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The Role of Security Personnel and Village Information Systems to Reduce Crime Rates in Rural Areas

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ABSTRACT Crime rates in rural areas have been increasing in recent years. This surge in criminal activity has fostered a climate of fear and insecurity among rural residents. Several factors contribute to this phenomenon. Many rural areas lack a sufficient number of security personnel, hindering effective deterrence and response to crime. Moreover, community members patrol (*ronda*), often struggles with ineffectiveness due to a lack of organization and resources. Furthermore, low awareness of basic security measures among rural residents leaves them vulnerable. Village information system also need to consider as one of the factors which might be influence the crime activities in villages. However, economic factors like poverty and unemployment can push individuals towards criminal activity. This study investigates the impact of increasing security personnel on crime rates and crime reporting in Indonesian villages using panel data from the PODES survey and SUSENAS from 2018-2022. The study employs a propensity score matching (PSM) model to examine the relationship between security personnel, crime rates, and crime reporting, considering other factors such as regulations, social assistance and socioeconomic factors. The study found that increasing security personnel has a significant negative impact on crime rates, indicating that a higher number of security personnel leads to a lower crime rate in villages. Additionally, enhancing village information system also has a significant positive impact on crime reporting which finally reduce crime. This research breaks new ground by comprehensively analyzing the interconnected nature of crime and its reporting within rural Indonesian communities. By demonstrating the effectiveness of increased security personnel and village information system will not only reducing crime rates but also encouraging reporting.

KEYWORDS *Rural Crime; Security Personnel; Crime Reporting; Panel Data; Village Information System.*

INTRODUCTION

National crime statistics in Indonesia indicate that the total number of recorded criminal incidents declined to 561,993 cases in 2024, with an overall crime rate of 204 incidents per 100,000 population, according to the Crime Statistics 2024/2025 report published by Badan Pusat Statistik (BPS), which integrates police administrative records, socio-economic survey results, and village potential data for spatial context (Badan Pusat Statistik [BPS], 2025). While these macro-level figures show a general downward trend compared with 2023, they mask important spatial distinctions: urban areas tend to experience more frequent and diverse criminal activity, such as petty theft and property crime associated with high population density and social inequality, in contrast to rural regions where absolute crime counts are lower and interpersonal or localized offenses are relatively more prominent (BPS, 2025; Maftuhin, 2024).

Although BPS national publications do not yet include explicit crime rates per 100,000 population disaggregated by urban and rural areas, they do incorporate village potential data that covers crime presence and other community characteristics at the village level, providing a foundation for rural analysis (BPS, 2024). Criminological research contextualizes these patterns by highlighting how urban socio-economic conditions—such as greater unemployment, inequality, and mobility—correlate with higher crime incidence, whereas rural areas, despite showing lower crime intensity, are influenced by factors such as limited infrastructure and social services that can contribute to interpersonal deviance (Maftuhin, 2024).

Furthermore, rural areas across Indonesia have experienced a disturbing rise in crime rates, encompassing a range of offenses that include theft, drug trafficking, sexual assault, and even mass violence. This surge in criminal activity has fostered a climate of fear and insecurity among rural populations, further aggravating already existing social and economic challenges. According to the United Nations Office on Drugs and Crime (UNODC), 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 (UNODC, 2020).

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.

Therefore, this research addresses four critical policy challenges in rural Indonesia:

Insufficient Security Personnel Rural communities face critically low police-to-population ratios, severely compromising crime prevention capabilities and law enforcement responsiveness. This personnel deficit undermines community safety and enables unchecked escalation of criminal activities.

Weak Village Information Systems Fewer than 50% of Indonesian villages possess functional digital crime-reporting systems (BPS, 2021). This infrastructure gap creates significant delays in incident reporting, evidence collection, and emergency response, allowing persistent underreporting of crimes.

Ineffective Community Participation Traditional community patrols (*ronda*) operate suboptimally due to poor coordination, inadequate resources, and lack of formal training. These limitations reduce their deterrent impact and prevent meaningful bridging of security gaps.

Socioeconomic Drivers of Crime Persistent rural poverty (World Bank, 2020) and unemployment create conditions that fuel criminal behavior. Economic desperation particularly among youth increases vulnerability to engagement in illicit activities as survival mechanisms.

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. Drug trafficking, in particular, has been a growing problem in these areas, as organized crime groups exploit the lack of local enforcement and socioeconomic desperation to expand their operations.

This study aims to analyze the impact of increasing security personnel and village information systems on crime reduction and the improvement of crime reporting in rural Indonesia. The focus encompasses: (1) The influence of additional security personnel; (2) The role of information systems; and (3) The synergy between these two factors in enhancing village safety.The research employs panel data from the PODES *survey* and SUSENAS KOR for the period 2018–2022 to investigate the impact of enhancing law enforcement on crime rates and reporting mechanisms. This study also takes into account other factors such as regulations, social assistance programs, education, religious infrastructure, and broader socioeconomic conditions, which are known to influence crime dynamics in rural settings.

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. Fondel (2021) and Cabrera et al. (2019) found that security presence decreases theft and vandalism. This deterrent effect is echoed by Region Security Guarding (2021) and Titan Security Europe.

Enhanced information systems in villages also positively impact crime reduction. Well-designed information systems enhance decision-making by enabling swift and precise actions, which plays a crucial role in crime prevention. Additionally, Igwe (2024) demonstrated crime prevention and control are essential for community safety, especially in rural areas with limited formal law enforcement, making local community involvement crucial. Similarly, Cabrera (2019) and Bell et al. (2022) 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 (Bell et al., 2022). Quality public facilities also contribute to lower crime rates. Beyond physical amenities, smart public spaces integrate real-time information systems, community-driven governance, and responsive service delivery, which together enhance safety, accessibility, and user satisfaction. In this view, adequate and inclusive public amenities, when combined with intelligent design and technological innovation, not only improve environmental quality but also foster a sense of security and belonging among diverse urban populations (Itair, 2023).

High poverty levels often correlate with increased crime, driven by individuals striving to meet their needs, as explained by Bell et al. (2022). Community participation in social activities is crucial for reducing crime. Tical (2024) and Wo (2023) emphasized that social capital plays a pivotal role in enhancing public security, not only by fostering strong community bonds but also by shaping both the perception and reality of safety. Defined through networks of mutual trust, shared norms, and reciprocity, social capital facilitates cooperation between citizens and authorities, enabling effective crime prevention and strengthening community resilience. Easier communication access can potentially lower crime rates through various mechanisms. Easier family contact reduces prison recidivism, demonstrating a positive impact on criminal behaviour (De Clair & Dixon, 2017). Conversely, Zhang and Yue (2016) 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.

Crime concentration studies reveal that crime tends to cluster in specific areas. Simon and Jichova (2022) conducted an empirical study on crime concentration in a post-socialist city, revealing that both crime incidents and crime harm are less spatially clustered than typically observed in cities such as those in the US or UK. Using the law of crime concentration at places and the Cambridge Crime Harm Index at the street segment level, their findings challenge conventional expectations, suggesting that place-based policing strategies—often effective in Western contexts—may require adaptation. This highlights the importance of theory testing and contextual sensitivity when transferring crime prevention models across different urban and socio-political environments. Places of worship, enhancing social capital and control, can reduce crime, as seen in Wo's (2023) study in Washington DC.

Certain types of places influence crime rates (Sikorsi et al., 2024). 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; indicated that higher educational attainment and school quality significantly reduce crime.

Human, social, and criminal capital also impact crime choices. There is significant effects of education (human capital) and peer influence (social capital) on adult criminality. Economic conditions also play a role. Bell et al. (2022) showed that higher income and education levels reduce crime likelihood, with unemployment's impact being marginal due to alternative income sources.

While street lighting is often believed to deter crime, empirical findings remain mixed. Bonner (2021), using a pre/post-comparison design in two micro-places, found only modest effects of improved lighting on crime reduction. The study, which applied both situational crime prevention and informal social control perspectives, revealed that while some benefits were observed, the overall results did not support strong deterrent effects. Moreover, the absence of a control area and variation in illumination levels limited the conclusiveness of the findings, suggesting the need for more rigorous future evaluations. 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. 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.

Data And Method

The data used in this study are secondary data from PODES (2018-2021) and SUSENAS KOR (2018-2022). 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.

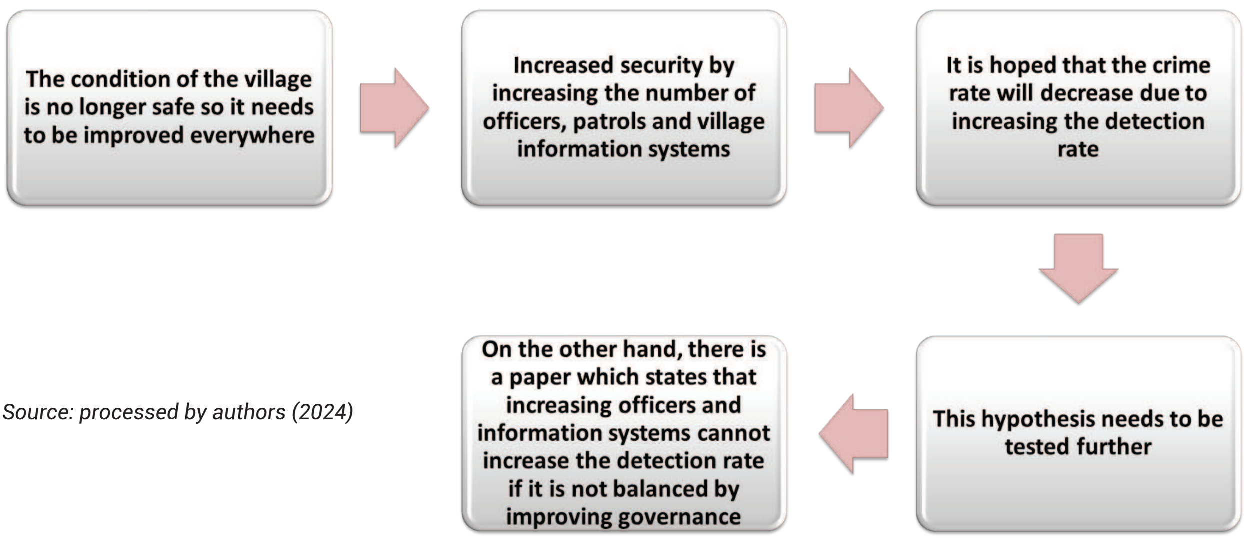
This study is replication and modification from Fondevila's (2022) work by combining household and community data, minimizing unobserved heterogeneity bias. It examines the impact of increasing security personnel on village crime rates, noting the correlation between improved information and security systems (e.g., additional security personnel, neighborhood watch, mandatory guest reporting, security teams, and police posts) and crime rates.

The study integrates three complementary theoretical foundations:

Routine Activity Theory establishes that crime requires three elements: motivated offenders, suitable targets, and *absence of capable guardians*. Here, security personnel function as active "guardians" whose presence disrupts criminal opportunities.

Deterrence Theory posits that visible law enforcement discourages criminal intent through perceived risk of apprehension. Increased security personnel heighten this perceived risk, reducing offense incidence.

Information Transparency Theory (Heald, 2006) argues that robust information systems build public trust and institutional accountability. Efficient crime reporting mechanisms empower communities and enable rapid law enforcement responses, creating a proactive crime management cycle.



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. Empirical analysis (PSM, Logit/Probit models) tests three core hypotheses:

H_1: Increased security personnel significantly reduce crime rates.

H_2: Enhanced village information systems increase crime reporting, subsequently reducing crime.

H_3: Security personnel and information systems interact synergistically, amplifying crime reduction beyond individual effects

Table 1. Variable Categories and Descriptions

Variable Type	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 the village.
Control Variable	Public Facilities	Quality of public facilities in the village.
Control Variable	Poverty Rate	Household poverty rate.
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: *various sources (2024)*

Model Specification

Crime Rate= $\beta_0 + \beta_i X_i + \gamma_i Z_i + \varepsilon$

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 Ɛ 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:

$$P(Y=1 \mid X) = \frac{1}{1 + e^{-(\beta 0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}$$

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:

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

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.

Model Selection: 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. Model Selection Basis

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.
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: 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.

DISCUSSIONS

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

Dependent variable Crime	Logit	Probit
	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%, **5%, ***1%*

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).

Model 1: The Impact of Security Personnel

Table 4.1 Step 1: Performing Logit Estimation for Propensity Score Matching 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
Readily 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

Table 4.2 Step 2: 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

Table 4.3 Step 3: Comparing PSM Covariates

Variable	Mean Treated	Mean Control	%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

Covariate Balance

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 Step 4: Average Treatment Effect Result

Variable	Coefficient	T	[95% 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

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, 2018, David, 2023), 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, 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. Furthermore, Hood and Di xon (2015) suggest that an efficient information system boosts administrative efficiency and responsiveness in handling crime cases, making the reporting process faster and more accurate. The integration of community security systems also has a significant impact. 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.

Model 2: The Impact of Village Security System

Table 5.1 Step One: 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
Easy to access the police station	0.3051	0.2943	0.53	0.596
Regulation	10.714	10.714	0.04	0.971

Variable	Mean Treated	Mean Control	T-test	p>|t|
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

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 5.2 Step Two: 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

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 5.2).

Table 5.3 Step Three: Comparing PSM Covariates Balance

Variable	Mean Treated	Mean Control	%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
Easy to access the 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

Table 5.4 Step Four: Average Treatment Effect Result

Variable	Coefficient	T	[95% 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

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 5.4).

The role of information technology in crime prevention is explained by Rabbi et al. (2025), who demonstrate that effective integration of information systems in the e-commerce sector can enhance digital security and prevent criminal activities, particularly cybercrime. The study emphasizes that proper utilization of technology supported by strong managerial leadership—not only strengthens data protection and operational security but also promotes more sustainable and ethical business practices. Thus, well-implemented information systems not only support operational efficiency but also play a critical role in building a secure and responsible digital ecosystem. 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 Hirschi (1969), 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.

CONCLUSIONS

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.

Implication

The implementation of robust village information systems has yielded several important implications for improving public safety and governance at the local level. Drawing from empirical findings, four key outcomes emerge.

First, crime reporting efficiency has significantly improved. The adoption of digital systems streamlines the reporting process, reducing communities' reliance on slow or informal communication channels. As a result, crime reporting has increased by 57.7% (β = 0.577, $p < 0.01$), enabling law enforcement agencies to respond more quickly and effectively to incidents.

Second, these systems have led to greater transparency and public trust. With real-time tracking and public access to crime data, village residents are empowered to monitor institutional actions, fostering a sense of accountability among authorities. This openness helps reassure residents that their reports will be taken seriously, thereby reducing the tendency to underreport criminal activity.

Third, there is evidence of crime deterrence through visibility. By making reports publicly accessible, offenders perceive a higher risk of detection—a core principle of Deterrence Theory. As more crimes are reported and publicly documented, the likelihood of arrest increases, which in turn has a preventive effect on potential offenders.

Fourth, village information systems allow for better resource optimization by law enforcement agencies. The use of data analytics enables more strategic deployment of security personnel, particularly in identified crime hotspots such as theft-prone areas. This targeted approach enhances the effectiveness of patrols and contributes to overall crime reduction.

Policy Recommendation

The findings have clear policy implications for enhancing rural security in Indonesia. Investment in village information systems transforms passive communities into proactive, digitally connected networks that support crime reporting. This transformation creates a virtuous cycle: more reports lead to faster police responses, which build public trust, in turn encouraging more reports. Furthermore, these systems serve as a complement to physical security measures by offering a form of digital guardianship that strengthens the community's resilience against crime.

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