EGMs Expenditure vs Drug-and-Alcohol-Related Crimes

Group W01G4

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I. Research Question

What is the relationship between annual expenditure on Electronic Gaming Machines (EGMs) and the annual prevalence of addictive substance use and incidence of disorderly alcohol-related crimes within each local government area between 2014 and 2020?

II. Executive Summary

The study investigates the relationship between annual expenditure on Electronic Gaming Machines (EGMs) and the prevalence of drug-and-alcohol-related offences across local government areas (LGAs) in Victoria from 2014 to 2020. Two datasets were used: the **"EGM.csv"** capturing gaming losses, and the **Table 02 of "LGA_Offences.xlsx"** detailing crime counts.

Data preprocessing involved addressing inconsistencies such as missing LGAs and the grouping of certain LGAs, which limited the analysis to 57 LGAs. Line plots and heatmaps were implemented during data exploration to reveal initial trends.

For analysis, scatter plots, Pearson correlation, and mutual information were applied to evaluate the relationship between gaming losses and offence counts. A strong **cross-sectional correlation** was identified, where LGAs with higher gaming losses also showed high offence rates. However, the **temporal analysis** indicated no strong year-to-year correlation, suggesting that static population characteristics may drive this relationship.

Two machine learning models were used: **linear regression** to predict offences based on gaming losses, and **K-means clustering** to group LGAs into high/low gaming losses and offence clusters. The findings underscore the complexity of crime as a social phenomenon and provide a foundation for researchers and policymakers to further explore the socioeconomic factors that influence gambling and crime.

III. Introduction

This report aims to explore the correlation between the annual expenditure on Electronic Gaming Machines (EGMs) and the yearly prevalence of problematic substance use, as well as the incidence of disorderly alcohol-related crimes recorded in local government areas (LGAs) in Victoria from 2014 to 2020 (Payne et al., 2012). Specifically, the research seeks to determine whether high expenditure on EGMs is associated with an increase in substance abuse and disorderly incidents due to alcohol. This issue is crucial to local governments as they deal with public health, safety, and community well-being concerns.

The data used in the project will be an extension of the data used in the previous assignment. It includes additional datasets that provide electronic gaming losses and crime-related (e.g., assault, murder, theft, drug dealing) data for Victorian local government areas. These expanded datasets enable a deeper investigation into patterns associated with addictive behaviours and criminal activity.

The findings of this analysis can inform local government of key areas requiring attention and help identify opportunities for targeted investments and support. These insights can be integrated into government strategies that address specific regional needs, considering the unique characteristics of each region or LGA. Ultimately, this study could contribute to implementing data-driven policies that enhance effective planning and community interventions at the local level.

IV. Methodology

The methodology is divided into three key stages: data preparation, data analysis, and interpretation.

1. Data Preparation

Two original datasets were used: the "EGM.csv" captures annual gaming losses on EGMs of every LGA; and the Table 02 of "LGA_Offences.xlsx" records crime counts, categorized by type of crime, LGA, and year.

Filtering and Cleaning

Specific subsets of data relevant to the research question were filtered from both datasets. This involved extracting relevant fields, including EGM losses and crime statistics specifically related to drug use and alcohol-related disorderly offences between 2014 and 2020.

Handling LGA Inconsistencies

LGAs appearing in the crime dataset but absent in the EGM dataset were removed to ensure alignment between two datasets. Additionally, some LGAs in the crime dataset were aggregated based on definitions provided in the EGM dataset, ensuring consistent geographical boundaries.

Grouping data

Data in the crime dataset was grouped by LGA and year using groupby method in pandas. This aggregation facilitated the analysis of trends and relationships across time and geographical areas.

Normalization

For the K-Means Clustering (Supervised Machine Learning Technique), to ensure the data was on a comparable scale, Z-score normalization (Standardization) was applied to the relevant data fields.

2. Data Analysis

Line Charts

Time-series line charts were generated using matplotlib to visualize the annual trends in EGM losses and specific crime types for some LGAs. These charts offered a preliminary look at the data, helping to identify overall trends, such as increases and decreases over time.

Heat Maps

Heat maps, created with seaborn library, were employed to visualize correlations between variables across LGAs and years. This provided insight into potential relationships between EGM expenditure and crime rates in a more granular way. Once the data was cleaned and initial trends were visualized, further statistical analysis was performed to quantify the relationship between EGM losses and crime.

Scatter Plots

Scatter plots were created to visualise the direct relationship between gaming losses and offence counts, allowing for a clear comparison between two continuous variables.

Correlation Computation

Pearson correlation and mutual information were computed using the scipy.stats and sklearn to quantify the relationship between EGM expenditure and crime rates.

3. Interpretation

Linear Regression

For cross-sectional analysis, linear regression was used to model the relationship between total offence counts and gaming losses over six years. By implementing sklearn.linear_model and relevant metrics, the regression model was trained and test to assess its predictive accuracy. To evaluate the performance of the model, three metrics were used: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 score. This helped understand the strength and direction of the relationship between gaming expenditure and crime.

To further illustrate the model's performance, a visualization was created by plotting the predicted regression line alongside the actual test data points. This helped provide a clear comparison between the model's predictions and the observed values, demonstrating how well the linear regression model fit the data.

K-means Clustering

For the unsupervised method, K-Means clustering was employed to identify patterns between total gaming losses and total offences count across different LGAs. The data was normalised using Standardization to handle the varying scale and outliers present in the dataset.

The K-Means algorithm was implemented using sklearn.cluster with the number set to 2, aiming to group LGAs into two distinct categories: one characterized by high gaming losses and high offence rate, and the other by low gaming loss and low offence rate. This cluster definition was based on the previous analysis that there is linear correlation between total gaming losses and total offences count in different LGAs.

To evaluate the clustering, the LGAs were visually represented on a scatter plot, with different colours assigned to each cluster, highlighting the distinct groupings based on their gaming losses and crime rates.

V. Data Exploration and Preprocessing

1. Data Preprocessing

To ensure that the datasets were properly prepared for analysis, several data cleaning steps were performed using the Python pandas library. Two datasets were used, the "EGM.csv" file, and the Table 02 from the "LGA Offences" dataset. Given the differences in structure and content between the datasets, cleaning was necessary to harmonize them for analysis.

Offence Dataset Cleaning

The first step in cleaning the Table 02 of the "LGA Offences.csv" includes filtering the data to retain only the relevant columns, including **Year**, **LGA**, **Offence Subgroup**, and **Offence Count**. To focus specifically on drug-related and alcohol-related crimes, we identified which offence subgroups fell into these categories based on predefined mapping (the exact offence types are documented in the attached code file). The dataset was then filtered to include only rows containing drug or alcohol-related offences.

Two separated dataframes were created at this stage, one for drug-related offences and another for alcohol-related offences, and each underwent the same subsequent cleaning steps. The name of the LGAs in these dataframes were mapped to the definitions provided in the "EGM.csv" file, which involved grouping multiple LGAs into a single "combined" LGA. It is important to note that the original LGA names in the dataset were in standard form (e.g., "Ballarat), while the combined LGA names were in uppercase (e.g., "ALPINE").

Following this mapping, the data was grouped by **Year** and then further grouped by **LGA**, with the total offence count for each LGA and year being aggregated using the sum function. Years 2021 through 2023 were subsequently dropped, as there was no corresponding gaming loss data for these years. Additionally, rows for LGAs that were absent from the "EGM.csv" dataset were removed (9 missing LGAs, whose names are listed in the attached code file).

A new column named "Sum" was created to represent the total number of offences recorded for each LGA between 2014 and 2020. After this step, two cleaned dataframes were produced.

Gaming Losses Dataset Cleaning

The cleaning process for the “EGM.csv” dataset started by dropping unnecessary columns, including “Region” and data for years 2011 through 2013, as no corresponding offence data was available during those years. The LGAs names in the dataset were standardized to match the offence dataframes by simplifying names (e.g., converting “City of Melbourne” to “Melbourne).

During this process, it was discovered that the “Moreland” LGA in gaming losses dataset is corresponding to the “Merri-bek” LGA in the offence datasets. Therefore, the “Moreland” cell was updated to its new name. After this step, the dataset was sorted alphabetically by LGA name for consistency.

A new column named “Sum” was created in the gaming losses dataset to reflect the total gaming losses from 2014 to 2020. This produced a final cleaned dataframe containing gaming losses information for each LGA.

Clustering Data Preparation

After cleaning the offence and gaming losses datasets, a new dataframe was created specifically for the clustering process. Each row in this dataframe represents an LGA, and it includes two key columns: total gaming losses (sum of losses from 2014 to 2020), and total offence count (sum of drug-and-alcohol-related offences over the same period). This structure was designed for clustering analysis aimed at identifying LGAs with similar patterns of gaming expenditure and offence counts.

Given the presence of outliers in the data, Standardization (also known as Z-score normalization) was applied to the data. This normalization process ensured that both variables were scaled, making them directly comparable.

2. Data Exploration

The data exploration phases involved analysing trends and patterns in the cleaned datasets above through a combination of line plots and heatmaps. By using these visualizations, key insights regarding the temporal trends and variations across LGAs were derived.

Offence Data Exploration

To explore the offense datasets, line plots were used to visualize the trends in offence counts across the first five LGAs in the datasets. Two separated line plots were created, one for drug-related offences and one for alcohol-related offences (Figure 1).

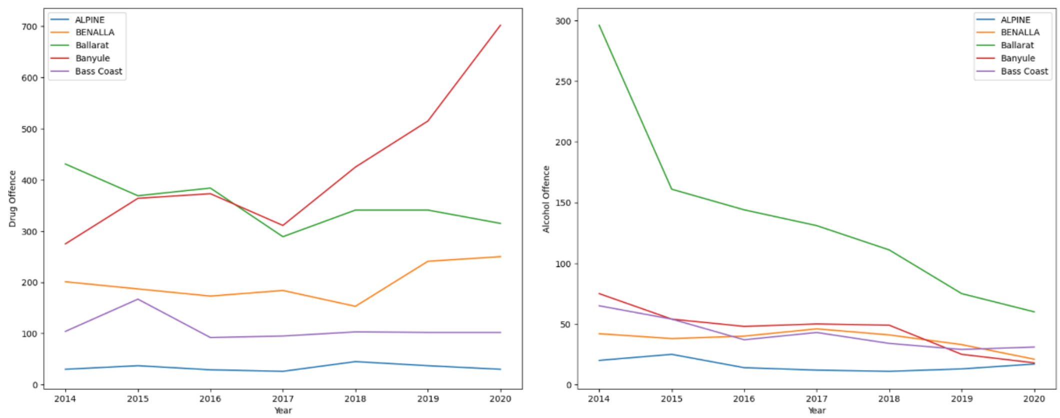

Figure 1: Line plots illustrating drug-and-related offenses from 2014 to 2020 across five LGAs.

The plots highlight how offence patterns can vary significantly between different LGAs, with some areas seeing increases in specific offences type while others show reductions. These variations suggest that regional factors may play a vital role in influencing offence rates.

To analyse the broader picture across all 57 LGAs, heatmaps were generated to visualize the offence rates over 6 years. This provided a comprehensive overview of how drug and alcohol-related offences varied across regions (Figure 2).

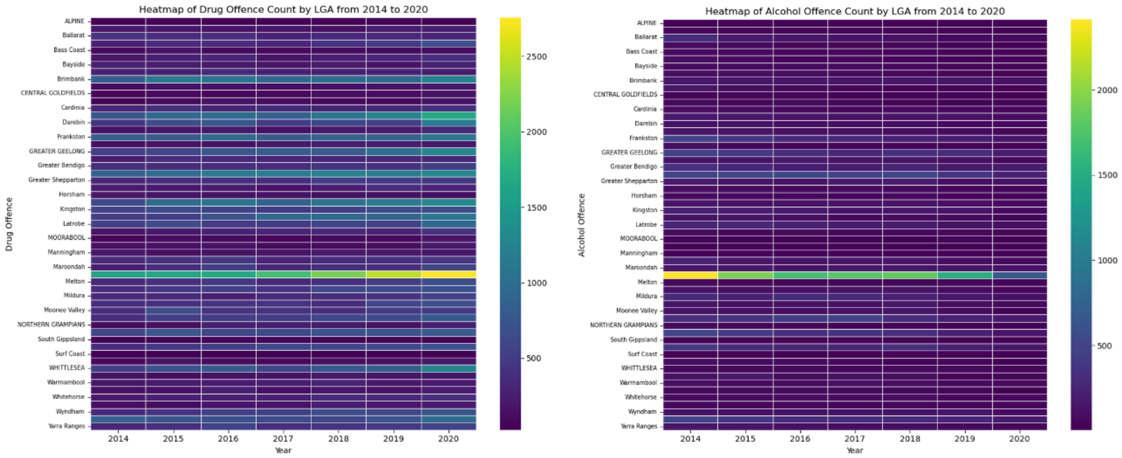

Figure 2: Heat maps illustrating drug-and-related offenses from 2014 to 2020 across fifty-seven LGAs.

The heatmaps reveal clear regional variations, with some LGAs consistently reporting higher offence counts than others. Melbourne stands out as a significant outlier, with notably higher offence for both drug and alcohol compared to other LGAs. In contrast, several LGAs maintained lower and more stable offence counts throughout six-year period. The heatmaps also highlight a general decrease in alcohol-related offences across many LGAs, which is more visible compared to the trends for drug-related offences, where the patterns are more variable across regions.

Gaming Losses Data Exploration

In parallel with the exploration of the offence data, the gaming losses dataset was visualized to understand how gaming expenditure changed over the same period. Line plots were used to visualize the trends for the first 5 LGAs, while heatmap provided a comprehensive view of all 57 LGAs (Figure 3).

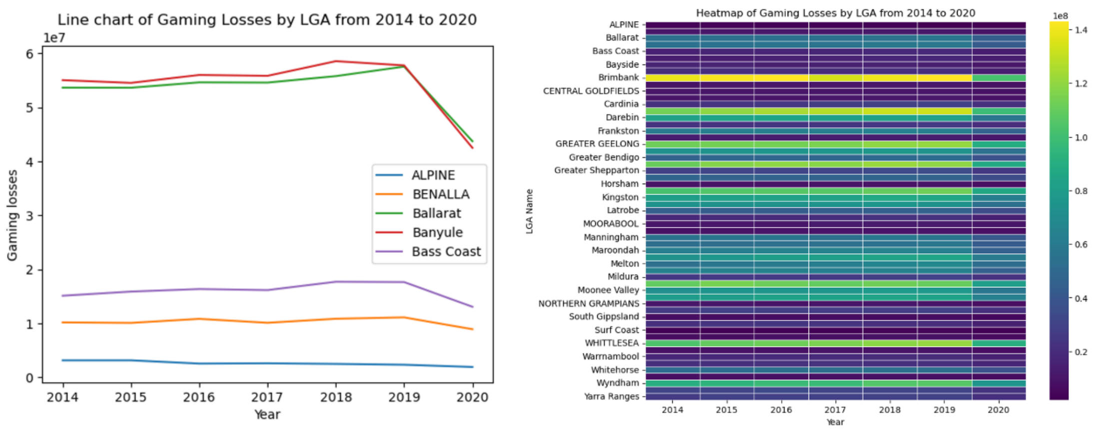

Figure 3: Trends in EGM losses from 2014 to 2020 across different LGAs.

The line plot shows a relatively stable trends for most LGAs during the 2014-2019 period, with minimal fluctuations. Notably, there was a sharp decline in gaming losses across all LGAs in 2020, which can be attributed to the closure of gambling venues during the COVID-19 pandemic.

The heatmap further illustrates this pattern. Most LGAs experienced stable gaming losses between 2014 and 2019, with Brimbank and Casey standing out as LGA with the highest gaming expenditure. However, the 2020 decline is prominently visible across all regions, reinforcing the impact of pandemic-related restrictions on gaming activities.

3. Data Analysis

Both cross-sectional and temporal analyses were conducted using scatter plots, Person correlation, and mutual information to gain deeper insight into these relationships.

Cross-sectional Analysis

The cross-sectional analysis examined the relationship between total gaming losses and total offence count over the six-year period across different LGAs. Two primary scatter plots were generated to visualize this relationship (Figure 4).

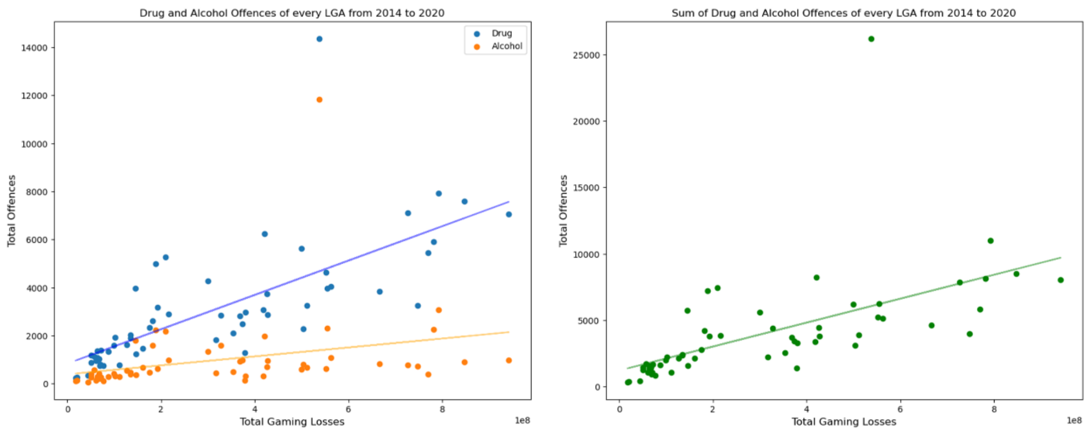

Figure 4: Scatter plots illustrating relationship between EGM losses and total offence count across fifty-seven LGAs.

The first scatter plot has different colours representing each offence type (drug-related and alcohol-related). The plot reveals a clearer positive relationship between gaming losses and drug-related offences, as the points are more concentrated along the trend line, suggesting a stronger linear relationship. In contrast, the relationship between EGM expenditure and alcohol-related offence appears to be weaker.

The second scatter plot combines the total drug-related and alcohol-related offences into a single category. The trend lines for both plots illustrate the best-fit relationships, and the slopes indicate that the influence of gaming-losses on drug-related offence is more pronounced.

It is notable that one LGA stands out as an outlier with significantly higher offence counts compared to others, which is like Melbourne. This observation aligns with the findings from the Data Exploration section, where Melbourne consistently exhibited elevated levels of both drug and alcohol-related offences.

The Pearson correlation and mutual information were calculated to quantify the strength of these relationships (Table 1).

Table 1: Pearson correlation and mutual information for relationship between EGM losses and total offence count across fifty-seven LGAs.

	Pearson correlation	**Mutual Information**
Gaming Losses vs Drug Offences	0.725	0.749
Gaming Losses vs Alcohol Offences	0.293	0.319
Gaming Losses vs Total Drug and Alcohol Offences	0.587	0.697

These results suggest a moderate-to-strong linear relationship between gaming losses and drug-related offences, with a weaker relationship for alcohol-related offences.

Temporal Analysis

The second analysis explored how changes in gaming losses from year to year affected changes in offences with each LGA. For this, scatter plots were created to visualize the relationship between year-on-year changes in gaming losses and offence counts for several selected LGAs, with each LGA assigned a different colour in the plots.

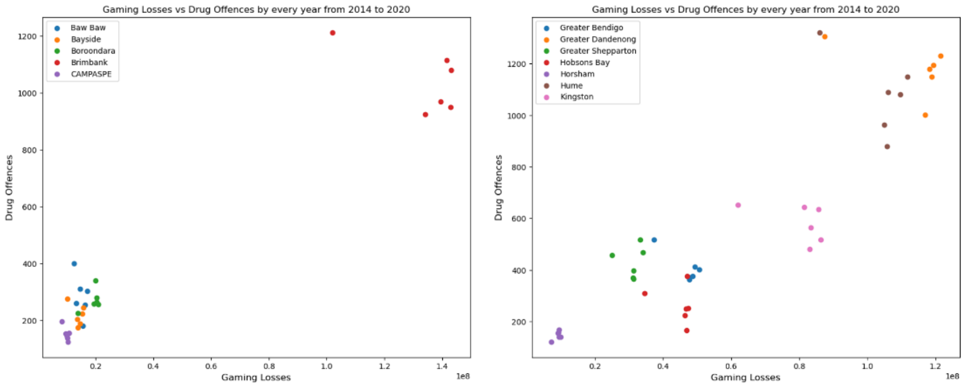

Figure 5: Changes in EGM losses and drug-related offence count from 2014 to 2020 across twelve LGAs.

The scatter plots show a weak correlation between changes in gaming losses and changes in drug-related offence from year to year for the selected LGAs (Figure 5). For each LGA, points were scattered, with no clear pattern indicating a strong temporal correlation between two variables.

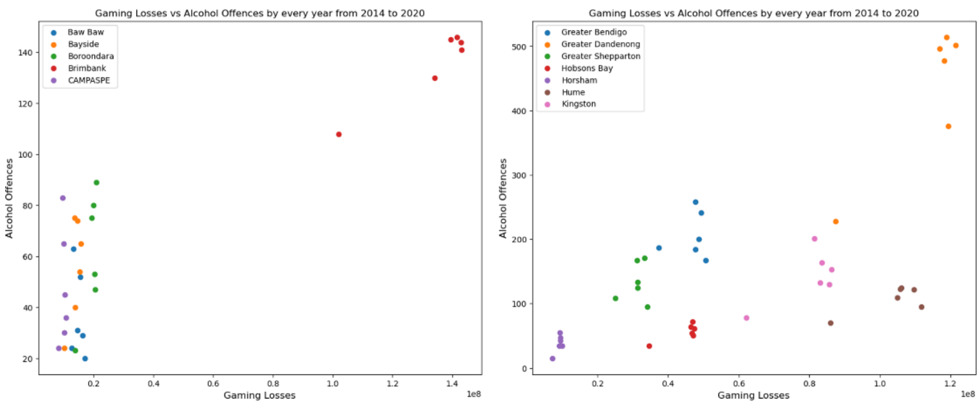

Figure 6: Changes in EGM losses and alcohol-related offence count from 2014 to 2020 across twelve LGAs.

Similarly, the scatter plots for alcohol-related offence exhibit a lack of strong correlation (Figure 6). The points remain widely distributed, indicating that year-on-year changes in gaming losses do not significantly affect alcohol

To further quantify this observation, the average Pearson correlation and mutual information were calculated across 57 LGAs for each offence category (Table 2).

Table 2: Average Pearson correlation and mutual information for changes in EGM losses and offence count from 2014 to 2020 across fifty-seven LGAs.

	Pearson correlation	Mutual Information
Gaming Losses vs Drug Offences	-0.342	0.394
Gaming Losses vs Alcohol Offences	0.077	0.103

These results emphasize that there is no strong temporal relationship between gaming losses and either offence category when examining changes from year to year within each LGA. The negative Pearson correlation for drug-related offence suggests that in some LGAs, gaming losses may decrease while offences increase, but it is likely because the EGM dataset stopped updating data in mid-2020, and this trend is not consistent across all areas.

VI. Data Modelling

For this study, two distinct machine learning techniques were used: linear regression (a supervised learning method) and K-means clustering (an unsupervised learning method).

1. Linear Regression

Given the known linear relationship between total gaming losses and total offence counts across LGAs, linear regression was selected as a predictive model to estimate the total number of offences for a given amount of gaming losses. The LinearRegression class from the sklearn library was used for this purpose.

Model Implementation:

Features selection: Total gaming losses over six years for each LGA were used as the independent variable, and total offence counts (both drug-related and alcohol-related) over the same period were used as the dependent variable.

Training and Testing: The model was trained on 80% of the data, with the remaining 20% for testing. The goal was to predict offence counts based on gaming losses and evaluate the model's performance.

Evaluation Metrics:

To access the model's accuracy, three evaluation metrics were calculated:

- Root Mean Squared Error (RMSE) = 1630 offences
- Mean Absolute Error (MAE) = 1076 offences
- R^2 Score = 0.704, showing that 70.4% of the variance in offence counts is explained by gaming losses.

Visualization:

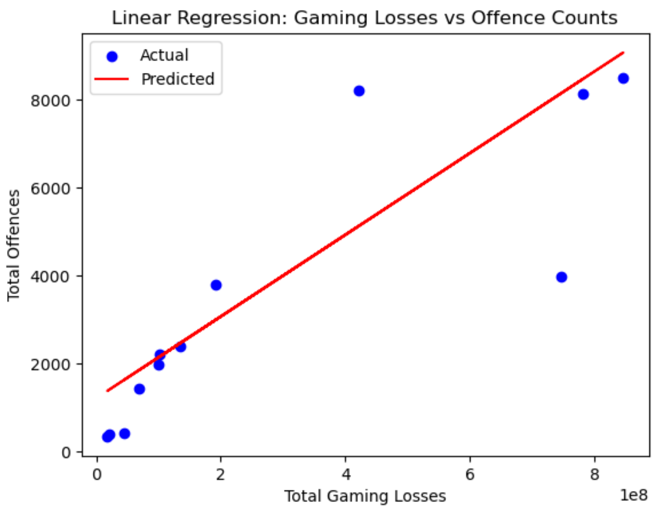

Figure 7: Plot illustrating model's prediction and actual data points

The plot of the predicted linear regression line and actual data points further illustrates the model's performance (Figure 7). While the model captures the overall trend of increasing offences with higher gaming losses, several outliers deviate significantly from the line.

Results Discussion:

Despite the reasonably good performance of the model, as evidenced by R^2 score and the visual alignment of many data points with the predicted line, the presence of outliers, as suggested by the significantly higher of RMSE than MAE, indicates that other factors may be influencing offence counts. These outliers, combined with the moderate error metrics, imply that while total gaming losses are a significant predictor of offences, additional factors could improve the model's accuracy.

However, this model does not fully address the research question, particularly in understanding the temporal relationship between annual changes in gaming losses and offence rates within LGAs. The earlier temporal analysis demonstrated that changes in gaming losses from year to year do not strongly influence changes in offence counts, meaning this cross-sectional linear regression is limited in capturing the dynamic, year-over-year fluctuations in these factors.

2. K-Means Clustering

To explore patterns between LGAs in terms of gaming losses and offence counts, K-means clustering was selected. The purpose was to categorize LGAs into two distinct groups: high gaming losses with high offence counts, and low gaming losses with low offence counts. Prior to clustering, both variables were normalized using Standardization to ensure they were on the same scale.

Model implementation:

Features selection: The two key features – total gaming losses and total offence counts across six years – were used for clustering.

Clustering process: The K-Means algorithm from sklearn was applied to cluster the 57 LGAs into two groups based on these variables. The two resulting clusters reflect LGAs with either high gaming losses and high offence counts or low gaming losses and low offence counts.

Visualization:

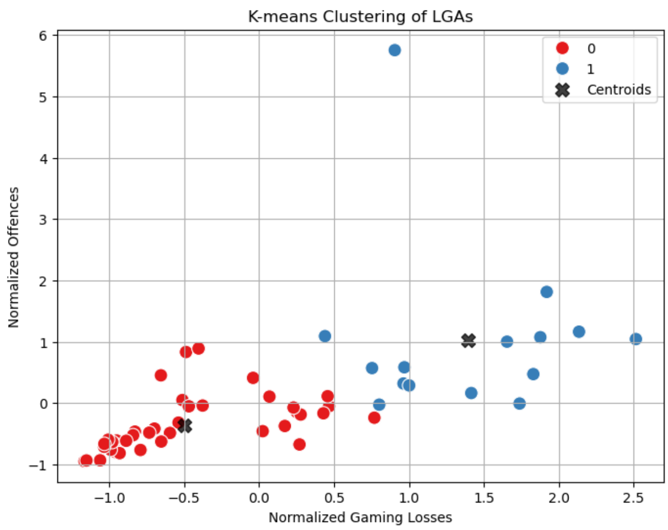

Figure 8: Scatter plot illustrating data points and model's two cluster groups.

The scatter plot depicts the results of the K-means clustering, with each cluster represented by a different colour (Figure 8). The centroids of each cluster are also shown on the plot, providing a reference point for the central tendency of each group. LGAs in the high gaming loss and high offence group (Cluster 1) are distinguishable from those in the low gaming loss and low offence group (Cluster 0). Additionally, the detailed table showing which LGA belongs to which cluster group was included in the attached code file.

Results Discussion:

The rationale behind using K-means clustering stems from need to group LGAs based on similar characteristics in gaming losses and offence counts. This technique effectively reveals pattern that align with the hypothesis of a linear relationship between these two factors. However, it is important to note that clustering is not designed to infer causality or explain the precise nature of the relationship between gaming losses and offences. Furthermore, similar to the linear regression model, the clustering results do not fully address the research question regarding year-to-year changes in gaming losses and offences within individual LGAs. The earlier temporal analysis suggests that year-by-year fluctuations do not exhibit a strong correlation, implying that the clustering results capture only static patterns and not dynamic changes over time.

VII. Discussion and Interpretation

The findings are discussed in two parts: insights from the data analysis and insights from the machine learning models.

1. Data Analysis

- **High Gaming Losses Correlate with High Crime Rates:** The cross-sectional analysis, visualized through scatter plots and quantified with Pearson correlation, shows a clear trend: LGAs with high gaming losses also tend to have high drug-and-alcohol-related offence counts.
- **Difference between Drug-Related and Alcohol-Related Offences:** Drug-related offences displayed a stronger connection to gaming losses compared to alcohol-related offences. This suggests that certain types of crime, particularly those involving drug use, maybe more sensitive to factors linked to gaming expenditure.
- **No Strong Temporal Relationship:** Looking at year-over-year changes within individual LGAs, the analysis showed that changes in gaming losses did not strongly correlate with changes in offence counts. The average Pearson correlation across 57 LGAs stated a negligible relationship. This indicates that while LGAs with higher gaming losses tend to higher crime rates overall, fluctuations in gaming losses do not appear to directly influence crime trends over time within those same LGAs. This finding points to the complexity of social phenomena like crime, where multiple factors likely influence year-to-year variations.

2. Predictive Modelling

- **Linear Regression Reveals a Predictive Relationship:** The linear regression model successfully captured the overall relationship between total gaming losses and total offences across LGAs. R^2 score of 0.704 demonstrated that gaming expenditure is a significant predictor of crime rates. However, the model also showed considerable errors in some predictions, particularly for outliers like Melbourne, which had notably higher offence counts than predicted. This implies that while gaming losses are important, additional not included in the model may also contribute to the crime rates.
- **K-means Clustering Identifies Distinct Group:** The K-means clustering results revealed two clear clusters of LGAs: one group characterized by high gaming losses and high offence counts and another by low gaming losses and low offence counts. This clustering aligns with the findings from the data analysis, reinforcing the idea that LGAs can be grouped based on their overall levels of gaming expenditure and crime. Although the clusters provide useful insights into patterns across LGAs, they do not fully address the complexities of the year-to-year variations in crime rates.

3. Key Findings

- LGAs with higher gaming losses tend to have higher crime rates.
- Changes in gaming losses do not correlate strongly with year-to-year changes in crime rates within individual LGAs, indicating that crimes rates are influenced by more than just fluctuations in gaming expenditure.
- Drug-related offences are more closely linked to gaming losses than alcohol-related offence.
- K-means clustering effectively groups LGAs into high and low offence categories based on gaming losses, reinforcing the cross-sectional relationship between gaming losses and crime. However, this approach does not account for temporal variations in the data.

4. Significance of Findings

The stronger relationship between drug offences and gaming losses raises important questions about the social impact of gambling on substance abuse and crime. Understanding these connections more deeply could guide interventions targeted at reducing both gambling-related harm and drug-related crimes. Furthermore, the two distinct groups identified by the clustering model present an opportunity for further research. Such studies could help policymakers implement more interventions to address the unique needs of each group.

5. Unexpected Insights

The relatively weak correlation between gaming losses and alcohol-related offences was unexpected, as it was hypothesized that both types of crime might show a similar relationship to gaming losses. This could be a topic for further investigation, exploring why alcohol-related offences do not exhibit the same sensitivity to gaming expenditure as drug-related offences.

The temporal analysis provided an unexpected finding: despite the overall correlation between gaming losses and crime, year-over-year changes in gaming losses did not significantly impact offence rates within individual LGAs. This suggests that short-term changes in gambling activities may not directly drive short-term changes in crimes rates, emphasizing the complexity of crime as a social phenomenon.

VIII. Limitations and Improvement Opportunities

1. Limitations

Incomplete LGA Coverage

The analysis was constrained by missing data from the EGM dataset, which omitted 9 LGAs that exist in the crime dataset. Additionally, some LGAs were grouped into “combined” LGAs (capitalized in the dataset), reducing the total number of LGAs analysed to 57 instead of the full 79 LGAs in Victoria. This reduction in number of LGAs may have limited the generalizability of the findings, as the omitted or grouped LGAs might have displayed different trends in gaming losses of crime rates.

Incomplete Gaming Loss Data for 2020

A considerable limitation is the impact of the COVID-19 pandemic on gaming losses. With the closure of gaming venues in March 2020, the gaming loss data for that year is incomplete and significantly reduced. This may have led to an inaccurate or misleading comparison of gaming losses and crime rates in 2020, as the reduction in gaming losses does not reflect normal economic activity. Any conclusions drawn from the 2020 data should be treated with caution.

Short Timeframe

The analysis was limited to a six-year period between 2014 and 2020, which may not be long enough to capture the full scope of temporal trends in both gaming losses and offence rates. Social phenomena like crime can be influenced by long-term patterns and external factors. This limited timeframe may have also hindered the ability to detect any delayed effects of gaming losses on crime rates.

Assumptions about Crime Subgroups

The classification of crime subgroups into drug-related and alcohol-related categories was based on assumptions and subjective decisions. While these classifications were necessary to conduct the analysis, they may have introduced biases into the study. Certain offences might have misclassified or overlooked, potentially affecting the accuracy of the crime data used in the analysis.

2. Improvement Opportunities

Incorporating Additional LGAs

Future research could improve by obtaining complete datasets for all 79 LGAs in Victoria. This would improve the generalizability of the findings to all LGAs.

Extending the Timeframe

An extension in the timeframe beyond 2020 would allow for a more thorough exploration of long-term trends in both gaming losses and crime rates. By incorporating data from earlier years or collecting data in future years, researchers could better assess how gaming losses influence crime over time and whether any delayed effects.

Incorporating Socioeconomic Variables

Future analyses would benefit from integrating socioeconomic variables such as population density, income levels, employment status, and education attainment. By considering these additional factors, it would be possible to assess how socioeconomic conditions interact with gaming losses to influence crime rates, providing a more nuanced understanding of the drivers of crime and could improve the predictive power of the machine learning models.

Having known that changes in gaming losses did not strongly correlate with changes in crime rates year-to-year, future research could explore nonlinear models or more sophisticated techniques such as time-series models to better capture the dynamic relationships between these variables. This could help determine whether the relationship between gaming losses and crime is more complex than a simple linear trend and whether other patterns emerge over time.

IX. Conclusion

Overall, the analysis revealed a strong cross-sectional correlation: LGAs with higher total gaming losses from 2014 to 2020 also exhibited higher drug-and-alcohol-related offence counts. This linear relationship suggests that gambling expenditures and certain types of crime may be connected. However, the absence of strong temporal relationship – where changes in gaming losses over time did not significantly correlate with changes in offence rates – implying that this relationship may not be dynamic. The findings could suggest that LGAs with larger populations tend to have both higher gaming losses and higher offence count, and these trends remain relatively stable over years.

The clustering model used in the analysis provides a useful starting point for researchers to explore the distinct characteristics of LGAs in high gaming losses/high crime rates cluster versus low gaming losses/low crime clusters (Wheeler et al., 2010), offering opportunities to investigate how demographics, socioeconomic, and policy factors influence these patterns. This study opens the door for future research to delve deeper into the broader socioeconomic impacts of gaming on communities, helping local governments craft policies that promote public health, safety, and community well-being.

X. References

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(2) University of South Australia. (2010). *The relationship between crime and gaming expenditure in Victoria*. Wheeler, S., Round, D. K., & Wilson, J. K.