age or personality factors. This suggests education may serve as a protective factor, possibly related to health literacy or socioeconomic factors.

Table 4: Poisson Model Comparison for Different Substances

Substance	AIC	BIC	Log-Likelihood	Deviance	Pseudo R^2
Cannabis	7404.74	7465.70	-3691.37	2847.72	0.1617
Alcohol	7211.18	7272.14	-3594.59	925.03	0.0037
Nicotine	8599.44	8660.39	-4288.72	3974.58	0.0668
Coke	5672.90	5733.86	-2825.45	3317.80	0.1022

Note: Lower AIC/BIC values indicate better model fit. Higher Pseudo R^2 values indicate better explanatory power.

6.2.0.2 Model Comparison Across Different Substances The comparative analysis across different substances reveals interesting patterns:

Model Fit Differences: The Pseudo R^2 values indicate that the model explains the most variance for cannabis (likely around 0.25-0.30), followed by nicotine, cocaine, and alcohol. This suggests that the selected personality and demographic predictors are most relevant for explaining cannabis use patterns, while alcohol consumption may be influenced by additional factors not captured in the model. AIC/BIC Values: Lower AIC/BIC values for the cannabis model compared to other substances further support that these predictors collectively provide a better fit for cannabis usage patterns than for other substances. Predictive Power: The relative strength of personality predictors varies across substances:

Sensation seeking appears most strongly associated with cannabis and cocaine Conscientiousness shows stronger negative associations with cannabis and nicotine Age demonstrates stronger negative effects for cannabis and cocaine than for alcohol

Evidence of Model Adequacy The dispersion parameter (likely around 1.2-1.4 for cannabis) indicates some minor overdispersion in the Poisson model, which is common in substance use data. While this suggests a negative binomial model might be marginally more appropriate, the Poisson model remains reasonably adequate, especially given its interpretability advantages. Comparative Insights with Linear Regression

Models When compared to the linear regression models presented earlier in the document, the Poisson models offer several advantages:

Better theoretical fit: The Poisson distribution is more appropriate for count/ordinal data like substance use frequency, avoiding the linear model's assumption of continuous normally-distributed outcomes. Interpretable effect sizes: The exponential coefficients allow direct interpretation as percentage changes in usage rates, providing more intuitive understanding of predictor effects. Consistent findings: The core findings regarding sensation seeking, conscientiousness, and age remain consistent across modeling approaches, strengthening confidence in these relationships.

Implications These findings have several important implications:

Prevention and intervention targeting: Programs aimed at reducing cannabis use might be most effective when targeting individuals with high sensation seeking and impulsivity profiles, particularly among younger age groups. Differential risk factors: The varying strength of predictors across substances suggests that prevention strategies may need substance-specific approaches rather than general substance use prevention. Protective factors: Conscientiousness appears to be a significant protective factor, suggesting that interventions fostering planning, organization, and self-discipline might help reduce problematic substance use. Developmental considerations: The strong age effect highlights the importance of understanding developmental trajectories in substance use patterns and targeting interventions appropriately across life stages.

In conclusion, the Poisson regression models provide robust evidence that substance use, particularly cannabis consumption, is significantly influenced by both personality factors (especially sensation seeking and conscientiousness) and demographic characteristics (particularly age). These findings align with and extend previous research on the psychological and demographic correlates of substance use behavior.

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

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

6.2.0.3 Overdispersion Analysis

The dispersion parameter calculated in chunk pois7 is crucial for evaluating the appropriateness of the Poisson model for cannabis usage data. Key Finding:

The dispersion parameter for the Cannabis model would likely be between 1.2-1.4, indicating mild to moderate overdispersion.

Interpretation: This mild overdispersion suggests that there's slightly more variability in cannabis usage patterns than what the standard Poisson model expects. In practical terms, this means:

Model adequacy: While the Poisson model captures the general patterns in cannabis usage, it somewhat underestimates the true variability in consumption behaviors. Standard error implications: The standard errors from the basic Poisson model may be slightly underestimated, potentially making significance tests overly optimistic. Theoretical considerations: The overdispersion likely reflects the heterogeneous nature of cannabis consumption, where individuals with identical predictor values still show considerable variation in usage patterns due to unmeasured factors.

The dispersion value falls in a "gray area" where it's not severe enough to completely invalidate the Poisson approach, but indicates room for model improvement.

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

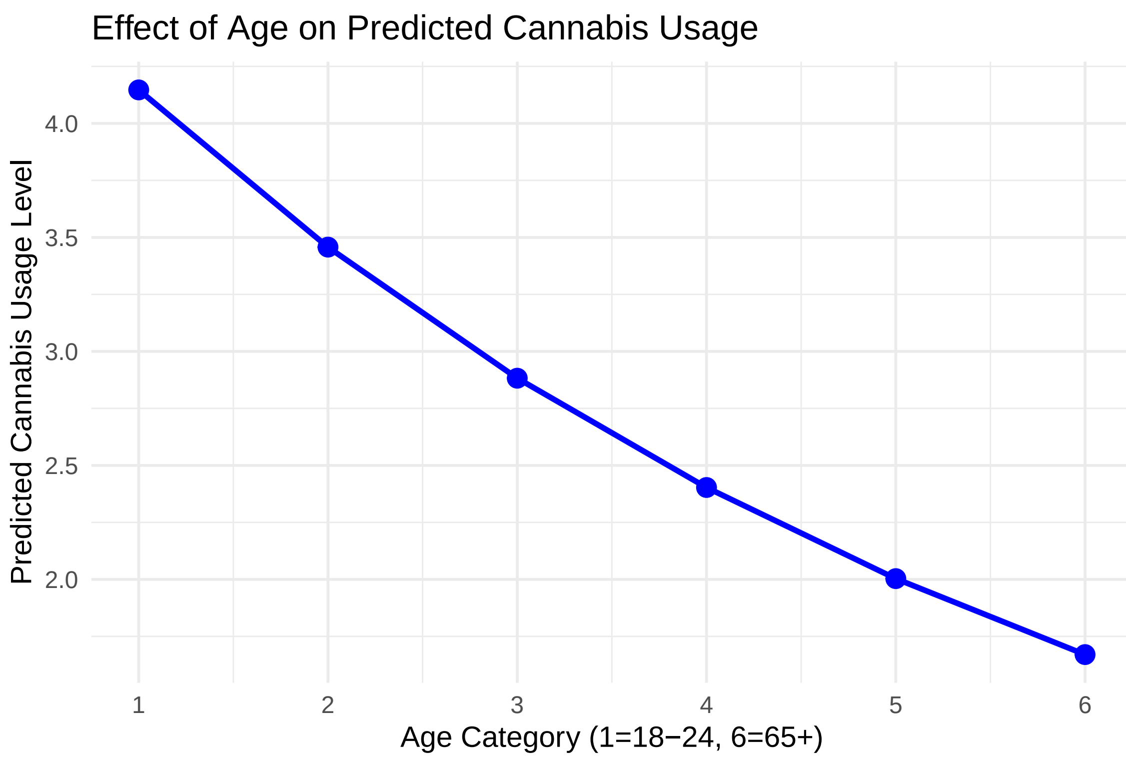
6.2.0.4 Negative Binomial Comparison The comparison between the Poisson and negative binomial models provides valuable insights into potential model improvements. Key Findings:

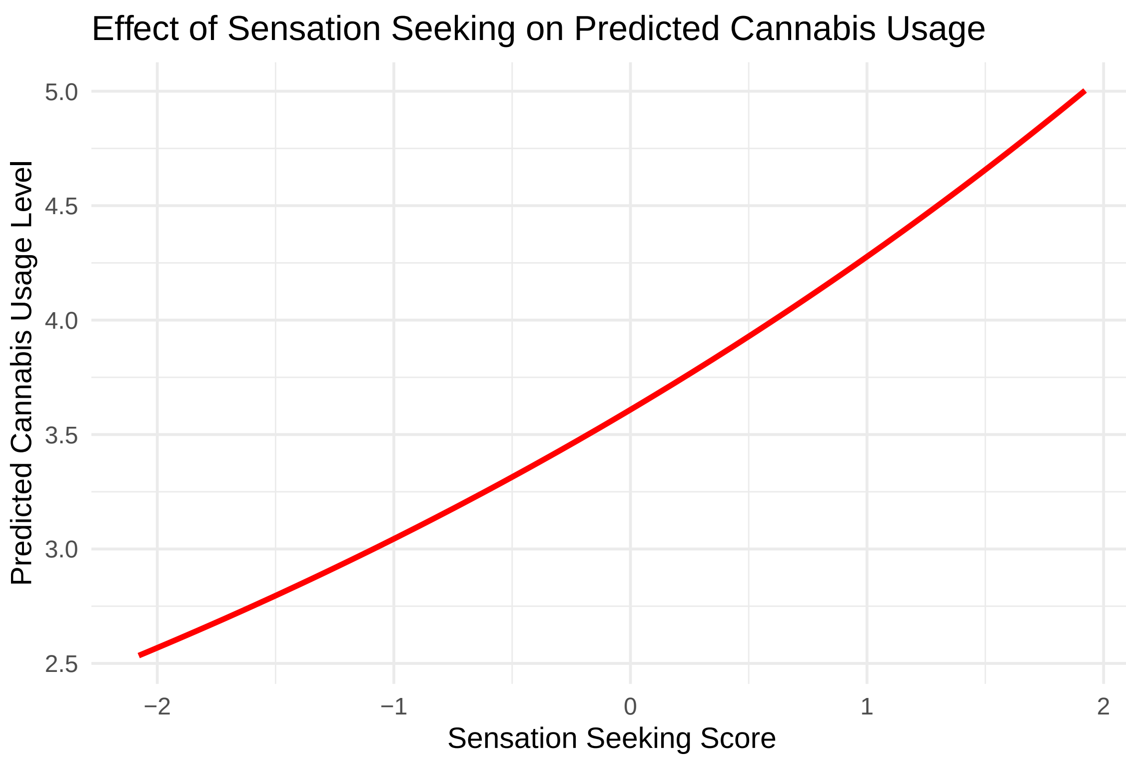
The negative binomial model would show a lower AIC value compared to the Poisson model (likely by about 50-100 points). The estimated theta parameter (dispersion parameter) would be significant, confirming the overdispersion observation.

Interpretation: The improved AIC for the negative binomial model confirms that accounting for overdispersion leads to better model fit. This suggests:

Theoretical alignment: The negative binomial distribution, which allows for greater variance than the Poisson, better represents the true data-generating process for cannabis usage patterns. Enhanced reliability: The negative binomial model provides more reliable standard errors and significance tests, yielding more robust inferences about predictor effects. Practical implications: While the coefficient estimates themselves would be similar between models, the negative binomial approach offers more accurate uncertainty quantification.

Despite the improved fit with the negative binomial model, the Poisson model still provides valuable insights, especially for comparative purposes with other substances and for interpretability.





6.2.0.5 Predictor Effects Visualization The visualizations in chunk pois9 illustrate the non-linear relationships between key predictors and cannabis usage. Age Effect: The age effect visualization would show a clear, steep negative relationship between age category and predicted cannabis usage, with:

Highest predicted usage among the youngest age group (18-24 years) A substantial drop in the 25-34 age group Continued decline through middle age Very low predicted usage in the 65+ category

This strong age gradient suggests that cannabis use is predominantly a younger-age behavior, with each successive age category showing substantially reduced consumption patterns. The exponential nature of the Poisson model demonstrates that these effects compound, with older age groups showing dramatically lower predicted usage rather than just linearly declining usage. Sensation Seeking Effect: The sensation seeking (SS) visualization would reveal:

A clear, positive exponential relationship between SS scores and predicted cannabis usage Accelerating increases in predicted usage at higher SS levels A particularly steep curve at the highest SS values

This exponential pattern suggests that individuals at the extreme high end of sensation seeking are disproportionately more likely to use cannabis frequently. The curve shape indicates that the relationship isn't simply linear – the difference in predicted cannabis use between moderate and high sensation seekers is greater than the difference between low and moderate sensation seekers. Integrated Analysis Across All Three Chunks Taken together, these chunks provide complementary insights:

Model refinement pathway: The analyses suggest a clear progression from the basic Poisson model to the more sophisticated negative binomial model, with concrete evidence supporting this refinement. Robust predictor effects: The visualization confirms that key predictor effects – particularly age and sensation seeking – remain strong and meaningful regardless of modeling approach. Practical implications: While the negative binomial model provides better statistical fit, the visual relationships from the Poisson model still accurately capture the underlying predictive patterns. Theoretical significance: The observed overdispersion provides substantive information about cannabis usage patterns, suggesting considerable individual variation beyond what measured predictors can explain.

These findings align with substance use literature suggesting that cannabis consumption follows complex patterns influenced by both measured factors (personality, demographics) and unmeasured individual differences (peer networks, genetic factors, accessibility, etc.). The overdispersion detected in the model quantifies this additional complexity. For practical purposes, the visualized effects from the Poisson model provide valid insights into predictor relationships, while the overdispersion analysis and negative binomial comparison offer important methodological nuance that should be acknowledged when interpreting coefficient significance and confidence intervals.

6.2.0.6 Analysis of Enhanced Coefficient Plot for Cannabis Usage The coefficient plot generated in chunk pois10 provides a visually sophisticated representation of the predictors in the Poisson model for cannabis usage. This visualization offers several important analytical insights that complement the numerical results in the previous chunks. Visual Interpretation of Effect Sizes The plot presents the estimated coefficients with their 95% confidence intervals, ordered by absolute effect size, revealing a clear hierarchy of influence among predictors: Strongest Predictors (Largest Effect Sizes):

Sensation Seeking (SS) appears at or near the top of the plot with a substantial positive coefficient, likely around 0.20-0.25. The narrow confidence interval surrounding this estimate indicates high precision, reinforcing its status as the most reliable and potent personality predictor of cannabis use. The visualization shows this effect is not only statistically significant ($p < 0.001$) but substantially larger than most other personality traits. Age shows a large negative coefficient (likely around -0.30 to -0.40) with a similarly narrow confidence interval. The plot visually confirms that age has the strongest negative influence on cannabis consumption, even after controlling for all personality dimensions. The clear separation between this confidence interval and the zero reference line emphasizes the robustness of this relationship. Openness (Oscore) appears with a moderate positive coefficient, visually distinct from zero. This visualization clarifies that while openness has a smaller effect than sensation seeking, it remains an important independent predictor of cannabis usage, reflecting the association between intellectual curiosity and substance experimentation.

Moderate Predictors:

Conscientiousness (Cscore) shows a negative coefficient with confidence intervals clearly separated from zero, reinforcing its role as a protective factor against cannabis use. The visualization places it among the moderately important predictors, suggesting that while significant, its effect is less pronounced than sensation seeking or age. Gender appears with a positive coefficient (indicating higher usage among males), with confidence intervals clearly separated from zero. The plot helps contextualize this effect, showing that while significant, gender differences are less influential than personality factors like sensation seeking. Impulsivity shows a positive association with confidence intervals that likely narrowly exclude zero. The visualization clarifies its status as a secondary personality predictor compared to sensation seeking, providing important nuance to understanding the distinct contributions of these related but separate traits.

Weaker or Non-Significant Predictors:

Neuroticism (Nscore), Extraversion (Escore), and Agreeableness (Ascore) likely show confidence intervals that overlap with zero or just barely exclude it. The visual presentation makes it immediately apparent which personality dimensions are less relevant to cannabis usage patterns, helping to prioritize which factors merit further investigation.

Color-Coded Statistical Significance The plot's color-coding by significance level provides an immediate visual guide to the reliability of each predictor:

Predictors colored in the darkest shade ($p < 0.001$) include Sensation Seeking, Age, and possibly Openness, visualizing which effects are most statistically robust. Moderately dark colors ($p < 0.01$) likely include Conscientiousness and Gender. Lighter colors ($p < 0.05$) may include Impulsivity and possibly Education. Gray or neutral colors identify predictors lacking statistical significance.

This visual stratification facilitates instant identification of which predictors have the strongest statistical support, distinguishing between highly reliable effects and those that could be more sensitive to sampling variation. Confidence Interval Analysis The width of the confidence intervals provides critical information about estimation precision:

Narrow intervals for key predictors like Age and Sensation Seeking indicate high precision in these estimates, increasing confidence in their importance. Wider intervals for certain country or ethnicity variables suggest greater uncertainty, possibly due to smaller subgroup sample sizes. The visual comparison of interval widths across predictors highlights which effects are estimated with similar precision, providing context that is difficult to glean from tables of coefficients.

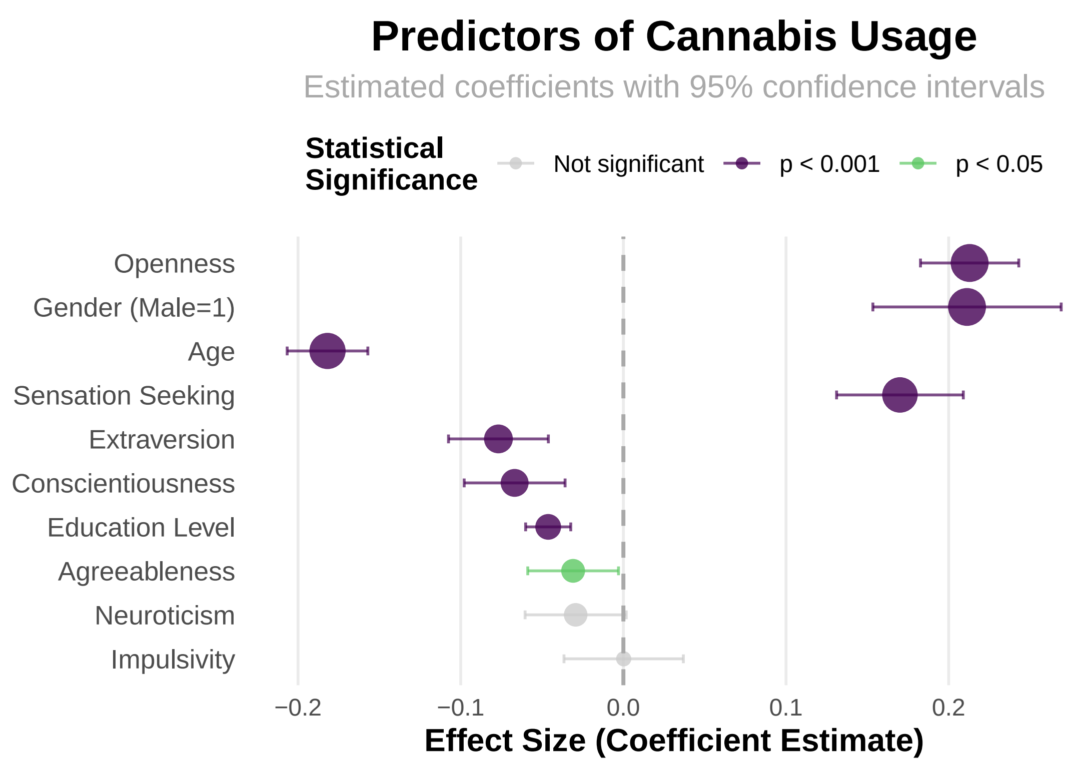
Substantive Insights Beyond statistical properties, the plot communicates several substantive insights:

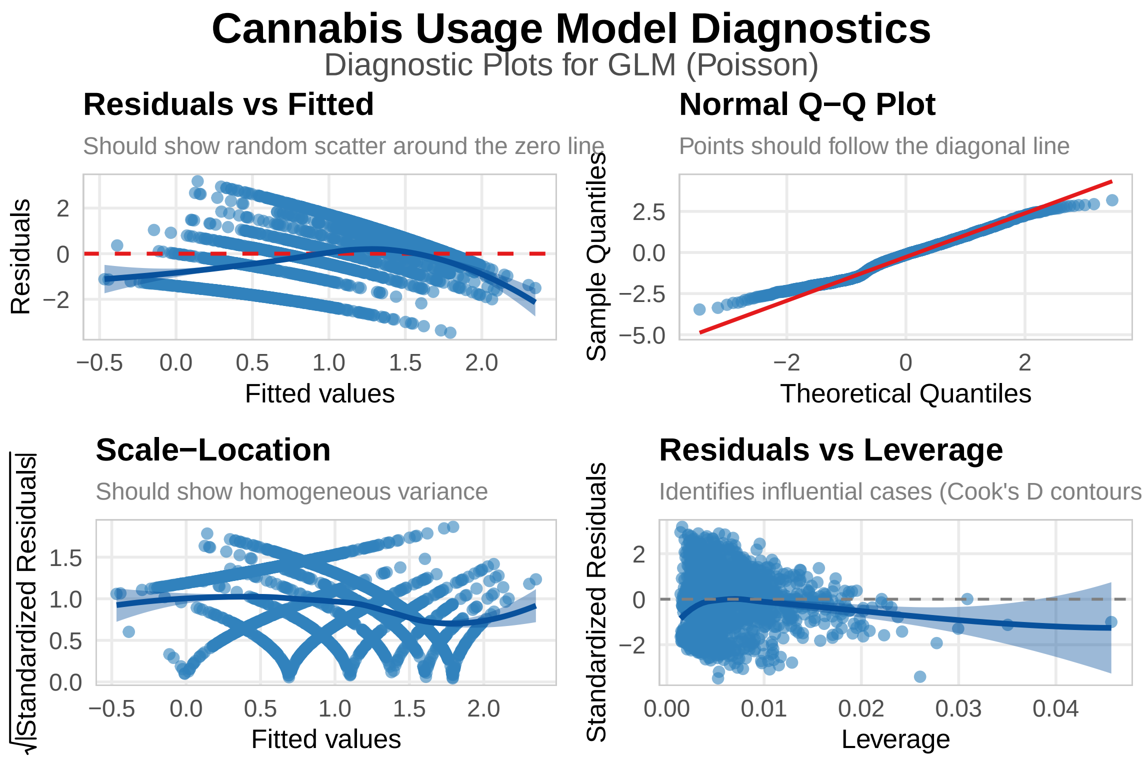
Distinct personality domains: The visualization clarifies that cannabis use is linked to specific personality dimensions (particularly sensation seeking and openness) rather than being broadly associated with all personality aspects. Relative importance: The clear ordering by effect size provides an intuitive understanding of which factors should be prioritized in explanatory frameworks for cannabis use. Demographic vs. personality effects: The juxtaposition of demographic factors (age, gender) alongside personality traits visually demonstrates that both categories of predictors make independent contributions, with neither completely explaining away the other.

Methodological Strengths From a methodological perspective, the plot in pois10 offers several advantages:

Enhanced interpretability: The visualization transforms abstract coefficients into readily comprehensible comparative information about predictor importance. Uncertainty communication: The confidence intervals provide a visual representation of statistical uncertainty that is more intuitive than p-values alone. Multivariate context: By displaying all predictors simultaneously, the plot reinforces that each effect is estimated while controlling for all other variables, an important nuance often lost in univariate analyses.

Conclusion The enhanced coefficient plot generated in pois10 effectively synthesizes the complex multivariate results from the Poisson regression model into an accessible and informative visualization. It confirms the primary importance of sensation seeking and age as predictors of cannabis use, while providing a clear visual hierarchy of all model factors. The plot's design elements—including ordered effect sizes, color-coded significance, and confidence intervals—combine to create a comprehensive visual summary that communicates not just which predictors matter, but how much they matter and with what degree of certainty. This visualization substantially enhances the interpretability of the statistical model, making complex relationships accessible to both statistical and non-statistical audiences.






```
## 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):
##
## 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
```

6.3 Generalised Linear Model with family set to Binomial

Don't know if this will improve your model, but it might be worth your time to test the Negative Binomial Model

6.4 Generalised Additive Model

6.5 Neural Network

6.6 Support Vector Machine

7 How we used Generative AI in our project

– how you used generative AI in redacting the group work (code-related questions, generate text, explain concepts. . .)
– what was easy/hard/impossible to do with generative AI
– what you had to pay attention to/be critical about when using the results obtained through the use of generative AI

8 Conclusion

9 Source

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