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Integrated Rural Security Innovation: Evidence from Village Information Systems and Crime Mapping in Indonesia

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Abstract

Background/Problem: In recent years, rural areas in Indonesia have witnessed an increase in crime, leading to heightened fear and insecurity among residents. This rise in criminal activity is largely attributed to a shortage of security personnel, ineffective community patrols, and a general lack of awareness about security measures. Economic challenges such as poverty and unemployment further contribute to the issue. Objective: analyze the effect of increased security personnel on crime rates and reporting in Indonesian villages. The research uses panel data from the 2018-2022 PODES and SUSENAS surveys. It also investigates how village information systems, regulations, and socioeconomic conditions influence crime dynamics. Methods: applies a Propensity Score Matching (PSM) model to assess the impact of enhanced security personnel on crime rates and reporting. The analysis also incorporates various factors, including village-level information systems, local regulations, and socioeconomic conditions. Results/Key Findings: increasing the number of security personnel is significantly associated with a reduction in crime rates in rural villages. Furthermore, a more robust village information system encourages greater crime reporting, which in turn leads to further reductions in crime. These results highlight the interconnectedness between crime prevention and reporting. Implications: This research emphasizes the importance of improving security measures, such as increasing security personnel and strengthening village information systems, to address crime in rural Indonesia. The implementation of a crime map could serve as an innovative tool to aid both crime prevention and reporting, further enhancing security in these communities.

Introduction

Indonesia's crime index in 2025 stands at 6.85, placing it as the second-highest in ASEAN thus marking a critical challenge for national security and social stability (Yonatan, Agnes Y, 2025). This alarming status is underscored by data from Indonesia's Central Statistics Agency (BPS), which recorded a staggering 584,991 criminal cases in 2023 equating to one crime reported every 53 seconds. This data represents a drastic, 56 percent increase from the 372,965 cases documented in 2022, when a crime occurred every 84 seconds (Badan Pusat Statistik (BPS), 2018).

Crime in rural areas is not only a growing problem globally but also a critical issue in developing countries like Indonesia, where rural infrastructure and governance systems may not be as robust as those in urban areas (United Nations Office on Drugs and Crime (UNODC), 2020). A disturbing surge in crime has also engulfed rural areas, where communities are confronting a rise in offenses ranging from theft and drug trafficking to sexual assault and mass violence. This trend has fostered a pervasive climate of fear and insecurity, further intensifying the region's existing social and economic hardships.

Several factors contribute to this rise in rural crime. One of the primary issues is the lack of sufficient security personnel. Data from Indonesia's Central Statistics Agency (BPS) indicates that many rural areas suffer from a low police-to-population ratio, which severely hinders the ability of law enforcement to deter and respond to criminal activities effectively (Badan Pusat Statistik (BPS), 2018). For instance, in some districts, the police presence is so thin that entire villages rely on community-based security initiatives like *ronda*, where residents take turns patrolling their neighbourhoods. While well-intentioned, these community patrols often struggle due to poor organization, lack of training, and insufficient resources (Blair et al., 2021; Cabrera-Barona et al., 2019; Kuo et al., 2013; MacDonald et al., 2016).

However, Blair et al. (2021) conducted a comprehensive study examining the impact of community policing initiatives in the Global South, specifically focusing on whether these programs foster trust in law enforcement or reduce crime. Through large-scale randomized control trials across six countries, the researchers found that community policing, as implemented in these regions, failed to significantly improve public trust in the police or lead to a noticeable reduction in crime rates. The absence of formal security structures leaves rural communities vulnerable to a range of criminal activities that would otherwise be deterred by a more significant law enforcement presence.

Moreover, many rural areas also lack basic awareness of security measures. Villagers are often unaware of how to protect themselves or report crimes effectively. This gap in knowledge makes them easy targets for criminals, who take advantage

of their isolation and lack of preparedness. Compounding these challenges is the underdevelopment of village information systems, which are vital for tracking, reporting, and responding to crime. In many villages, there is a significant delay in communication between residents and law enforcement, as many communities still rely on traditional, slow, or even informal methods of relaying information. According to a study by Badan Pusat Statistik (2021) less than 50 percent of villages in Indonesia have functioning digital information systems that could facilitate crime reporting and prevention. The lack of a formal and accessible reporting mechanism hampers the ability of residents to report crimes in a timely manner, allowing criminal activity to go unchecked for extended periods.

Another crucial factor is the socioeconomic environment in rural areas, where poverty and unemployment are persistent issues. According to the World Bank (2020), rural poverty rates in Indonesia remain significantly higher than in urban areas, with many families struggling to meet basic needs. The lack of economic opportunities often drives individuals, particularly young men, toward criminal activities as a means of survival.

These socioeconomic challenges, coupled with weak local governance and limited access to education, create fertile ground for criminal networks to operate in rural communities. While several studies have addressed crime in rural areas globally, few have specifically focused on rural crime dynamics in Indonesia, particularly with respect to the impact of increased security personnel and village information systems. Existing research has largely concentrated on urban crime patterns and the effectiveness of community policing, without deeply exploring how rural settings, where governance and resources are more limited, affect crime dynamics. For example, studies by Blair et al. (2021) and Kuo et al. (2013) emphasize the challenges of community policing in low-resource areas, but they have not sufficiently addressed the role of local information systems in facilitating crime reporting and prevention in rural Indonesia. Furthermore, while the literature underscores the importance of socioeconomic factors, like poverty and unemployment, in driving crime (Smith, 2019), it fails to link these factors directly to the enhancement of law enforcement or the role of digital crime reporting systems in mitigating crime.

This study fills this gap by investigating the combined effect of increased security personnel and improved village information systems on crime rates and reporting in rural Indonesia. Previous studies have not fully explored the synergy between crime reporting systems and community involvement in rural settings, particularly in the Indonesian context. By using panel data from PODES and SUSENAS and applying Propensity Score Matching (PSM), this research aims to provide a clearer understanding of how security personnel and digital reporting infrastructure impact crime rates and the timeliness of crime reports in rural areas. The research employs panel data from the PODES survey and SUSENAS KOR for the period 2018 and 2022 to investigate the impact of enhancing law enforcement on

crime rates and reporting mechanisms (Wooldridge, 2010). This study also considers other factors such as regulations, social assistance programs, education, religious infrastructure, and broader socioeconomic conditions, which are known to influence crime in rural areas.

The study uses a Propensity Score Matching (PSM) model to estimate the effect of increasing security personnel on crime reduction and reporting in rural areas. PSM helps control for selection bias by matching villages that received additional security resources with similar villages that did not. This allows for a more accurate estimation of the true effect of increased security personnel on crime outcomes. Wooldridge (2010) explains that Propensity Score Matching (PSM) is a reliable method for aligning treatment and control groups based on observable characteristics, improving the analysis of non-experimental data. Research highlights several factors influencing crime rates in villages, demonstrating a significant correlation between certain variables and crime levels. Increased security personnel, for example, can reduce crime. Cabrera-Barona et al., (2019) found that security presence decreases theft and vandalism. This deterrent effect is echoed by Bako et al. (2018).

Enhanced information systems in villages also positively impact crime reduction. Kuo et al. (2013) highlighted that well-designed information systems enhance decision-making by enabling swift and precise actions, which plays a crucial role in crime prevention. Additionally, Habibullah et al. (2016) demonstrated a strong link between the implementation of village security regulations and reduced crime rates. Similarly, research by Cabrera-Barona et al. (2019); Yildiz et al. (2013) revealed that individuals receiving direct cash transfers (BLT) are less inclined to engage in criminal activities, as financial assistance helps alleviate economic pressures that might otherwise lead to crime. Improved access to education is linked to decreased crime. Study found that better education reduces criminal involvement (Hjalmarsson & Lochner, 2012; Yildiz et al., 2013). Quality public facilities also contribute to lower crime rates. Painter & Farrington (2001) indicated that adequate public amenities create a safer environment.

High poverty levels often correlate with increased crime, driven by individuals striving to meet their needs, as explained by Yildiz et al. (2013). Community participation in social activities is crucial for reducing crime. Williams et al. (2015); Wo, (2023) emphasized that active social engagement strengthens community bonds, enhancing security and order. Easier communication access can potentially lower crime rates through various mechanisms. Easier family contact reduces prison recidivism, demonstrating a positive impact on criminal behaviour (Claire & Dixon, 2017). Conversely, Zhang et al. (2015) noted that while internet censorship doesn't directly affect crime, it can provide access to information useful for criminal activities. Efficient communication among law enforcement agencies is crucial, as poor communication can hinder crime-fighting. Studies by United Nations Office on

Drugs and Crime (UNODC) (2020) highlight the misuse of new information technologies by criminals and the importance of timely, accurate crime data.

Crime concentration studies reveal that crime tends to cluster in specific areas. Weisburd (2015) noted that despite high crime fluctuations, concentration remains within narrow ranges over time. For example, 50 percent of Chicago's crimes occur in 3 percent of the city. Places of worship, enhancing social capital and control, can reduce crime, as seen in Wo (2023) study in Washington DC. Certain types of places influence crime rates. Williams et al. (2015) found that alcohol-selling establishments (except nightclubs) and high schools are associated with higher property and drug crimes, whereas places of worship show no significant crime relationship.

Smith (2019) examines the relationship between marginalized populations and rural crime rates, highlighting how social and economic exclusion contributes to increased crime in rural areas. The study finds that marginalized groups, due to factors like poverty and limited access to resources, are more likely to be involved in or affected by crime. Smith argues that addressing the root causes of marginalization is essential for reducing rural crime rates and improving community well-being. Education level inversely correlates with crime rates; (Hjalmarsson & Lochner, 2012) indicated that higher educational attainment and school quality significantly reduce crime.

Human, social, and criminal capital also impact crime choices. Williams et al., (2015) analyzed these factors, finding significant effects of education (human capital) and peer influence (social capital) on adult criminality. Economic conditions also play a role. Yildiz et al. (2013) showed that higher income and education levels reduce crime likelihood, with unemployment's impact being marginal due to alternative income sources.

Street lighting improvements can deter crime. (Nagin, 1998) demonstrated significant crime reductions in well-lit areas, with financial savings outweighing lighting costs. However, gaps in understanding policy impacts on criminal behavior remain. Short- and long-term effects, risk perception, interaction mechanisms, and data quality are key research areas needing attention. Micro-level crime concentration patterns vary by crime type. Shiode & Block (2015) found stable hotspots for drugs and robbery in high-crime Chicago areas, while thefts were sporadic and short-term. Focused deterrence strategies, such as "pulling levers," effectively reduce crime. Braga & Weisburd (2012) reviewed ten studies, finding significant crime reduction in nine, supporting the strategy's effectiveness against gang violence.

This study seeks to address one key question whether increasing security personnel and improving village information systems reduce crime rates and improve crime reporting in rural areas. This research demonstrating the effectiveness of increasing security personnel and enhancing village information systems in reducing crime rates and improving crime reporting in rural Indonesia. Thus,

provide a framework for policymakers to address the growing crime problem in these communities. By offering a comprehensive analysis of the relationship between security measures and crime dynamics, this study highlights the critical need for an integrated approach that combines law enforcement, community engagement, and technological advancements to combat rural crime effectively.

Methods

The data used in this study are secondary data from PODES (2018 and 2021) and SUSENAS KOR (2018 and 2022). PODES data, collected by BPS biennially, covers all Indonesian villages and provides insights into village potential, including indicators like the Geographic Difficulty Index (IKG) and the evaluation of village development and funding. PODES respondents include village heads, sub-district heads, and regional secretaries.

SUSENAS data gathered semi-annually (March and September), offers socio-economic information on education, health, housing, fertility, family planning, and more. The March survey with a larger sample, is representative at the district/city level, while the September survey is representative at the provincial and national levels. SUSENAS respondents are randomly selected households, with March involving 960 households and September involving 240 households. Key indicators from SUSENAS include the poverty rate, Gini Ratio, Poverty Depth Index, Poverty Severity Index, Human Development Index (HDI), School Participation Rate, and Literacy Rate.

This study builds on (Fondevila et al., 2022) work by combining household and community data, minimizing unobserved heterogeneity bias. It examines the impact of increasing security personnel on village crime rates, noting the correlation between improved information and security systems such as additional security personnel, neighborhood watch, mandatory guest reporting, security teams, and police posts) and crime rates.

Analytical Framework

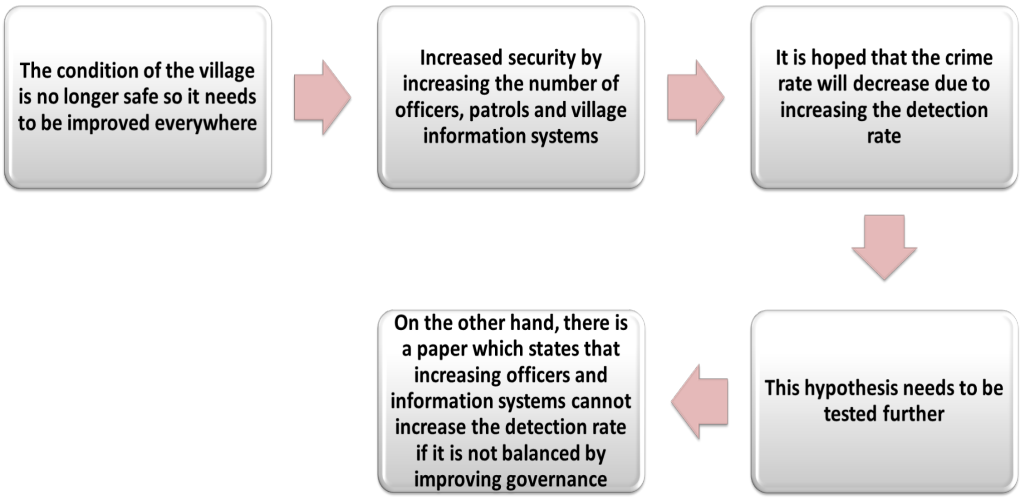

Figure 1. Research Framework
Source: processed by authors (2024)

The study compares villages with enhanced information and security systems (treatment group) to those without (control group). Given the qualitative nature of the dependent variable, logistic regression, probit, and propensity score matching (PSM) are used.

Table 1. Variable Categories and Descriptions

x	Variable Name	Description
Dependent Variable	Crime Rate	Crime rate in the village.
Independent Variable	Security Personnel	Number of security personnel in the village.
Independent Variable	Information System	Quality of the crime reporting information system in the village.
Control Variable	Regulations	Number of village regulations related to security.
Control Variable	BLT (Cash Transfer)	Number of recipients of direct cash transfers in the village, serves as a proxy for poverty.
Control Variable	Education	Access to educational facilities in the village.
Control Variable	Marginal Groups	Presence or arrival of marginal groups (homeless, sex workers, or beggars) in village.
Control Variable	Public Facilities	Quality of public facilities in the village.
Control Variable	Poverty Rate	Household poverty rate.

x	Variable Name	Description
Control Variable (dummy)	Employment	Employment status (whether employed or not).
Control Variable	Social Activities	Involvement in social activities.
Control Variable	Communication	Access to communication in the village.
Control Variable	Community Cooperation	Level of community cooperation in the village.
Control Variable	Police Post	Readily accessible police station.

Source: processed from (Badan Pusat Statistik (BPS), 2018, 2021)

While the use of secondary data from PODES and SUSENAS offers extensive coverage and robustness for a national-level study, it also presents certain limitations. A primary constraint is the lack of granularity in the data. The village-level aggregation in PODES may obscure important intra-village variations in crime, security presence, and socioeconomic conditions. Furthermore, crime data in such surveys are often based on reported incidents, which can be subject to underreporting bias, especially in rural areas where trust in authorities may be low or reporting mechanisms inaccessible. This can lead to an underestimation of the true crime rate. Another limitation is the potential for unobserved confounding variables. Despite the use of PSM to balance observed characteristics, there may be unmeasured factors—such as subtle shifts in community morale, the specific quality of local leadership, or informal dispute resolution practices that influence both the allocation of security resources and crime outcomes.

To mitigate these limitations, several strategies were employed. The combination of PODES (village-level) and SUSENAS (household-level) data was a key step, as it helped to cross-validate findings and reduce unobserved heterogeneity bias by incorporating both community and individual perspectives. The application of Propensity Score Matching (PSM) was crucial for addressing selection bias, as it created a more comparable counterfactual by matching treated villages (with enhanced security/information systems) to control villages with similar observed characteristics. To enhance the robustness of the findings, the study utilized multiple model specifications (Logit, Probit, and PSM), with consistent results across models increasing confidence in the conclusions. Finally, control variables were carefully selected based on established theoretical frameworks to account for a wide range of socioeconomic, institutional, and demographic factors known to influence crime, thereby reducing the potential for omitted variable bias. While these steps cannot

fully eliminate all limitations inherent in secondary data analysis, they significantly strengthen the internal validity and reliability of the causal inferences drawn.

Model Specification

Crime Rate=$\beta_0 + \beta_1 X_i + \gamma_i Z_i + \varepsilon$ (i)

Where: β0 is a constant term, Xi is the independent variable of the village information system and additional officers, Zi is the control variable (j = 1……..n), and ε is *error term*

Logistic Regression Model

Logistic regression is used to model the probability of occurrence of a binary event, in this case the crime rate in the village. This model is suitable for use because the dependent variable is binary. The logistic regression function is as follows:

$$P(Y = 1|X) = \frac{1}{(1 + e-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n))} \quad \text{(ii)}$$

Where: Y is a binary dependent variable (for example, crime rate). X_1, X_2, ..., X_n is is the independent variable (Officers, Information, Regulations, BLT, Education, Public Facilities, Poverty, Employment, involvement in social activities).

Probit Regression Model

Probit regression is similar to logistic regression but uses the cumulative function of the normal distribution to estimate probabilities. The probit regression function is as follows:

$P(Y = 1|X) = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)$ (iii)

Where: Φ is the cumulative distribution function of the standard normal distribution.

Propensity Score Matching (PSM)

Study uses Propensity Score Matching (PSM) to reduce bias that may arise from differences in characteristics between the treatment and control groups. PSM is a statistical method used to balance the distribution of covariates between treatment and control groups so that the analysis of treatment effects is more accurate. Propensity Score Matching (PSM) is a method commonly used in econometrics to estimate causal treatment effects in non-experimental settings, helping to address selection bias in observational data. As outlined by (Wooldridge, 2010), the process begins with determining the propensity score. This involves using a logistic regression model to estimate the probability that each unit in the study will receive the treatment, based on observed covariates. This estimated probability is the propensity score, which helps in balancing the treatment and control groups by accounting for the covariates that influence the treatment assignment.

After determining the propensity score, the next step is matching. Wooldridge explains that units in the treatment group are matched with units in the control group that have similar propensity scores, ensuring that the treatment and control groups are comparable on observed covariates. Various matching algorithms can be used to create pairs of treated and untreated units with similar characteristics.

Finally, once matching is complete, the treatment effect is estimated by comparing the outcomes of the treatment group with those of the matched control group. As (Wooldridge, 2010) emphasizes, because matching ensures that the treatment and control groups are balanced on observed covariates, the difference in outcomes between the two groups can be interpreted as the causal effect of the treatment, thus providing a more robust estimate of the treatment effect.

The choice between Probit and Logit models often depends on the nature of the data being analyzed and interpretation preferences. If a normal distribution better fits the data, a Probit model may be more appropriate. On the other hand, if interpretation via the odds ratio is more important, the Logit model is usually more reliable. PSM helps in minimizing selection bias and allows a fairer evaluation of the effect of treatment (increased information systems and/or improved information systems) on crime rates.

Table 2. Foundation of Model Selection

Model	Description	Advantages
Logit	Logistic regression (Logit) is a statistical technique used to model the probability of a binary event (e.g., yes/no, success/failure). This model uses the logit function to link a binary dependent variable with one or more independent variables.	- Logit model assumes that the error terms follow a logistic distribution. - Coefficients in the Logit model can be directly interpreted as the logarithm of the odds ratio, facilitating interpretation in the context of risk or odds. - **Simplicity in Computation**: The Logit model is usually easier to implement and compute, and converges faster on many datasets. - **Robustness to Model Misspecification**: The Logit model tends to be more robust against incorrect model specification or errors in the distribution of independent variables.
Probit	Probit regression is a statistical method similar to logistic regression, but it uses the cumulative normal distribution function to estimate the probability of a binary event.	- **Coefficients in the Probit model are easier to interpret** in the context of cumulative probability from the standard normal distribution. - **The Probit model tends to handle extreme values or outliers** better due to the nature of the normal distribution.

Model	Description	Advantages
PSM	Propensity Score Matching (PSM) is a statistical method used to reduce selection bias by balancing the distribution of confounding variables (covariates) between the treatment and control groups.	- **Reducing selection bias**: Ensures the treatment and control groups are comparable in terms of confounding characteristics. - **Internal validity:** Improves the internal validity of treatment effect estimates. - **Flexible use:** Can be applied to various types of observational studies where randomization is not feasible.

Source: processed from (Wooldridge, 2010)

A Propensity Score Matching (PSM) estimation was conducted to evaluate the impact of increasing security personnel and improving village information systems on crime rates in rural areas from 2018 to 2021. The main variables analyzed include enhancements to the security system and village information infrastructure, along with control variables such as accessibility to police posts, the presence of community institutions, public facilities, marginalized groups, village regulations, and socioeconomic factors like poverty and employment levels.

Result

1.1.Logit and Probit Model

This section may be organized into subheadings for clarity and better structure. It should offer a concise and precise description of the experimental results, highlighting the key findings in a clear and straightforward manner.

Table 3. Comparison Results between Logit and Probit Model: The Impact of Village Information System on Crime

Dependent variable	**Logit**	**Probit**
Dummy Crime	**Coefficient**	**Coefficient**
Village information system	**0.939*** (41.38)**	**0.5776431** (0.0181536)**
Dummy security	**0.763*** (26.34)**	**0.3698932** (0.0198696)**
Public facility	**0.320*** (16.62)**	**0.0983038** (0.0169457)**
Community institution	**-1.807*** (-24.40)**	**-0.4857301** (0.0067934)**

Gotong royong	**-0.706*** (-4.47)**	**-0.1672452** (0.0064752)**
Accessible police station	**-2.650*** (-156.48)**	**-1.447716** (0.0082564)**
Regulation	**-0.00669*** (-10.97)**	**-0.0484721** (0.0059436)**
Police station	**-4.804*** (-222.03)**	**-0.3184227** (0.0143872)**
Marginal	**2.720*** (31.61)**	**1.408157** (0.0189027)**
Internet signal	**3.486*** (98.66)**	**0.0849107** (0.0332735)**
Dummy work	**-0.0977*** (-17.84)**	**-0.0574036** (0.0032735)**
Dummy assistance	**0.270*** (38.45)**	**-0.1483428** (0.0041934)**
N	**1193379**	**1004981**
R^2	**0.346**	**0.6014**

Standard error is in parentheses, significance level: *10 percent, **5 percent, ***1 percent
Source: processed by authors using STATA (2025)

The first step involved logit estimation, which estimates propensity scores without incorporating dependent or outcome variables, specifically the village information system in this case. This method allows for balancing treatment and control groups, facilitating a robust analysis of the causal impact of security measures on crime reduction (Table 4.1)

1.2 First Model: The Impact of Security Personnel

Table 4.1 First Step: Performing Logit Estimation for Propensity Score Estimation

Variable	Mean Treated	Mean Control	T-test	p>|t|
Security	0.3064	0.2944	1.07	0.286
Public Facility	0.3051	0.2964	-0.48	0.63
Community institution	0.3051	0.2943	-1.55	0.12
Gotong royong	0.3051	0.2944	-1.65	0.105

Variable	Mean Treated	Mean Control	T-test	p>|t|
Accessible police station	0.3051	0.2943	0.53	0.596
Regulation	10.714	10.714	0.04	0.971
Police station presence	0.3051	0.3051	0.06	0.95
Marginal	0.3051	0.3051	0.05	0.964
Dummy work	0.3051	0.3051	0.08	0.94
Dummy assistance	0.3051	0.3051	0.05	0.964

Source: processed by authors using STATA (2025)

Table 4.2 Second Step: Performing Matching with Propensity Score Matching (PSM)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Dummy Crime	Unmatched	-0.7458	0.071178	-0.7458	0.000945	299
Dummy Crime	ATT	-0.7458	0.181019	-0.0644	0.125943	-0.51

Source: processed by authors using STATA (2025)

Table 4.3 Third Step: Comparing PSM Covariates

Variable	**Mean Treated**	**Mean Control**	**Percent Bias**	**T-test**	**p>|t|**
Security Officer	0.9944	0.99429	0	1.02	0.308
Public Facility	0.98531	0.9854	0	-0.49	0.622
Community institution	0.99954	0.99938	0.2	4.95	0
Gotong royong	0.99992	0.99998	-0.1	-1.58	0.115
Readily accessible police station	0.09598	0.09567	0	0.48	0.627
Regulation	10.714	10.702	0.2	1.12	0.261
Police station presence	0.4161	0.416	0	0.14	0.887
Marginal	0.00006	0.00004	1.7	18.39	0

Dummy work	0.99679	0.99677	0	0.7	0.484
Dummy assistance	0.46761	0.46708	0	0.05	0.964

Source: processed by authors using STATA (2025)

The covariate balance results show the average covariate values for treated and control groups before and after matching, along with t-tests and p-values to evaluate the similarity of covariate distributions. Variables security, public facility, community institution, and others also show similar distributions between treated and control groups with non-significant p-values, indicating successful matching in creating covariate balance.

Table 4.4 Fourth Step: Average Treatment Effect Result

Variable	**Coefficient**	**T**	**[95 percent Conf. Interval]**
Village information system	-0.06439614*** (0.000903)	-71.29	-0.06501578 to -0.06379624
Constant	-0.03101578*** (6.25E-05)	-496.32	-0.03210473 to -0.03194678

*Standard error is in parentheses, significance level: *10 percent, **5 percent, ***1 percent*

Source: processed by authors using STATA (2025

The Propensity Score Matching (PSM) estimation provides a clear picture of the differences in the main outcome, covariate balance, and regression results after matching. The PSM results highlight the differences in the main outcome, all crime, before and after matching. In the unmatched sample, the treated value is -0.74, while the control value is 0.071, resulting in a difference of -0.74. In the matched sample (ATT), the treated value remains -0.74, but the control value changes to 0.181, resulting in a difference of -0.064. This indicates that after matching, the difference between treated and control groups significantly decreases (Table 4.4).

The Propensity Score Matching regression results show the linear regression outcomes of the treatment variable after matching to estimate the adjusted treatment effect. Result shows that crime have significant negative effect of the treatment on crime rates. Village information system variable also indicating a significant negative effect on crime rate in rural areas. The effectiveness of adding security officers is shown by the study of (Bako et al., 2018; Ceccato, 2016; Gaviria & Pagés, 2002), which indicates that increasing the number of security officers can reduce the crime rate due to an increase in patrols and crime prevention. Adding security officers can increase residents' sense of security, thereby reducing crime incidents (Bako et al., 2018).

Overall, these estimation results indicate that after conducting Propensity Score Matching, the difference in crime rates between villages with and without an information system significantly decreases. Additionally, the covariate distribution between the two groups becomes more balanced. The linear regression also shows

that the treatment effect on the measured outcome is significant. Improvements in the village information system are significantly related to increased crime reporting. (Heald, 2006) posits that transparency and accountability in information systems enhance public trust in governmental institutions. A better information system reassures residents that their reports will be taken seriously, motivating them to report criminal incidents.

Furthermore, an efficient information system boosts administrative efficiency and responsiveness in handling crime cases, making the reporting process faster and more accurate (Claire & Dixon, 2017). The integration of community security systems also has a significant impact. (Putnam, 1994) found that community participation in activities like neighbourhood watch strengthens social networks and collective security. An active community security system empowers residents to engage in maintaining their environment's safety, which in turn increases crime reporting. Additionally,(Cohen & Felson, 1979) routine activity theory states that crimes occur when offenders encounter suitable targets in the absence of adequate guardianship. Activating community security measures improves surveillance, reducing crime opportunities and encouraging residents to report incidents due to a heightened sense of security.

1.3 Second Model: The Impact of Village Security System

Table 4.1 First Step: Logit Estimation for Propensity Score Estimation

Variable	Mean Treated	Mean Control	T-test	p>|t|
Security	0.3064	0.2944	1.07	0.286
Public Facility	0.3051	0.2964	-0.48	0.63
Community institution	0.3051	0.2943	-1.55	0.12
Gotong royong	0.3051	0.2944	-1.65	0.105
Accessible police station	0.3051	0.2943	0.53	0.596
Regulation	10.714	10.714	0.04	0.971
Police station presence	0.3051	0.3051	0.06	0.95
Marginal	0.3051	0.3051	0.05	0.964
Dummy work	0.3051	0.3051	0.08	0.94
Dummy assistance	0.3051	0.3051	0.05	0.964

Source: processed by authors using STATA (2025)

In the first stage, the logit model is used to estimate the propensity score based on several variables. The estimation results show that the variables security, public facilities, ease of reaching police posts, regulations, presence of police posts, marginal, communication, and work have a significant influence. The community institution variable has a significant negative influence, while the community mutual

cooperation variable and the aid dummy are not significant. These results indicate that most variables have a significant effect on the propensity score.

The results of logistic regression show that several variables have a significant effect on security with the coefficients and standard errors listed. The variable village information system has a coefficient of 3.194 which means that an increase in this variable significantly increases security. Likewise, the variables public facilities and community institutions, indicating a significant positive effect on security. Logistic regression analysis shows that several variables have a significant effect on security.

Table 4.2 Second Step: Performing Matching with Propensity Score Matching (PSM)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Crime	Unmatched	-0.7458	0.071178	-0.7458	0.000945	299
Crime	ATT	-0.7458	0.181019	-0.0644	0.125943	-0.51

Source: processed by authors using STATA (2025)

The results of the covariate balance evaluation show that most variables have significant t-test values, indicating a difference between the treated group and the control group. The regulation variable has a variance ratio outside the limits [1.00; 1.00], indicating a different variance between the treated group and the control group. The matching results show that the all crime variable has an average difference between the treated group and the control group. In the unmatched sample, the difference is 0.201 with a standard error of 0.001 and a t-statistic of 155.66, indicating a significant result. In the Average Treatment effect on the Treated (ATT), the difference is 0.170 with a standard error of 0.110 and a t-statistic of 1.54, indicating that the effect of treatment on the treated group is significant but with a lower level of confidence than the unmatched sample (Table 4.2).

Table 4.3 Third Step: Comparing PSM Covariates Balance

Variable	**Mean Treated**	**Mean Control**	**Percent Bias**	**T-test**	**p>|t|**
Security Officer	0.9944	0.99429	0	1.02	0.308
Public Facility	0.98531	0.9854	0	-0.49	0.622
Community institution	0.99954	0.99938	0.2	4.95	0
Gotong royong	0.99992	0.99998	-0.1	-1.58	0.115
Accessible police station	0.09598	0.09567	0	0.48	0.627
Regulation	10.714	10.702	0.2	1.12	0.261

Police station presence	0.4161	0.416	0	0.14	0.887
Marginal	0.00006	0.00004	1.7	18.39	0
Dummy work	0.99679	0.99677	0	0.7	0.484
Dummy assistance	0.46761	0.46708	0	0.05	0.964

Source: processed by authors using STATA (2025)

Table 4.4 Fourth Step: Average Treatment Effect Result

Variable	Coefficient	T	[95 percent Conf. Interval]
Village information system	-0.0643961*** (0.000903)	-71.29	-0.06501578 to -0.06379624
Constant	-0.0310157*** (6.25E-05)	-496.32	-0.03210473 to -0.03194678

*Standard error is in parentheses, significance level: *10 percent, **5 percent, ***1 percent*
Source: processed by authors using STATA (2025)

The result showed that improvement of the security system in the village shows a significant effect on reducing the crime rate. The implementation of the village information system, measured through the village information system has a significant correlation with increased reporting of crime cases so that it can reduce the crime rate in the village (Table 4.4). The role of information systems in crime reporting is explained by (Norris & Armstrong, 1999), who state that a good information system allows crime reporting to be more effective and efficient, so that more cases can be documented and followed up. With the existence of a village information system, transparency and accountability in handling crime cases increase, which in turn increases public confidence in reporting crimes (Johnston, 2017). This causes the crime detection rate to be high so that criminals think twice about committing crimes due to the high probability of being caught and punished. Ultimately, this leads to a decrease in crime rates.

Integration of community security systems through the activation of neighborhood watch has been shown to increase community participation in maintaining environmental security. This finding is in accordance with research by Felson and Clarke (1998) which states that community involvement in local security systems can significantly reduce crime rates. The addition of security officers and improvements to village information systems have been shown to have a significant impact on increasing crime reporting. Based on the theory of social control put forward by Putnam (1994) , the stronger the social ties and control in a community, the lower the crime rate in the area. The addition of security officers increases social supervision and formal control in village communities, which in turn reduces opportunities for crime. In addition, the community-based crime eradication model, as studied by (Aston et al., 2023) explore the role of information sharing in

community policing across Europe and its influence on public confidence in law enforcement. Result found that effective information sharing is critical for fostering public trust. The research concludes that improving these processes is essential for enhancing public confidence and strengthening the effectiveness of community policing in Europe. Therefore, residents feel more protected and are more willing to report crimes that occur.

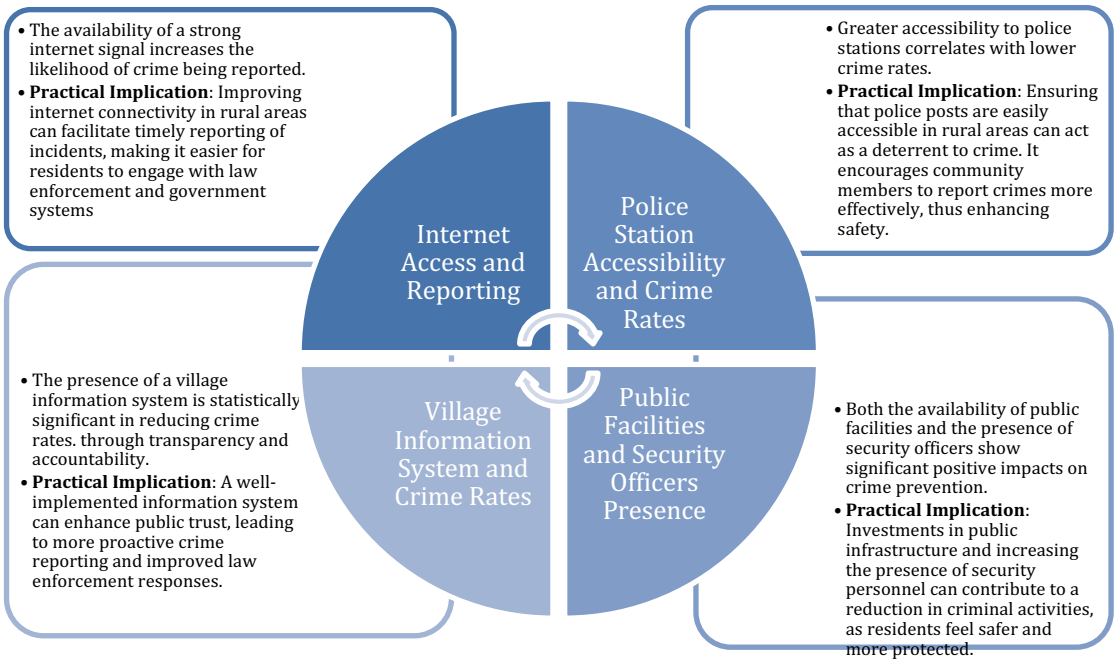

Figure 2. Summary Key Findings
Source: processed from STATA (2025)

The findings of this study make a significant contribution to the discourse on rural innovation and inclusive governance in developing contexts. Traditionally, rural security has been approached through a top-down, law-enforcement-centric lens. This research, however, demonstrates that innovation in rural areas is not merely about importing urban technologies, but about contextually integrating technology, human resources, and community structures. The proposed crime-mapping dashboard is a prime example of a frugal innovation that leverages existing, but often underutilized, public data (PODES, SUSENAS, police reports) to create a public good. This moves beyond traditional, siloed government operations and represents a innovative, systemic approach to problem-solving that is both scalable and adaptable to the specific needs of rural communities.

Furthermore, the results underscore the pathway toward more inclusive governance. The finding that improved village information systems boost crime reporting is profound. It indicates that when the state provides transparent and accessible channels for citizen engagement, citizens respond by actively participating in their own security. This transforms villagers from passive recipients of security services into active co-producers of safety. The crime map proposal embodies this principle by creating a platform for two-way communication: the government

provides transparency (open data on crime), and the community provides intelligence (crowdsourced alerts). This process fosters accountability, as police performance becomes more visible, and empowers marginalized groups by giving them a direct, anonymized channel to report issues and access safety information, thereby ensuring that security planning is informed by the lived experiences of all citizens, not just the most vocal or connected. Ultimately, this research posits that effective rural security is an outcome of inclusive governance, where technological innovation serves to strengthen the social contract between the state and its rural citizens.

2.1 Innovation of Crime Mapping

To improve public safety and awareness, it's essential to develop a comprehensive crime mapping tool that visualizes crime data by region. This innovation is inspired by successful interactive dashboards in the UK, such as Crime Rate and the Police.uk crime maps (Police.UK, 2025). The system would provide real-time updates on dangerous areas, offering clear visibility into crime hotspots, planned demonstrations, and other high-risk events as they occur. This transparency helps residents stay alert and significantly enhances overall public safety.

This tool would also be invaluable for tourists and visitors. By offering clear insights into the safety of neighbourhoods and routes, it helps build confidence and minimizes the risk of victimization. Users can effectively plan their movements, knowing they have access to reliable, data-driven information that promotes safe travel and exploration.

To make the platform more dynamic, the crime map should integrate a community-driven warning system similar to Google Reviews. Users could report suspicious activity or unsafe incidents, and after moderation, these reports could trigger localized alerts. This crowdsourced input would complement official data, creating a more responsive and effective safety network. This dual approach of official and user-generated data ensures the system is both comprehensive and up-to-date.

2.2 Best Practice Crime Map: Case Study UK

The success of these types of platforms is well-documented in the UK. For example, the interactive Crime Rate map serves as a prime case study. It allows users to filter data by offense type and view crime rates at the neighbourhood, town, or street level.

The platform's highly visual, real-time interface dynamically highlights hotspots, proving the effectiveness of a user-friendly and data-rich approach to crime mapping. This model demonstrates how clear, accessible visualization can empower the public and aid in crime prevention.

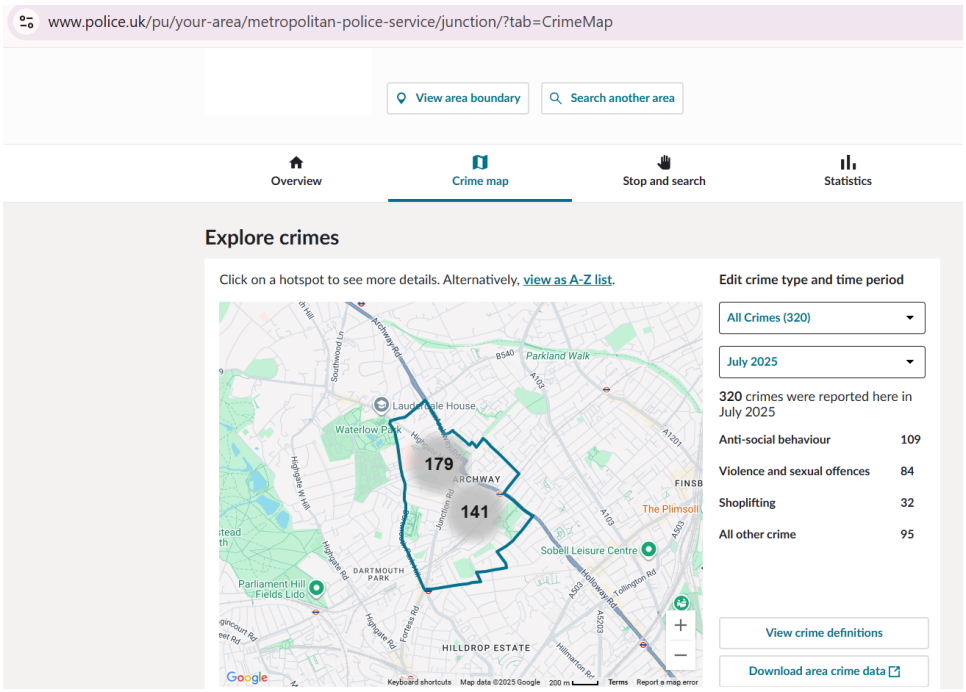

Figure 3. UK Crime Map Dashboard
Source: (Police.UK, 2025)

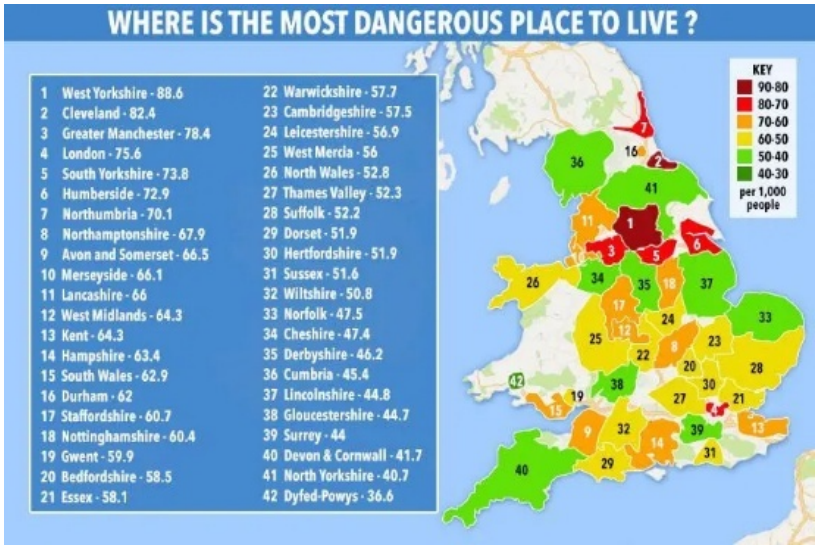

Figure 4. Crime Map Across UK
Source: (Police.UK, 2025)

2.3 Approach of Crime Mapping Dashboard

The UK constructs its crime map through a structured, multi-step process. This approach could be adopted by the Indonesian National Police to enhance public safety and reduce victimization.

2.3.1 Open and Regularly-Updated Data Infrastructure

The Police.uk platform publishes street-level crime data across England and Wales, updated monthly from police records or police information systems. Crime

data includes categories like burglary, violent crime, vehicle crime, and anti-social behaviour, with location anonymisation to protect privacy if a crime is too precise or revealing. Features like “Draw Your Own Area” let users generate custom maps for specific neighborhoods or route.

2.3.2 Interactive Public Interface

The dashboard shows crimes pinned on a Google Maps interface, displaying each incident near a specified location, often accurate to within a few houses. Additional tools include "Compare My Area" and neighbourhood policing team details to improve transparency and civic accountability.

2.3.3 Crime Data Integration Platform

The platform now integrates data from criminal justice agencies, showing case outcomes, and links crimes to points of interest such as train stations or shopping centres.

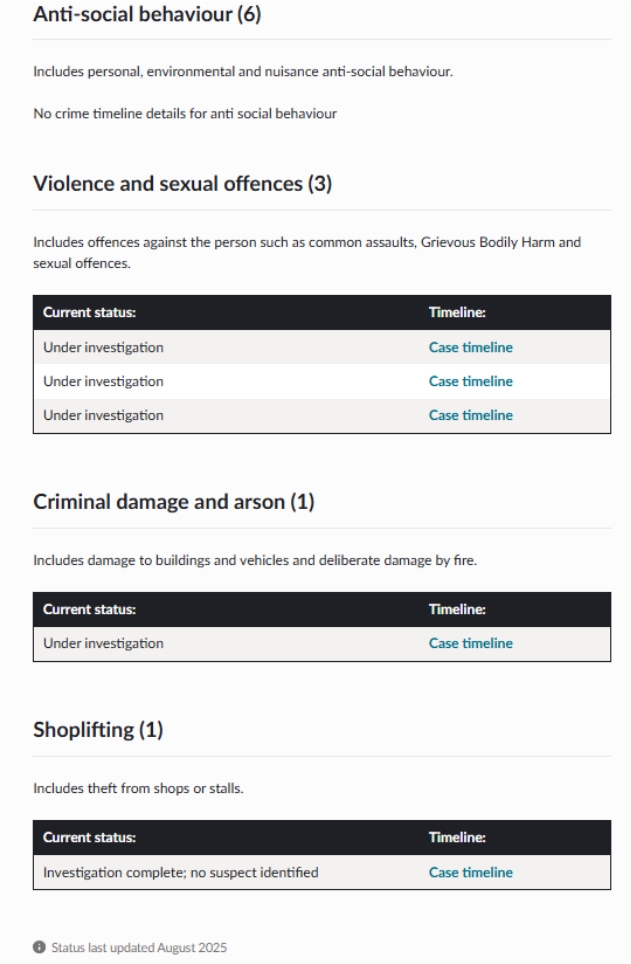

Figure 5. Crime data case integration
Source: Police.uk (2025)

City-level dashboards (e.g., Greater London Authority) visualize crime trends over time by ward or borough, supporting strategic planning.

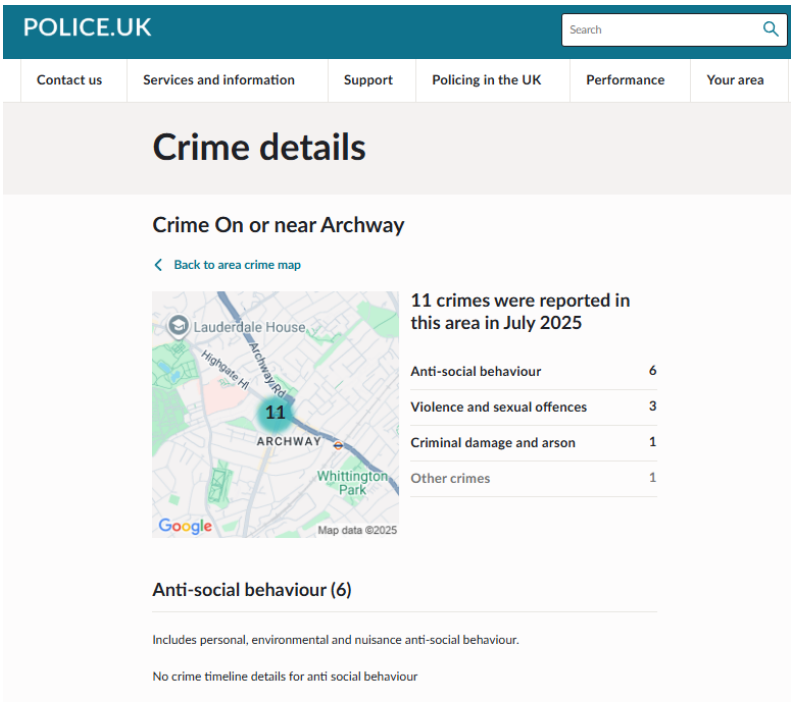

Figure 6. Mapping crime type
Source: Police.uk (2025)

2.3.4 Crime Mapping using AI (Artificial Intelligence) and Predictive Analysis

T he UK is currently developing a ground-breaking AI-driven crime mapping tool designed to predict future crime hotspots. This innovative system will combine vast amounts of data from police, local councils, and social services to identify patterns and forecast potential high-risk areas. The goal is to create a live, predictive dashboard by 2030, with initial prototype rollouts slated for 2026.

This technology isn't just about prevention; it's also a powerful resource to help police and justice agencies catch criminals more effectively. By providing predictive insights, the system will enable authorities to proactively allocate resources and intervene before crimes occur.

However, the use of such a powerful tool must be approached with caution. It is crucial that the implementation of this technology includes strict measures to protect privacy and civil liberties. The system's design and usage must be governed by clear ethical guidelines to ensure that it is used responsibly and does not infringe upon individual rights. Balancing the benefits of public safety with the essential need for privacy will be a critical challenge moving forward.

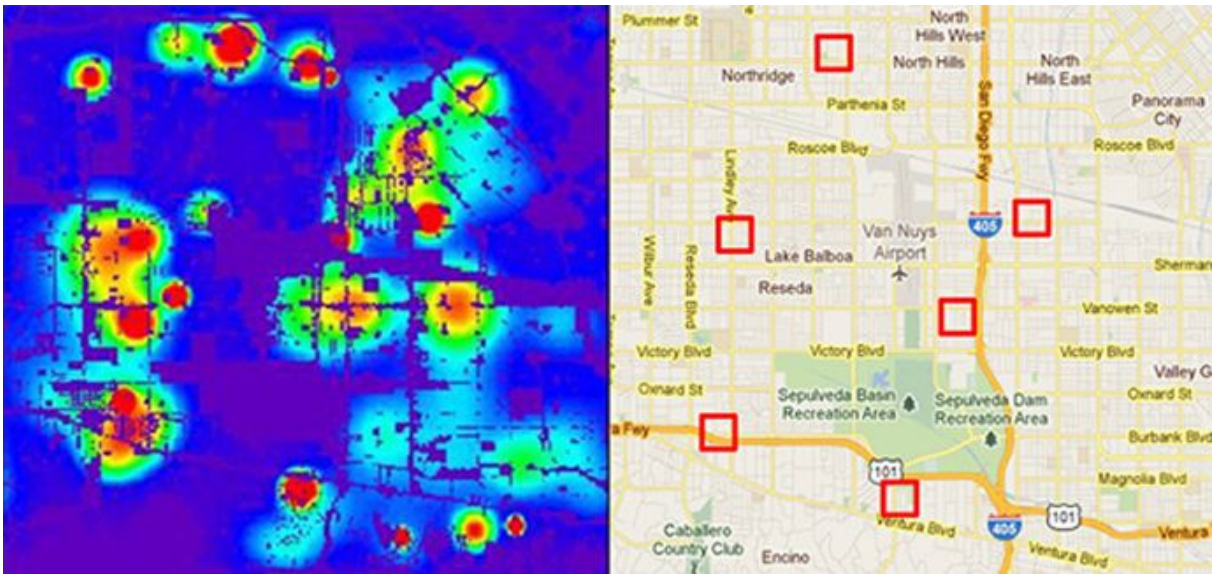

Figure 7. Crime prediction using AI (Artificial Intelligence)
Source: Police.uk (2025)

A unified crime mapping and data visualization system offers significant benefits for various groups. For residents, it provides a crucial tool to stay informed of nearby crime activity, enabling them to take proactive measures to enhance their personal safety. They can use the data to avoid high-risk areas and plan their daily routes accordingly, fostering a greater sense of security in their communities.

Tourists and the general public can also greatly benefit from this system. By providing open data visualizations of safe routes and neighbourhoods, the platform builds trust and confidence. Visitors can gain assurance when exploring a new city, knowing they have access to reliable information to help them navigate safely. This transparency can make a city more welcoming and accessible to everyone.

The system is a powerful resource for authorities. It allows law enforcement and city planners to proactively and transparently focus resources where crime is increasing. By visualizing crime trends over time, they can allocate patrols, implement community programs, and deploy other crime prevention strategies more efficiently. This data-driven approach not only improves public safety but also builds trust between the authorities and the communities they serve.

2.4 A Blueprint for Building a Comprehensive Crime Dashboard in Indonesia

The effective management of public safety in Indonesia requires a strategic, data-driven approach. Following the global trend toward police transparency and digital governance, implementing a national crime dashboard offers a transformative solution. This initiative, moving beyond traditional reporting, would empower citizens and provide law enforcement with critical intelligence. By establishing a robust, multi-layered system, Indonesia can build a platform that fosters trust, enhances public safety, and transitions policing from a reactive to a proactive model. This blueprint outlines the systematic steps necessary to achieve such a goal.

2.4.1 Foundation and Data Integrity through Unified Reporting and Standardization Framework

A foundational prerequisite for a functional crime dashboard is the establishment of a standardized, unified national crime reporting framework. This process begins with the integration of local police information systems, such as the Crime Reporting Information System (CRIS), into a centralized database. The objective is to mandate that all police forces across provinces submit data in a consistent and uniform format, capturing essential details like the crime category, date, and anonymized location. A critical component of this framework is the requirement for monthly data updates for public openness. This standardization is crucial for eliminating data silos and creating a single source of truth for all crime-related data.

2.4.2 Geospatial Infrastructure and Data Governance

Building upon the data foundation, the next critical phase involves the development of a robust Geographic Information System (GIS) infrastructure. This centralized GIS database must be capable of mapping anonymized crime incidents with a high degree of precision, correlating them to specific neighborhoods, streets, or even building blocks. Crucially, this system must be governed by stringent data privacy protocols, drawing lessons from models like the UK's where crime incidents are anonymized to the street or block level to protect individual privacy while still providing valuable locational context. The establishment of these clear guidelines ensures that the platform can serve as a powerful public tool without compromising the security of victims or sensitive personal information.

2.4.3 Developing a Public-Facing Interactive Dashboard

The culmination of these efforts is the deployment of a public-facing interactive dashboard accessible via a web portal. This platform would empower citizens to visualize recent crime events by simply entering a neighborhood, a specific address, or a defined area. To enhance user experience, the dashboard should incorporate dynamic tools, such as the ability to "draw your own area" and to apply overlays that highlight police beats, historical crime hotspots, or other relevant data points. The platform's design should also include comparative tools, allowing users to analyze crime rate trends across different neighborhoods or timeframes, and to access contextual information, such as the locations of nearby police stations or designated safe havens.

2.4.4 Dashboard Features and Functionality

The crime map dashboard offers filtering by crime type and timeframe. To foster a culture of shared responsibility and collaboration, the platform should feature an open Application Programming Interface (API), allowing civic tech innovators and third-party developers to leverage the crime data for creating their own public safety applications. Implement custom alerts for users subscribed to receive notifications for incidents in their area.

2.4.5 Enable Community Input & Warning System

Integrate a crowdsourced warning system which allow users to report incidents like demonstrations or suspicious activity, subject to moderation. Similar to Google Reviews, this would help warn others while enriching official crime data.

2.4.6 Advanced Analytics and Prediction System

Incorporate machine learning models to analyze historical patterns and predict potential future hotspot. Drawing inspiration from international models, such as the UK's initiatives in AI-driven crime prevention, these systems would generate dynamic dashboards that alert law enforcement to potential risks, enabling targeted resource deployment and proactive intervention strategies. This analytical layer would serve as a powerful tool for strategic decision-making, optimizing police operations and significantly contributing to a safer community.

Table 4.5 The Implementation Steps for Indonesia

Phase	Key Actions
1. Data Setup	Standardize crime reporting; establish monthly data feeds.
2. GIS Mapping	Build a central geospatial database with anonymized crime data.
3. Dashboard	Develop public portal with interactive mapping, filtering, and insights.
4. Community Alerts	Enable user reports and alerts, managed via moderation.
5. Advanced Analytics	Use AI/ML for predictive policing and hotspot forecasting.

Source: processed from Police.UK (2025)

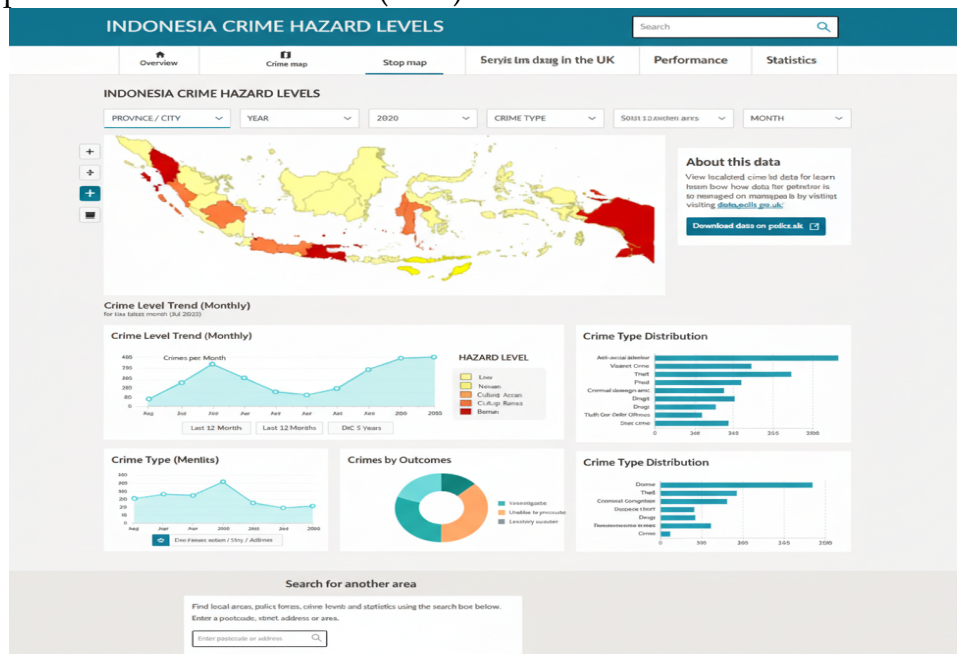

Figure 8. Indonesia Crime Map Hazard (National Level)

Source: processed by authors (2025)

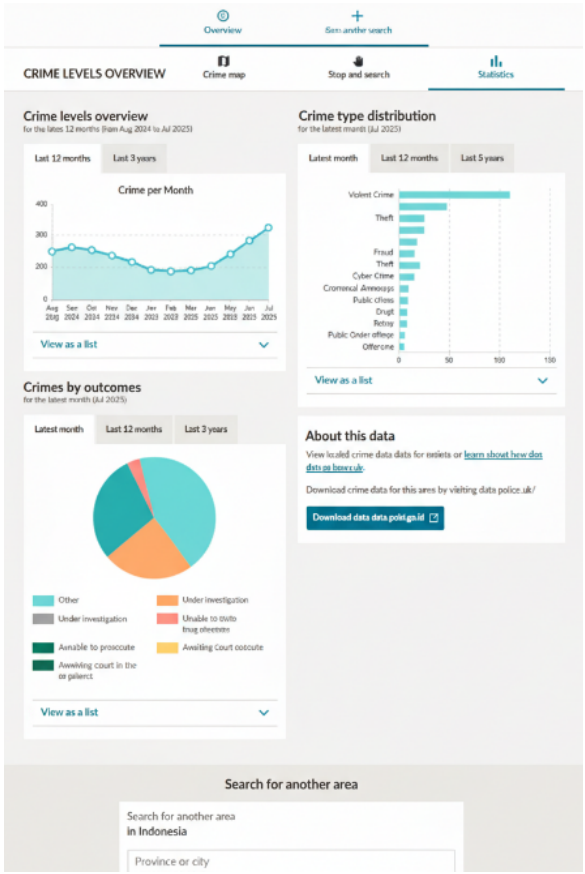

Figure 9. Illustration of Crime Map Statistics in a Regency**
Source: processed by authors (2025)
***Illustration of Sleman Regency*

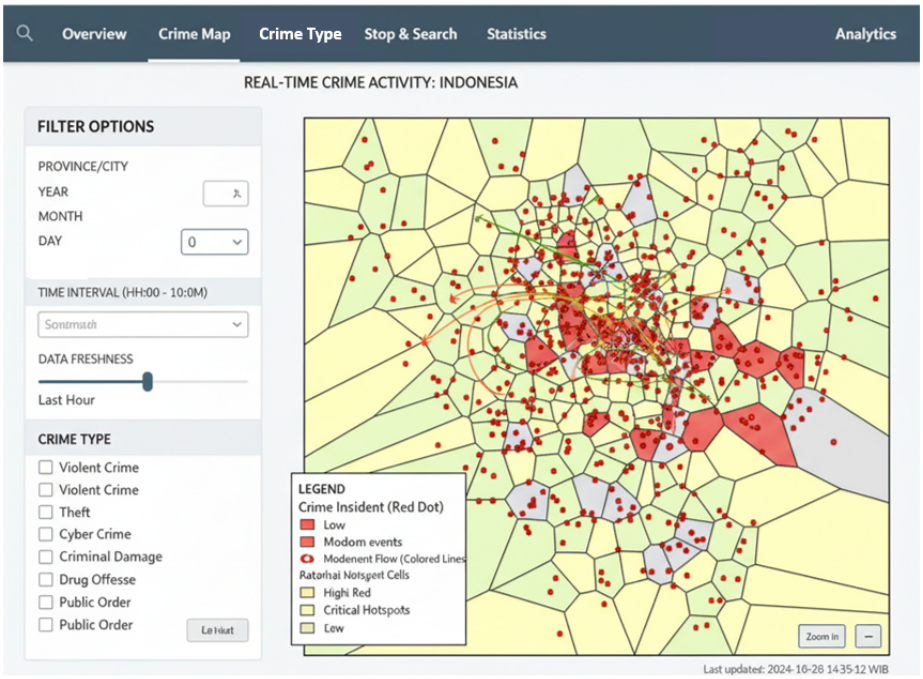

Figure 10. Real-Time Crime Activity Dashboard

Source: processed by authors (2025)

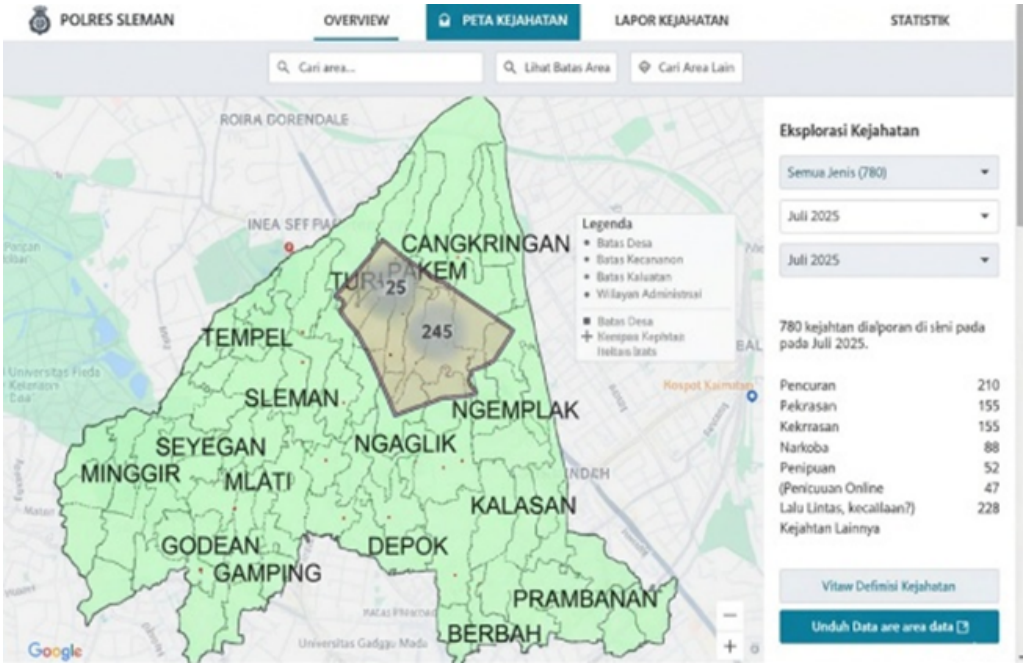

Figure 11. Illustration Crime Mapping Dashboard Based on Regency*

**this illustration shows Sleman Regency*

Source: processed by authors (2025)

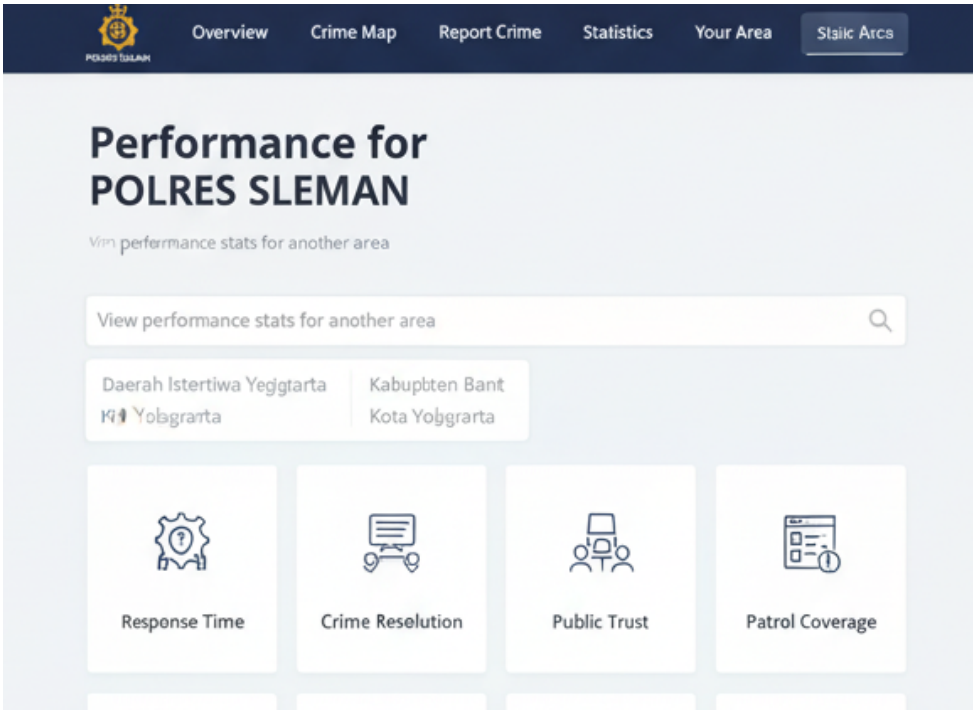

Figure 12. Illustration Police Performance Evaluation Dashboard*

**this illustration shows Sleman Regency*

Source: processed by authors (2025)

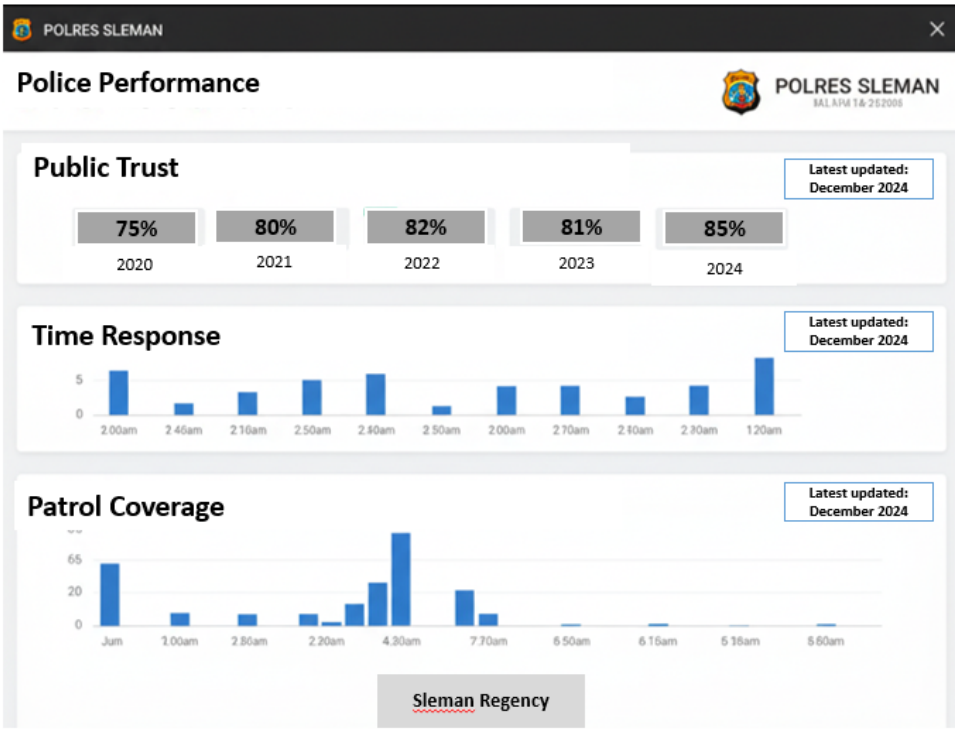

Figure 13. Illustration Police Performance Statistics Dashboard**
Source: processed by authors (2025)
***this illustration shows Sleman Regency*

2.5 A Data-Driven Development Strategy to Develop Crime-Mapping Dashboard

To successfully develop a functional crime-mapping dashboard in Indonesia, a strategic approach focused on integrating diverse data streams is essential. The process hinges on combining two primary data sources, each providing a unique perspective on the national crime landscape.

First, the platform would require location-specific crime incident data obtained directly from police records. This information is critical for conducting precise spatial analysis and creating accurate crime maps. For this data to be effective, it must be either geotagged or linked to specific administrative units, such as neighborhoods or urban districts.

Second, the dashboard's development should leverage victim-based survey data from the National Socio-Economic Survey (Susenas). The Susenas survey already includes modules that gather valuable information on household crime victimization, as confirmed by the 2023 BPS Criminal Statistics Report. Incorporating this data would provide a crucial and complementary perspective to official police records.

2.6 Ideal Characteristics of Crime Data for a Comprehensive Dashboard

For a crime dashboard to be truly effective and as useful as a model like the UK's Crime Map, the underlying data must possess several key characteristics. First, timeliness is paramount. The data needs to be updated with high frequency, ideally on a weekly or monthly basis, to provide near real-time insights into crime trends

and occurrences. Second, spatial granularity is essential for meaningful analysis. Crime incidents must be mapped at a micro-level, such as the neighborhood or block, while simultaneously ensuring individual privacy is protected through careful anonymization. Third, the data must have consistent classification. A uniform set of crime categories is critical for enabling users to easily filter the information and conduct meaningful comparisons. Fourth, the system's strength lies in its ability to handle multi-source integration, combining official police reports, the results from national surveys like Susenas, and even crowdsourced public alerts. Finally, for broader impact, the data must be made accessible via APIs, allowing developers and civic technology organizations to innovate and build upon the platform's foundation.

2.7 A Phased Implementation Pathway for Indonesia

Developing a sophisticated crime-mapping system in Indonesia requires a logical, multi-step implementation pathway.

2.7.1 First Step: Institutional Collaboration

The initial phase involves fostering strong collaboration between the National Police and the Central Statistics Agency (BPS). The goal is to establish a secure and efficient protocol for data sharing. This includes regular monthly updates of geocoded incident records from police departments and victimization data from the Susenas survey, ensuring a continuous and rich flow of information.

2.7.2 Second Step: Data Integration and GIS Infrastructure

Following the establishment of data protocols, a centralized Geographic Information System (GIS) database must be built. This system would serve as the core repository, intelligently combining official police incident data with the valuable insights from victim-based reports. Throughout this process, strict protocols must be enforced to properly anonymize data and safeguard the privacy of all individuals.

2.7.3 Third Step: Dashboard Development

A public-facing web portal should be developed, designed with an intuitive and familiar user experience in mind. The dashboard should feature interactive crime maps with filtering options and tools that enable users to define their own areas of interest. The ability to compare crime trends across different neighborhoods or time periods would also be a crucial feature, empowering the public with analytical capabilities.

2.7.4 Fourth Step: Community Reporting and Alert System

To enhance the system's real-time relevance, the platform should incorporate a community-driven reporting system for incidents like suspicious activities or minor offenses. This feature would operate with a moderation system, much like an online review platform, to filter out false information while complementing the official police data with valuable, localized information from the public.

2.7.5 Fifth Step: Analytical Layers & Predictive Features

In a later phase, the system could be enhanced with advanced analytics. By leveraging machine learning, the platform could analyze historical crime patterns to generate dashboards that not only track trends but also forecast future hotspots. This

would be a powerful tool for law enforcement, enabling more strategic and proactive deployment of resources.

2.7.5 Sixth Step: Public Engagement & Transparency

The feature also must include a comprehensive public education and engagement campaign. The public must be educated on how to effectively use the dashboard's features, with clear information provided on data sources, update schedules, and privacy safeguards. This transparency is vital for building trust and ensuring that the dashboard successfully serves its purpose of empowering residents and tourists with greater situational awareness.

Conclusion

Initial findings from the research indicate that increasing the number of security personnel in rural areas has a significant negative impact on crime rates, meaning that a higher police presence leads to lower crime rates. This finding is consistent with the deterrence theory, which suggests that the visibility and presence of law enforcement discourage potential offenders from engaging in criminal activity. Furthermore, the study shows that improving village information systems has a significant positive effect on crime reporting. Villages with better information infrastructure saw higher rates of crime reporting, which in turn facilitated quicker responses from law enforcement and, ultimately, a reduction in crime. These findings align with the broader literature on crime prevention, which emphasizes the importance of timely information flow and communication between communities and law enforcement agencies in curbing crime.

Recommendation

To improve rural security, policymakers should invest in increasing security personnel, including police and community agents, and provide comprehensive training in crime prevention, law enforcement, and building trust with residents. Emphasizing community policing and engagement fosters cooperation between security personnel and locals. Establishing local reporting centers and mobile units simplifies crime reporting, while outreach programs educate residents on effective reporting. Specialized training in cultural sensitivity and local issues is crucial. Regular monitoring of crime rates and community feedback helps refine strategies, allowing policymakers to adapt and continuously enhance safety measures.

Further Research

Conducting interviews with villagers and security officers offers valuable insights into community perceptions of security and the effectiveness of crime reporting systems. By comparing villages that have implemented additional security measures and improved information systems, policymakers can assess differences in crime rates and the effectiveness of these strategies. Therefore, future research can used Difference in Difference Method supported with qualitative method from in depth interview.

Declarations

No ethical issues were encountered during the course of this study, and all procedures adhered strictly to established ethical standards.

Authors contribution statement

The first author served as the lead researcher for this study, taking primary responsibility for conceiving the research design, overseeing the project's execution, and developing the methodologies for data processing. The second author's critical contributions focused on the comprehensive development and execution of the data analysis, ensuring the robustness and accuracy of the findings.

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Data availability statement

The data supporting the findings of this study are available from Statistics Indonesia (Badan Pusat Statistik - BPS). The datasets for the National Socio-Economic Survey (Susenas KOR) for 2018 and 2022, and the Village Potential Survey (PODES) for 2018, were obtained through the BPS microdata catalog. Access to these datasets is available upon request to BPS, subject to their data access policy and a purchasing fee.

Declaration of interests' statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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