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MODELLING OF NARCOTICS CRIME INCIDENTS IN MALAYSIA: A GENERALIZED LINEAR MODEL BY USING THE POISSON AND NEGATIVE BINOMIAL REGRESSION APPROACHES

(*Pemodelan Insiden Jenayah Narkotik di Malaysia: Model Linear Teritlak Menggunakan Pendekatan Regresi Poisson dan Binomial Negatif*)

LIM CHOONG WEI*, RAZIK RIDZUAN MOHD TAJUDDIN,
MOHD AFTAR ABU BAKAR, MOHD FIRDAUS-RAIH, MOHAMMAD KASSIM
& AHMAD AZWAN AMIN NORDIN

ABSTRACT

This study analyses the spatial patterns of narcotics crime incidents in Malaysia using Poisson regression and negative binomial regression approaches. The data set comprises the number of narcotics-related arrests categorized by state, gender, age group, ethnicity, and type of offence. Arrests recorded under the Dangerous Drugs (Special Preventive Measures) Act 1985 and Poisons Act 1952 in Perlis by female offenders, aged over 60 and minority ethnic considered as the reference group for this study. The analysis found that the negative binomial regression model is more suitable than the Poisson regression model, as indicated by a lower AIC value. The analysis revealed that each state has a positive and significant incidence rates of narcotics crime compared to Perlis. In terms of demographics, males and individuals aged 19 to 39 years were the most dominant groups among those arrested. The Malay ethnic group showed a high and significant positive association with incident rates compared to other ethnic groups. Offence categories related to drug distribution and possession demonstrated negative relationships, whereas positive urine test results were positively associated with arrest counts. Drug distribution and possession offences usually involve more planned and targeted operations. So, they are linked to specific locations and groups of people. On the other hand, positive urine test results often come from random screenings of large numbers of individuals, which leads to mass arrests. Therefore, the two types of offences show different patterns. The study shows that where crimes happen and who is involved are key factors in explaining why narcotics crime rates vary across Malaysia.

Keywords: narcotic crime Malaysia; negative binomial regression; Poisson regression

ABSTRAK

Kajian ini mengaji corak ruangan jenayah narkotik di Malaysia dengan menggunakan model regresi Poisson dan model regresi binomial negatif. Data kajian ini diperolehi daripada tangkapan kes narkotik dan kami akan buat analisis mengikut kategori negeri, jantina, umur, etnik, dan jenis kesalahan. Negeri Perlis dijadikan kumpulan rujukan bersama kategori pesalah wanita berumur lebih 60 tahun daripada etnik minoriti di bawah Akta Dadah Berbahaya 1985 dan Akta Racun 1952. Hasil kajian menunjukkan bahawa model regresi binomial negatif lebih sesuai digunakan berbanding model Poisson berdasarkan nilai AIC yang lebih rendah. Analisis ini juga menunjukkan setiap negeri mempunyai kadar insiden jenayah narkotik yang positif dan signifikan. Perbandingan dibuat dengan Perlis sebagai rujukan.Dari aspek demografi, lelaki serta individu berumur 19 hingga 39 tahun merupakan kumpulan paling dominan dalam tangkapan. Analisis ini juga menunjukkan etnik Melayu mempunyai hubungan positif yang tinggi terhadap kadar insiden jika berbanding dengan etnik lain. Bagi jenis kesalahan, kes pengedaran dan pemilikan dadah didapati mempunyai hubungan negatif dengan kadar tangkapan, manakala kes ujian air kencing positif menunjukkan hubungan positif. Perbezaan ini berpunca daripada sifat kes pengedaran dan pemilikan yang lebih terancang, berbanding ujian air kencing yang melibatkan saringan rawak berskala besar. Secara keseluruhan, faktor ruangan dan demografi memainkan peranan penting dalam variasi jenayah narkotik serta membantu pihak berkuasa merangka strategi pencegahan yang lebih berkesan.

Kata Kunci: jenayah narkotik Malaysia; regresi binomial negatif; rRegresi Poisson

1. Introduction

Narcotics-related crime is still a serious problem in Malaysia. It needs new policies and better enforcement strategies. Even though authorities have made many efforts, but drug activities are now more complex and spread across many areas. Therefore, the methods we usually use to prevent crime are less effective. Because of this, there is a need to use simple and clear data-based methods to understand the patterns and causes of these crimes.

In recent years, spatial analysis has become an important method in crime studies. It helps to study where crimes happen and how they are grouped in certain areas. This method can show differences between places and help to identify high-risk areas. With this data, government can form a policy in a better and more focused way. Spatial analysis also helps to explain the trend of narcotics-related crimes across different states. So, it can also support Malaysia's goals like Malaysia Madani and the Sustainable Development Goals (SDG), which focus on public safety, strong communities, and better governance.

By using spatial analysis, Hashim *et al*. (2020) found drug addiction hotspots in Selangor. The study shows clear differences in narcotics-related crimes across states. This supports the use of spatial methods to improve enforcement and crime prevention.

Demographic factors are also important in analysis drug crimes. Ismail *et al*. (2024) found that male teenagers in high-risk environments are more likely to use drugs in urban areas. Ngah *et al*. (2021) also found factors like age and ethnicity has relationship with narcotics-related activities among monitored individuals. These results are similar to other studies that show drug crimes are more common among males, young adults, and certain ethnic groups.

This situation show that drug crimes are not only caused by personal factors like stress or peer pressure, but it also affected by social and economic conditions, education level, and living environment. To ensure the policies applied effectively, we should consider both location and population factors.

To analyse drug crime cases in Malaysia, we will use the Generalized Linear Model (GLM) in this study. The GLM will be supported by Poisson regression as the basic model to count data and Negative Binomial regression to handle data with high variation.

1.1. *Research objectives*

For this research, to identify important factors that explain narcotics-related crime incidents by using count data regression methods is the main objective. We also aim to choose the most suitable model to explain and predict narcotics-related crime incidents, based on simple statistical measures, such as AIC and model fit.

1.2. *Spatial crime analysis and narcotics-related offences*

In crime studies, spatial modelling is a useful tool. We might able to find crime hotspots and to predict crime trends. Cesario *et al*. (2024) shows that drug crimes and other crimes often happen in certain urban areas in his study. This is because these areas have different levels of density and are often linked to social and economic problems. The method they use can better detect high-risk areas, especially in crowded and low-income urban places.

To study the spatial distribution of narcotics-related arrests across states in Malaysia, we will use Poisson regression and negative binomial regression These models help to predict how socio-demographic factors and types of offenses affect the number of arrests. The purpose is to find important geographic hotspots and demographic factors related to drug arrests. This can help support better and more focused enforcement planning.

1.3. *Poisson and negative binomial regression in crime studies*

To set up count data like the number of crime cases, Poisson regression is a basic method for us to use. It assumes that the mean and variance are the same, but, in real data we collected, not always be the same. In this study which related to crime, the data usually show higher variation. This may cause wrong estimation and weak results when using the Poisson model.

We will use negative binomial regression, which allows extra variation in the data, to solve this higher variation problem. It is more suitable for real crime data and can analyse better the differences in crime patterns across places and groups of people.

Statistical models have also helped in studying narcotics-related crime. Methods like Poisson and negative binomial regression can find important factors linked to drug arrests. The negative binomial model is often used for analysis because crime data usually have high variation. These methods can help Authorities to form better policies, such as random urine tests, focused enforcement, and better planning of resources.

In other countries, researchers often use Generalized Linear Models (GLM), such as Poisson and negative binomial regression, to study crime patterns. For example, in China, Chen *et al.* (2020a) used this method to study drug crime patterns. Chen *et al.* (2020b) also showed the need to handle variation in crime data by using negative binomial models. In Malaysia, the use of these models is still limited. Many past studies they do not use advanced regression models, but use simple or descriptive methods. This shows that more studies using these methods are needed in Malaysia.

2. Methodology

2.1. *Data*

For this study, we had collected dataset from Royal Malaysia Police (Polis Diraja Malaysia, PDRM), which includes official records of narcotics-related arrests for the year 2022. There are 165,140 cases from all 13 states and 3 federal territories in Malaysia. From these data, we had grouped them by state, gender, age group, ethnicity, and type of offense. This allows a clear spatial and demographic analysis.

Descriptive results show that about 92% of offenders are male, and 68% of the offenders are in the age range between 19 to 39. With this data, we can say that young adults are the main group involved in drug crimes. When refer to the ethnicity, Malays take up about 73% of arrests, followed by Chinese (13%), Indians (8%), and others (6%).

For the group by type of arrest, possession with the most cases, around 45%, followed by positive urine tests (32%), distribution (18%), and other offenses (5%). These arrests are recorded under laws such as the Dangerous Drugs Act 1952, the Poisons Act 1952, and the Dangerous Drugs (Special Preventive Measures) Act 1985.

In this study, number of arrests for each demographic group is the dependent variable, while the independent variables include categorical indicators representing the state in which the arrest occurred, the gender of the offender (male or female), the age group of the offender (below 18 years, 19–39 years, 40–59 years, and above 60 years), the ethnicity of the offender (Malay, Chinese, Indian, or Others), and the type of offense (drug distribution, possession, positive urine test, or other categories). For modelling purposes, the reference category is defined as female offenders aged above 60 from minority ethnic groups (classified as "Others") who were arrested in the state of Perlis, and whose offences other than distribution, possession, positive urine that falls under the Dangerous Drugs (Special Preventive Measures) Act 1985 and the Poisons Act 1952. All regression coefficients are interpreted relative to this baseline group.

2.2 *Modelling approach*

2.2.1. *Poisson regression model*

Model Specification:
Let Y_i represent the count of narcotics-related arrests for subgroup i. The Poisson model assumes:

$$Y_i \sim \text{Poisson}(\lambda_i), \qquad \log(\lambda_i) = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \varepsilon_i \tag{1}$$

where λ_i is expected arrest count, and X_{ij} represents the j^{th} predictor.

In this formulation, β_0 is the intercept, while β_j $(j = 1, 2, \dots, p)$ are the regression coefficients that quantify the effect of each predictor variable on the logarithm of the expected count. Specifically, each coefficient β_j represents the expected change in the log count of narcotics-related arrests associated with a one-unit increase in X_{ij}, holding other variables constant.

For interpretability, the exponential form of the coefficients, e^{β_j}, is often used and is referred to as the incidence rate ratio (IRR). The IRR indicates the multiplicative change in the expected count of arrests for a one-unit increase in the corresponding predictor. An IRR greater than one suggests an increase in the rate of occurrence, while an IRR less than one indicates a decrease.

A key assumption of the Poisson model is equidispersion, where the mean and variance of are the same, i.e., $E(Y_i) = Var(Y_i) = \lambda_i$. However, in real crime data, we seldom met this condition due to the data usually have higher variation. This can lead to less accurate estimates and smaller standard errors.

2.2.2. *Negative binomial regression model*

Model Specification:
When overdispersion occurs, the negative binomial model is used as an extension of the Poisson model. This model can handle higher variation in the data.

$$Y_i \sim \text{NB}(\mu_i, \theta), \quad \log(\mu_i) = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \varepsilon_i \tag{2}$$

where μ_i represents the expected count for subgroup i, θ is the dispersion parameter that captures the degree of variability beyond the Poisson assumption.

Similar to the Poisson model, β_0 denotes the intercept, and β_j are the regression coefficients that describe the relationship between the predictors and the log of the expected count. The interpretation of β_j remains consistent, where e^{β_j} represents the incidence rate ratio (IRR), indicating the proportional change in the expected count associated with a one-unit increase in the predictor.

The variance is the main difference between Poisson model and Negative Binomial model. In Negative Binomial model, the variance is defined as:

$$Var(Y_i) = \mu_{\mathrm{i}} + \theta\mu_i^2 \tag{3}$$

The variance in this formula can be higher than mean. It removes the strict equidispersion assumption used in the Poisson model. The dispersion parameter θ helps the model to handle extra variation and unobserved differences in the data. These features are common in crime data. Because of this, Negative Binomial model gives more stable and reliable estimates when overdispersion exists. It is more suitable for modelling narcotics-related crime data (Hilbe, 2011).

2.2.3. *Modelling software*

Statistical analysis in this study was carried out using R software (R Core Team 2025). R provides a flexible tool for modelling count data under the Generalized Linear Model (GLM) framework. The analysis followed several steps.

First, exploratory data analysis (EDA) was done to check the distribution of narcotics-related arrests. Descriptive statistics such as mean and variance were calculated. This was used to check whether the Poisson assumption was suitable. Histograms were also used to view the distribution of the data.

Second, the Poisson regression model was fitted using the glm() function in R with family = poisson (link = "log"). This model was used as the baseline model for count data. It models the log of the expected number of arrests as a linear function of the predictors. All socio-demographic and offense-related variables were included as predictors.

Third, model adequacy was checked by testing for overdispersion. This was done by comparing the mean and variance of the dependent variable. A formal test was also carried out using the dispersiontest() function from the AER package (Kleiber & Zeileis 2019). A value greater than one shows overdispersion, which means the Poisson model is not suitable.

Since overdispersion was found, the Negative Binomial regression model was then used. This model was fitted using the glm.nb() function from the MASS package (Venables & Ripley 2002). It includes an extra dispersion parameter to handle excess variation. The same variables were used so that both models could be compared.

Finally, model performance was checked using the Akaike Information Criterion (AIC). The regression coefficients from both models were converted into incidence rate ratios (IRRs) to make the results easier to interpret.

Overall, the GLM approach in R provides a clear and flexible way to analyse count data. It helps to better explain differences in narcotics-related crime across locations and demographic groups in Malaysia.

2.2.4 *Incidence rate ratios (IRRs) and akaike information criterion (AIC)*

In this study, we will use incidence rate ratios (IRRs) to explain regression results. The IRR is taking from e^{β_j}. It shows how the expected number of narcotics-related arrests affected when a predictor increases by one unit, while other variables stay the same. Rate increase if IRR value greater than one, while case decrease if IRR smaller than one.

Model performance is compared using the Akaike Information Criterion (AIC). The AIC is used to choose the best model by balancing fit and complexity. It is defined as:

$$AIC = -2\log(L) + 2k \tag{4}$$

where L denotes the likelihood of the model and k represents the number of estimated parameters. A lower AIC value shows a better model fit. It also shows a better balance between model accuracy and simplicity. In this study, the model with the lowest AIC value is chosen as the best model for further analysis.

3. Results and Discussion

The objectives of this study have been successfully achieved through a systematic modelling approach Prior to regression modelling, a descriptive analysis was conducted to summarize the characteristics of the dataset and identify potential patterns. The dataset contains 165,140 records of narcotics-related arrests in Malaysia for the year 2022. We had grouped the data by state, gender, age group, ethnicity, and type of offense. In both Poisson and negative binomial regression models, the coefficients *(β)* show the log of the expected count. We had changed the values into incidence rate ratios (IRR) using exponentiation, because these values are not easy to interpret directly. Formula for IRR as shown below:

$$IRR_j = \exp(\beta_j) \tag{5}$$

This IRR shows the multiplicative effect of a one-unit increase in each predictor variable, while other variables are held constant. By converting regression results into IRRs, it helps us to understand more easily how each factor affects the outcome, especially in fields like epidemiology and social science where interpreting real-world impact is important.

3.1. *Model comparison and selection*

Table 1 shows the results and variable effects from Poisson and Negative Binomial models. After compared the results from both models, Negative Binomial model fits the data better. Akaike Information Criterion (AIC) for the Negative Binomial model is 26,124, where the value is much lower than the Poisson model, which is 278,723. The Negative Binomial model has a better balance between fit and model complexity. The large difference in AIC values shows that the Negative Binomial model is the better choice for this data.

In addition, the estimated dispersion parameter for the Negative Binomial model is 1.28763, which is greater than zero, indicating the presence of overdispersion in the dataset. These findings match the earlier tests and show that the Poisson model assumption of equidispersion is not met. So, the Poisson model may give less efficient estimates and smaller standard errors than it should.

The regression results also show that some explanatory variables have important effects on narcotics-related arrests. These effects are explained using incidence rate ratios (IRRs), and they show how each predictor changes the expected number of arrests. An IRR greater than one means an increase in the arrest rate. An IRR less than one means a decrease.

Overall, the results in Table 1 show that the Negative Binomial model handles the overdispersion problem better and gives more stable and easier-to-interpret results. Therefore, this model is selected as the final analytical framework, and all subsequent analyses and discussions are based on its results.

Table 1: Model comparison poisson vs negative binomial regression

Coefficients	Poisson Regression			Negative Binomial Regression		
	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	p-value	$\hat{\boldsymbol{\beta}}$	$\exp(\hat{\boldsymbol{\beta}})$	p-value
Intercept	- 2.47851	0.08387	< 0.0001	- 2.32152	0.09812	< 0.0001
Selangor	1.84824	6.34866	< 0.0001	2.26607	9.64140	< 0.0001
Kelantan	1.56037	4.76057	< 0.0001	1.20012	3.32052	< 0.0001
Perak	1.33581	3.80309	< 0.0001	1.38740	4.00444	< 0.0001
Pulau Pinang	1.30883	3.70186	< 0.0001	1.56356	4.77578	< 0.0001
Sabah	1.94196	6.97242	< 0.0001	2.99125	19.91065	< 0.0001
Johor	1.56869	4.80037	< 0.0001	1.67363	5.33148	< 0.0001
Terengganu	1.86652	6.46577	< 0.0001	1.43451	4.19761	< 0.0001
Kuala Lumpur	1.32387	3.75794	< 0.0001	1.88517	6.58748	< 0.0001
Kedah	1.39517	4.03564	< 0.0001	1.13734	3.11847	< 0.0001
Negeri Sembilan	0.71841	2.05116	< 0.0001	0.86047	2.36427	< 0.0001
Pahang	1.90089	6.69187	< 0.0001	1.62233	5.06489	< 0.0001
Sarawak	1.53518	4.64217	< 0.0001	2.20198	9.04292	< 0.0001
Melaka	0.46150	1.58645	< 0.0001	0.57782	1.78215	0.0002
Malay	1.83226	6.24798	< 0.0001	2.12235	8.35076	< 0.0001
Chinese	- 0.00343	0.99658	0.757	0.55938	1.74959	< 0.0001
Indian	0.23880	1.26972	< 0.0001	0.70301	2.01982	< 0.0001
Drug Distribution	- 2.20407	0.11035	< 0.0001	- 1.77885	0.16883	< 0.0001
Drug Possession	- 0.20626	0.81362	< 0.0001	- 0.08634	0.91728	0.0641
Positive Urine Test	0.61953	1.85805	< 0.0001	0.62656	1.87117	< 0.0001
Dispersion value	-			1.28763		
AIC	278,723			26,124		

By inserting the estimated coefficients into the equation, the expected number of narcotics-related arrests for subgroup *i* can be written as:

$$\begin{aligned}\log(\hat{\mu}_i) = -2.32152 &+ 2.26607(Selangor) + 1.20012(Kelantan)\\ &+ 1.38740(Perak) + 1.56356(Pulau\ Pinang) + 2.99125(Sabah)\\ &+ 1.67363(Johor) + 1.43451(Terengganu)\\ &+ 1.88517\ (Kuala\ Lumpur) + 1.13734\ (Kedah)\\ &+ 0.86047(Negeri\ Sembilan) + 1.62233\ (Pahang)\\ &+ 2.20198(Sawarak) + 0.57782(Melaka)\end{aligned} \tag{6}$$

This estimate equation analyses how each predictor affects the expected number of arrests. The size and sign of the coefficients indicate the effect of each variable. The exponential form of the coefficients makes it easier to interpret the results using incidence rate ratios (IRRs).

3.2. *State-level differences (geographic variation)*

The findings show significant differences in narcotics-related arrests between states in Malaysia, for example, Sabah, Selangor, and Sarawak record higher incidence rate ratios (IRRs), which means they have more arrests compared to the reference state (Perlis).

Urban and densely populated states tend to have more narcotics-related activities can be found in earlier studies by Ismail *et al.* (2024). This is related to higher population movement and stronger economic activity cause increase of both drug demand and supply. Urban areas directly become key locations for drug activity.

A similar pattern is found in other Southeast Asian countries such as Thailand and Indonesia. Urban areas in these countries also serve as main drug trafficking centres (United Nations Office on Drugs and Crime 2023). Malaysia also shows the similar social and economic conditions with those countries. This highlights how development, migration, and enforcement focus shape drug crime patterns.

Border states such as Kelantan, Perak, Perlis, and Kedah are located near Thailand. These states face higher risk of cross-border drug trafficking. Their location makes smuggling activities more common, so these states often record more narcotics-related crimes and need stronger enforcement than inland areas.

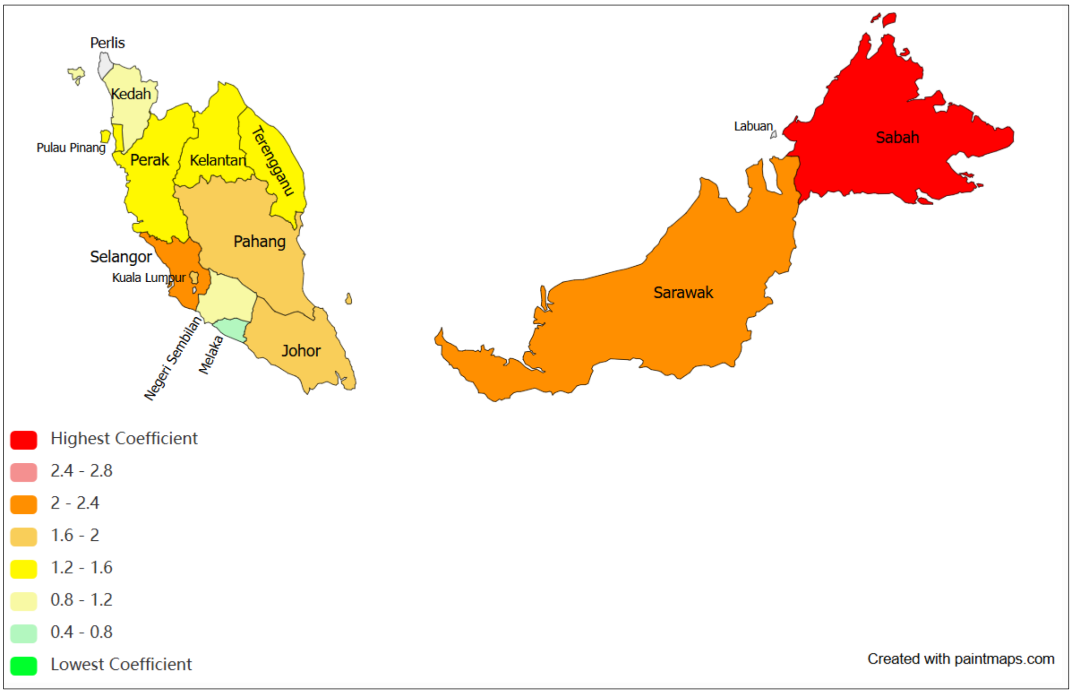

Figure 1: A plot showing negative binomial regression (NBR) result

Refer to the results from negative binomial regression (NBR) model, Sabah shows the highest relative increase in arrest incidence compared to Perlis, with an IRR of approximately 19.91 (β = 2.99125), follow by Selangor (β = 2.26607), Sarawak (β = 2.20198), and Kuala Lumpur (β = 1.88517) exhibited substantially elevated risks, suggesting a disproportionate concentration of narcotics-related activities in urban and economically dynamic regions. These results suggest that factors such as population density, economic conditions, and higher drug demand may lead to more narcotics-related arrests in these states. The spatial pattern of narcotics-related offenses shows the need for state-level policies that match the characteristics of each region.

These states generally have similar features, including high populations density, growing economies, and strong connection between area. These conditions make it easier for drugs to move and be used for others (Department of Statistics Malaysia 2022). At the same time, rapid urban growth may also create social issues, especially among young people. Some of them use drugs because they feel pressure from social and economic conditions.

From these findings, different states face different social, economic, and law enforcement challenges, so the policies should be adjusted based on each states' situation.

3.3. *Gender disparities*

The analysis shows a clear difference between males and females in narcotics-related offences, males are more likely to be involved than females. The incidence rate ratio (IRR) for male offenders is 7.59 ($\beta = 2.02673$, $p < 0.0001$), which means male are more than seven times more likely to be arrested for narcotics-related offenses compared to female. This finding is similar with the sociological study by Marinelli *et al*. (2023), which found a higher rate of narcotics-related crime among males in Malaysia.

This difference can be explained in several factors, such as behaviour patterns, peer influence, financial stress, and exposure to risky environments. In Malaysia, gender roles and social expectations often place men in situations that increase their risk of involvement in illegal activities like drug use and drug distribution. Cultural views that connect masculinity with risk-taking may make this pattern stronger.

National data also support this finding. About 96% of people arrested for narcotics-related offenses in Malaysia are male. This pattern is also seen in other countries and shows that narcotics-related behaviour is influenced by social, structural, and psychological factors (United Nations Office on Drugs and Crime 2024).

Because of this large gap, there is a need for programs that focus on males. Prevention and rehabilitation programs should consider behavioural, economic, and social factors that affect men. Programs that reduce peer pressure, improve economic opportunities, and strengthen social support can help reduce male involvement in narcotics-related crimes.

3.4. *Age-related trends*

The analysis shows that individuals age within the range of 19 to 39 are at the highest risk of narcotics-related arrests. Age range between 30 to 39 has the greatest risk, with an incidence rate ratio (IRR) of approximately 7.14 (β = 1.96517), followed by individuals aged range between 19 to 29 (β = 1.92032). These findings are similar with earlier research which highlights that young adults are more exposed to risks such as peer influence, unemployment, and experimentation with illegal drugs Ismail *et al*. (2022).

Many studies from Western and Asian report a similar age pattern. They show that younger people in a different social and cultural environment are more involved in narcotics-related activities (Nawi *et al*. 2021). In Malaysia, this pattern is also clear. National data show that more than 60% of narcotics-related arrests involve people aged range from 15 to 39. This shows that adolescence and early adulthood are high-risk stages for drug involvement.

The higher rate among young people is linked to social and structural factors. These include peer pressure, limited job opportunities, and earlier exposure to drugs during early life stages (Becker & Murphy 2022). Therefore, targeted prevention programs need to focus on specific age, especially youth and those challenges might be faced by young people.

These programs can build protective factors like education, job opportunities, and community support. At the same time, they can also reduce risk factors linked to drug use among young adults in Malaysia.

3.5. *Ethnicity*

The findings show significant difference in narcotics-related arrests among ethnic group in Malaysia. People identified as Malay have much higher likelihood of being arrest for narcotics-related offenses, with a regression coefficient of β = 2.12235 (p < 0.0001). This observation shows a high proportion of drug users among the Malay population, which is consistent with national data from the Agensi Antidadah Kebangsaan (2022).

Ethnic differences in narcotics-related offenses are often reported in Malaysia, but they are less discussed in international studies. This suggests that the connection between ethnicity and drug enforcement may depend on the local context. In the United States, similar disparities have been widely documented (Mitchell & Caudy 2017). A report by Human Rights Watch (2024) also shows that Black individuals are 4 to 5 times more likely to be arrested for marijuana-related offenses than White individuals, even when drug use rates are similar.

In Malaysia, most of the population is Malay, about 69%. The country also has a different ethnic group living together with different levels of income, education, and social integration. These conditions may affect drug use patterns and law enforcement results.

The findings show that Malays make up the largest group of drug offenders, followed by Indians and Chinese. These differences may be related to social and economic inequality, such as access to education, jobs, healthcare, and rehabilitation services. Cultural values, social support, and community strength may also affect these patterns. Because of these patterns, drug prevention and rehabilitation programs should take into consideration of cultural and social differences. Programs that match local needs, language, and socio-economic conditions may improve the effectiveness of drug control policies in Malaysia.

3.6. *Offense-type variations and their influence*

The analysis shows different in arrest based on the type of offense, highlighting fundamental differences in enforcement strategies and the narcotics-related activities operate. Arrests for drug distribution show a significant negative association with overall arrest counts (β = -1.77885), suggesting these arrests occur less frequently and are predominantly the result of targeted law enforcement operations. Such operations typically involve intelligence-led approaches, including surveillance and extended investigations, rather than indiscriminate or routine enforcement activities (Chainey & Ratcliffe 2020).

Arrests for drug possession show a small negative effect ($\beta = -0.08634$, $p = 0.0641$) and this suggests that these cases may also come from planned actions instead of random checks. In contrast, positive urine test results show a strong positive relationship with total arrests ($\beta = 0.62656$, $p < 0.0001$) and this means many arrests come from large-scale urine testing operations, such as joint narcotics operation.

These differences show that police actions vary by offense type. Distribution and possession cases need more time, effort, and planning. In contrast, arrests from urine tests come from wide screening activities. People caught through urine tests are more likely to be drug users rather than part of drug networks.

These findings show that different approaches are needed based on the type of offense. Efforts should focus more on high-risk states like Sabah, Selangor, and Sarawak, where arrest rates are higher and groups like young males are more affected.

4. Conclusion

This study helps criminology and spatial analysis by giving a statistical framework to model a narcotics-related crime in Malaysia. It uses the Generalized Linear Model (GLM) approach, especially Poisson and Negative Binomial regression, to study how spatial, demographic, and offense-related factors affect crime patterns.

Unlike basic descriptive methods, this study uses count data models that can handle overdispersion and improve accuracy of estimation. This is important because crime data often show high variation and there do not follow normal distributions.

From a practical view, the results give useful information for law enforcement and policymakers. They help identify high-risk areas and groups, and they support better resource allocation, focused enforcement, and policy decisions based on data collected. Spatial analysis also helps to improve planning at both local and national levels.

The study links statistical modelling with real crime prevention needs. It gives both methodological and practical contributions and can support researchers, policymakers, and enforcement agencies.

A limitation of global models like Poisson and Negative Binomial regression is that they assume relationships are the same across all areas, and this ignores spatial differences between regions. In real situations, factors such as socio-economic conditions, urban development, and enforcement strength vary across locations and they influence crime patterns.

Future research should use spatially adaptive methods such as geographically weighted Poisson and geographically weighted Negative Binomial regression. These methods allow relationships to change across space and they can better capture local patterns of drug-related arrests. This is useful for smaller areas such as districts or municipalities.

The findings of this study are match with both national and international research, and they support the need for targeted policies such as youth-focused rehabilitation, gender-sensitive programs, culturally appropriate outreach, and stronger state-level enforcement. These approaches can improve drug control strategies in Malaysia through data-driven decision making.

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Narcotics Crime Investigation Department
Royal Malaysia Police Headquarters
50560 Bukit Aman
Kuala Lumpur, MALAYSIA
E-mail: limchoongwei@rmp.gov.my, aazwan@rmp.gov.my*

Department of Mathematical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor, MALAYSIA
E-mail: rrmt@ukm.edu.my, aftar@ukm.edu.my

Department of Applied Physics
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor, MALAYSIA
E-mail: firdaus@mfrlab.org

Department of Chemical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor, MALAYSIA
E-mail: mb_kassim@ukm.edu.my

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*Corresponding author