

A PSYCHOSOCIOCULTURAL PERSPECTIVE OF BURGLARY IN INDONESIA

ANALISIS PSIKOSOSIOBUDAYA ATAS PERAMPOKAN DI INDONESIA

Amanda Beatrice Wuisan, Meyrichel Setiawan, Ananta Yudiarso*

Universitas Surabaya

s150122032@student.ubaya.ac.id, s150122064@student.ubaya.ac.id, ananta@staff.ubaya.ac.id*

ABSTRACT

This study examines burglary as a multidimensional social phenomenon shaped by structural, environmental, and psychological factors in Indonesia. A sequential exploratory mixed-method design was employed, combining machine learning analysis of provincial socioeconomic data with qualitative interviews of burglary victims. Results showed that population density and unemployment were significant positive predictors of burglary rates, while tree-based machine learning models identified population size and poverty as key contributing factors. Qualitative findings revealed fear and insecurity, environmental disorder, distrust toward institutional protection, and adaptive coping following burglary incidents. By integrating predictive modeling with victim narratives, this study provides a more comprehensive understanding of burglary and highlights the importance of addressing both socioeconomic vulnerability and victim recovery in crime prevention.

Keywords: Burglary, machine learning, mixed methods, social disorganization, victim psychology, crime prediction, Indonesia

ABSTRAK

Penelitian ini mengkaji perampokan rumah (burglary) sebagai fenomena sosial multidimensional yang dipengaruhi oleh faktor struktural, lingkungan, dan psikologis di Indonesia. Penelitian menggunakan desain mixed-method sequential exploratory yang menggabungkan analisis machine learning terhadap data sosial ekonomi tingkat provinsi dengan wawancara kualitatif terhadap korban burglary. Hasil penelitian menunjukkan bahwa kepadatan penduduk dan tingkat pengangguran merupakan prediktor positif yang signifikan terhadap tingkat burglary, sementara model machine learning berbasis pohon keputusan mengidentifikasi jumlah penduduk dan kemiskinan sebagai faktor yang paling berpengaruh. Temuan kualitatif mengungkap adanya rasa takut dan tidak aman, ketidakaturan lingkungan, rendahnya kepercayaan terhadap perlindungan institusional, serta strategi adaptasi pasca-kejadian burglary. Dengan mengintegrasikan pemodelan prediktif dan narasi korban, penelitian ini memberikan pemahaman yang lebih komprehensif mengenai burglary serta menegaskan pentingnya penanganan kerentanan sosial ekonomi dan pemulihan korban dalam upaya pencegahan kejahatan.

Kata Kunci: Disorganisasi sosial, machine learning, metode campuran, perampokan, psikologi korban, prediksi kejahatan, Indonesia

BACKGROUND

Urbanization and industrial transformation have reshaped social life by increasing access to economic opportunities while simultaneously generating new social pressures. Rapid urban growth is often accompanied by weakened social cohesion and rising patterns of deviant behavior and crime (Hagedorn et al., 1971; Bulegenova & Turemuratov, 2023). Among various forms of property crime, burglary has become particularly significant because it threatens both economic security and psychological well-being within the household environment (Kunst & Hoek, 2024; Clinard & Meier, 1963). Unlike ordinary theft, burglary involves the unlawful intrusion into personal living spaces, resulting not only in material loss but also in emotional distress and disruption to victims' sense of safety (Chiew, Amerudin, & Yusof, 2020; Vilalta et al., 2023).

Previous studies indicate that burglary is associated with socioeconomic inequality, weak guardianship, population density, and neighborhood instability (Li, Wang, & Liu, 2022; Chainey, 2021). Victims frequently experience fear, anxiety, hypervigilance, and reduced trust in their surroundings, suggesting that the consequences of burglary extend beyond financial damage into broader psychological and social domains (Beaton et al., 2000; Kunst & Hoek, 2024; Ehlers & Clark, 2000). Criminological perspectives such as Strain Theory, Routine Activity Theory, and Social Disorganization Theory further suggest that burglary emerges through the interaction of structural pressures, criminal opportunities, and weakened community controls (Merton in Meehan et al., 2024; Cohen & Felson, 1979; Shaw & McKay in McCaghy et al., 2016).

In Indonesia, burglary has become the most dominant form of non-violent property crime, increasing from 37,870 cases in 2022 to 62,872 in 2023. DKI Jakarta and North Sumatra recorded the highest number of incidents, while eastern provinces reported considerably lower rates. These regional disparities reflect uneven socioeconomic conditions, including unemployment, educational inequality, and persistent poverty (BPS, 2024). Previous research consistently demonstrates that poverty, unemployment, and education are important factors associated with criminal behavior (Ardefa et al., 2025; Ha et al., 2020; Tavares & Costa, 2021). Despite these findings, burglary remains underexplored as a multidimensional phenomenon that involves both structural conditions and individual experiences.

Several important gaps remain within Indonesian burglary research. Existing studies primarily focus on crime statistics or socioeconomic correlates without

examining the psychological consequences experienced by victims. Research integrating structural indicators with lived experiences is also limited, making it difficult to understand how environmental conditions, socioeconomic factors, and victim experiences interact in shaping burglary. Furthermore, the application of machine learning techniques to identify burglary related patterns remains uncommon in the Indonesian context.

This study addresses these limitations through several contributions. Methodologically, it combines mixed methods and machine learning analysis to examine burglary from both quantitative and qualitative perspectives. Substantively, it integrates psychological, sociological, and anthropological perspectives to provide a more comprehensive understanding of burglary as both a structural and lived phenomenon. By combining national socioeconomic data with victim narratives, this study contributes to the Indonesian burglary literature by linking macro level conditions with individual experiences, an approach that remains rarely explored in previous research.

Therefore, this study aims to examine burglary in Indonesia through a sequential exploratory mixed-method approach that combines quantitative and qualitative perspectives. Quantitative analysis utilizes national secondary data to explore the relationship between burglary and socioeconomic variables such as unemployment, education level, population density, and wage rate, while qualitative interviews explore victims' emotional reactions, coping strategies, and perceptions of safety. By integrating machine learning based analysis with victim narratives, this study provides a more comprehensive understanding of burglary from structural, psychological, and environmental perspectives. The findings are expected to contribute to Indonesian criminology, expand knowledge regarding the psychological impact of burglary, and demonstrate the value of machine learning approaches in crime related research.

METHOD

This study employs a sequential exploratory mixed-method approach where the study begins with the collection and analysis of qualitative data to explore a phenomenon, followed by the collection and analysis of quantitative data to test or generalize the initial findings (Susanto et al., 2024). The mixed-method design follows a sequential order: (1) literature review using PRISMA method to identify theoretical and empirical foundations; (2) secondary data analysis using machine learning and classical statistics to examine

structural predictors of burglary; and (3) qualitative interviews to capture victims' subjective experiences and coping mechanisms. Each phase informs the next, enabling an integrated interpretation of burglary as a multidimensional social phenomenon.

The first phase consists of a structured literature review following the PRISMA 2020 guidelines (Page et al., 2021) to identify major findings, theoretical explanations, and gaps related to burglary as a form of deviant behavior. PRISMA supports transparency by documenting how studies were selected, the inclusion and exclusion criteria, and the steps taken during data extraction.

The second phase examines secondary data from Indonesia's Central Bureau of Statistics (BPS) on burglary in 2024 using machine learning techniques in Orange Data Mining ver. 3.1 and also using JAMOVI to perform bivariate correlation, multiple linear regression, and collinearity diagnostics (VIF) for classical statistical validation. The following machine learning algorithms were applied such as Support Vector Machine (SVM), random forest, neural network, and decision tree. SVM is a supervised learning model for classification and regression that works well in high dimensional spaces (Cortes & Vapnik, 1995). Random forest is an ensemble method that uses multiple decision trees to improve prediction accuracy (Breiman, 2001).

Neural network is a deep learning model inspired by the structure of human neurons that can identify complex patterns in the data (LeCun et al., 2015). Decision tree is a tree-like model that organizes decisions based on feature splits (Quinlan, 1986). In this research, the model evaluation metrics are analyzed using Area Under the Curve, which measures classifier performance across thresholds, and Classification Accuracy, which reflects the proportion of correct predictions. F1 Score, which is the harmonic mean of precision and recall, was also evaluated. Precision represents the ratio of true positives to predicted positives, while recall or sensitivity represents the ratio of true positives to actual positives. Matthews Correlation Coefficient was also used as a balanced measure for binary classification. Feature importance was calculated as well to identify the predictors that most strongly influence burglary rates across provinces.

To ensure robust model evaluation given the limited provincial-level sample ($N = 34$), the following procedures were implemented. Because the dataset was relatively small, the machine learning analysis used an 80% training set and a 20% validation set to maintain sufficient data for model learning while still enabling performance

evaluation. Despite the small sample ($N = 34$ provinces), machine learning remains justifiable because the data constitute a complete enumeration of Indonesian provinces, thus inference to a larger population is unnecessary. Additionally, the study aims exploratory pattern detection, which does not require large samples, especially when tree-based models are regularized. The near-perfect AUC values are interpreted cautiously, and classical statistics (linear regression, VIF) provide cross-validation of the key findings.

To improve model reliability and reduce overfitting, preprocessing procedures, hyperparameter tuning were also applied during the training process. Data preprocessing was conducted through categorical data encoding to transform non-numeric variables into machine-readable formats prior to model training. Hyperparameter tuning was also performed to identify the optimal model parameters before the final process to improve predictive performance and reduce overfitting.

The third phase involves qualitative research, where four key participants are interviewed. Qualitative research emphasizes understanding context, meaning, and human experiences (Creswell & Poth, 2018). Participants were selected via purposive sampling with the following criteria: (1) having been a victim or witness of a residential burglary incident in Indonesia, (2) being over 18 years of age, and (3) willing to share detailed personal experiences of the event and its aftermath. Initial contacts were made through community networks, with subsequent snowball sampling. All interviews were audio-recorded, transcribed verbatim using speech-to-text software, and then meticulously checked for accuracy. Their narratives offer insight into how burglary affects perceptions of safety, trust, and daily functioning, which helps complement the quantitative findings by adding depth to the understanding of this social problem.

To ensure trustworthiness of the qualitative findings, two procedures were implemented. First, member checking was conducted by returning interview summaries to four participants, who confirmed the accuracy of their reported experiences and emotional responses. Second, peer debriefing involved independent reviewers, a lecturer specializing in qualitative research who examined thematic analysis, questioned interpretations, and helped reduce researcher bias.

RESULT

A. Structured Literature Review

This structured review followed the procedures outlined in the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA). The search process was carried out through the Google Scholar database using several keywords, including “burglary”, “psychology”, “sociology”, and “anthropology”. Articles were chosen based on quality standards, which included journals accredited by SINTA as well as reputable international journals, both SCOPUS indexed and non-SCOPUS indexed. The search was limited to studies published between 2015 and 2025.

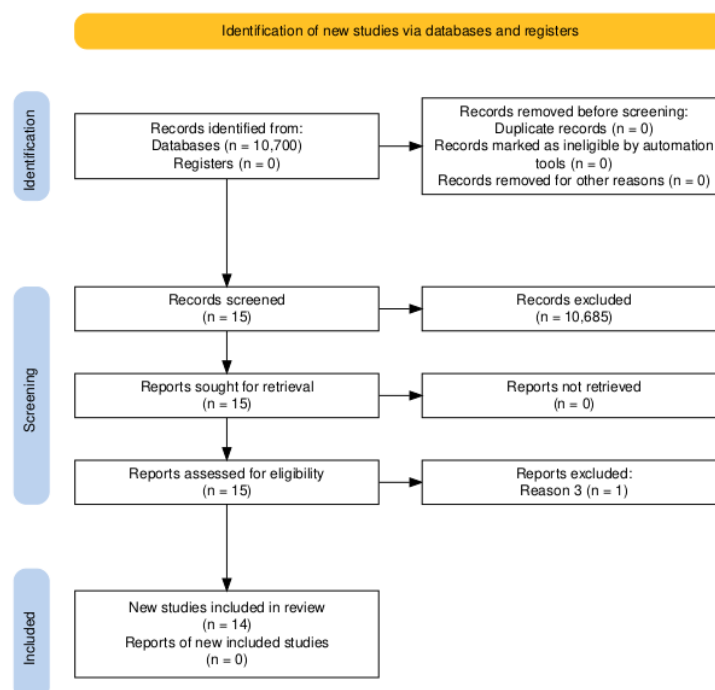


Figure 1. *Prisma Flow Chart*

The initial search identified 10,700 records, with no duplicates or automatically removed entries ($n = 0$). An independent screening was then conducted to filter studies according to criteria related to economic variables, educational level, crime, unemployment rate, population growth, and gender ratio. Each article was required to address at least one of these variables to proceed to the next stage. In this screening there are inclusion and exclusion criterias. For inclusion criterias, (i) articles must be written in English or Indonesian, (ii) address at least one factor variable, (iii) and published in an indexed peer-reviewed journal. For exclusion criterias, (i) article does not discuss the

keyword criteria “burglary”, “psychology”, “sociology”, or “anthropology”. This screening resulted in 15 studies being reviewed in full text, while 10,685 were excluded due to not meeting topic relevance or methodological requirements. After a more detailed assessment, 1 study was removed from the analysis due to not meeting inclusion criterion number 3 leaving a total of 14 journal articles that fulfilled all inclusion criteria for the final review.

Table 1. *Structured Literature Review*

Article	Methods	Result
Farrel, 2022	Longitudinal quantitative analysis of U.S. burglary trends and household security measures to examine the relationship between burglary rates and situational crime prevention technologies.	Major decline in U.S. burglary rates are associated with the widespread use of household security measures. The decline was linked more to reduced criminal opportunities than changes in offender motivation.
Fox & Farrington, 2016	Quantitative design using latent class analysis on 405 solved burglary cases in Florida between 2008 and 2009.	Significant associations emerged between offender developmental patterns and burglary styles, with high rate offenders linked to opportunistic offenses and chronic offenders to organized burglaries.
Katz, 2025	Qualitative ethnographic critique analyzing fieldwork studies on street crime, focusing on how participant observation and interview practices shape crime interpretation and representations of poverty.	Ethnographers often avoid documenting stigmatizing behaviors, limiting variation in crime data. Moral and political concerns frequently overshadow causal explanations and may unintentionally reinforce neoliberal narratives.
Kunst & Hoek, 2024	A systematic review following PRISMA guidelines analyzed 10 studies involving 1,511 burglary victims from multiple countries.	The review found that female victims, greater burglary related damage, and dissatisfaction with police response were associated with higher psychological distress.
Mendlein, 2021	Multilevel logistic regression analyzed data from 7,243 burglary victims across 35 countries from the International Crime Victims Survey. The study examined individual and country level predictors of burglary reporting.	Incident seriousness, stolen items, and property damage strongly increased reporting, while higher democracy and lower corruption also raised reporting rates. In contrast, higher burglary prevalence and income inequality reduced reporting.

Article	Methods	Result
Montoya et al., 2016	A case control design using multilevel multinomial regression analyzed 851 houses in Enschede, including burgled and non burgled homes.	Daytime burglary was associated with territoriality and access control, while night burglary was linked to access control and target hardening. Attached houses showed lower risk in both periods, whereas offender availability strongly increased night burglary.
Park & Lee, 2017	Review-based study examining research methods and approaches used to analyze residential burglars' target selection, environmental cues, and decision making strategies.	3D simulation and VR methods were highly effective for modeling burglars' cognitive processes and target selection decisions.
Rahman et al., 2025	A mixed method approach combining questionnaires, focus group discussions, interviews, and secondary data from police statistics, government reports, journals, and online sources to examine crime patterns in Bangladesh.	Crime in Bangladesh increased steadily from 2003 to 2017. Poverty, unemployment, political patronage, peer influence, and weak social control were identified as major contributors to crime.
Rock et al., 2023	Qualitative study using semi structured interviews with 50 young burglary offenders aged 11 to 18 in Western Australia.	Most young burglars reported opportunistic offending with little planning, mainly motivated by peer influence, drug use, boredom, and financial need.
Sanders et al., 2017	Cross-sectional survey of 422 incarcerated burglars across prisons in Kentucky, North Carolina, and Ohio.	Deliberate offenders were more financially motivated, planned ahead, and used more tools, while impulsive offenders were more drug motivated and easily deterred by alarms or obstacles.
Taylor, 2017	Semi structured interviews with 30 convicted residential burglars in England examined motivations and lifestyle rewards from burglary using thematic analysis and the Good Lives Model framework.	Burglars reported psychological and lifestyle rewards from offending, including autonomy, pleasure, and social status, beyond financial gain.
van Gelder et al., 2017	Experimental quantitative study using immersive virtual reality with 77 male university students simulating burglary in a virtual neighborhood.	Participants showed strong immersion and increased heart rate during the simulated burglary. High deterrence reduced burglary duration and the value of stolen items, while

Article	Methods	Result
		alarms had no significant effect. Sensation seeking predicted stealing more valuable items, whereas conscientiousness predicted less valuable theft.
Wollinger, 2017	Survey based quantitative study using multinomial regression on 1,329 burglary victims from five German cities to examine how psychological strain, personal characteristics, and living conditions predicted post burglary responses.	Most victims installed safety measures, while fewer moved or remained passive. Higher psychological strain increased active responses, renters were more likely to move, and older victims preferred safety investments. Social cohesion reduced relocation, whereas social disorganization increased it.
Yue & Zhu, 2021	Quantitative cross sectional study using 17,915 residential burglary cases in Wuhan between 2013 and 2015.	Residential burglary peaked in the morning and evening and clustered in central and northwestern districts. Burglary risk increased with higher intersection density, subway access, land use mix, and older or more expensive buildings, while residential land proportion and CCTV reduced burglary rates.

The reviewed studies indicate that burglary is shaped by interacting psychological, environmental, social, and structural factors. Aycock et al. (2017) show that burglary is embedded within broader racialized and gendered social narratives, while offender focused studies emphasize individual differences in criminal development and decision making. Fox and Farrington (2016), Sanders et al. (2017), and Rock et al. (2023) consistently find that burglars differ in motivation, planning, and offending style, with some acting strategically and others more impulsively. Taylor (2017) further demonstrates that burglary may provide psychological rewards such as autonomy, mastery, and personal fulfillment beyond financial gain.

Environmental factors also play a central role in shaping burglary opportunities. Montoya et al. (2016) and Yue and Zhu (2021) show that neighborhood accessibility, weak guardianship, and urban design features increase burglary risk, although predictors vary across contexts and times of day. Victim focused studies similarly reveal that

burglary has lasting consequences. Kunst and Hoek (2024) identify gender, property damage, and dissatisfaction with police response as factors related to psychological distress, while Wollinger (2017) finds that distress influences behavioral responses such as relocation and security investments.

At the structural level, Mendlein (2021) and Rahman and Hossain (2025) highlight the influence of political integrity, inequality, poverty, unemployment, and governance on burglary patterns and reporting behavior. Methodological advances are also evident, with van Gelder et al. (2017) and Park and Lee (2017) demonstrating the value of virtual reality for studying offender decision making in realistic yet controlled settings. Overall, the literature converges on the importance of opportunity structures, environmental vulnerability, and offender heterogeneity, suggesting that burglary is best understood through the integration of psychological, situational, and structural perspectives.

B. Secondary Data Analysis

In this research, secondary data were used to examine burglary in Indonesia and its relationship with key socioeconomic indicators, including unemployment, educational attainment, population density, and wage rates. Statistical analyses were conducted in JAMOVl using Pearson's correlation, multiple linear regression, and variance inflation factor (VIF) diagnostics to assess associations, predictor significance, effect sizes, and multicollinearity. To complement inferential analyses, machine-learning models were developed in Orange Data Mining and evaluated using confusion matrices, Receiver Operating Characteristic (ROC) analysis, and feature importance measures. Model performance was compared across five algorithms, consist of: support Vector Machine, Random Forest, Neural Network, AdaBoost, and Decision Tree—to identify the most effective predictive approach (Bansal et al., 2022).

Table 2. *Matrix Evaluation*

MODEL	AUC	CA	F1	Prec	Recall	MCC
Tree	0.996	0.964	0.963	0.966	0.964	0.876
SVM	0.217	0.786	0.799	0.820	0.786	0.377
AdaBoost	0.770	0.750	0.776	0.847	0.750	0.431
Neural Network	0.757	0.464	0.510	0.779	0.464	0.153
Random Forest	0.983	0.964	0.963	0.966	0.964	0.876

The evaluation identifies Decision Tree and Random Forest as the best-performing models based on their near-perfect scores across all metrics (AUC > 0.98, accuracy = 0.964, F1 = 0.963, MCC = 0.876). These tree-based algorithms are chosen because they can capture non-linear patterns and interactions among socioeconomic variables, which aligns with the complexity of burglary risk factors. However, their near-perfect performance may also indicate over-optimization to the small provincial dataset (N = 34). In contrast, AdaBoost and Neural Network produce less extreme performance values, suggesting more moderate prediction patterns. While the tree-based models are useful for exploratory feature importance, their results should be interpreted cautiously.

To further validate the machine learning results and directly respond to the need for classical statistical inference, we performed two standard procedures: (1) bivariate correlation testing (Table 3) and (2) multiple linear regression (Table 4). These provide regression significance, effect sizes, and model fit statistics that complement the predictive orientation of machine learning.

Table 3. *Correlation Validation for Machine Learning Results*

FACTORS	Pearson's r	p-value
Gender Ratio	-0.261	0.135
Population	-0.051	0.774
Annual Population Growth Rate	-0.477	0.004
Population Density per square kilometer (km ²)	0.725	<.001
Percentage of Poor Population	-0.203	0.250
Provincial Minimum Wage	0.216	0.219
Unemployment	0.550	<.001
Elementary School / Equivalent	0.245	0.163
Junior High School / Equivalent	0.249	0.155
Senior High School / Equivalent	0.361	0.036

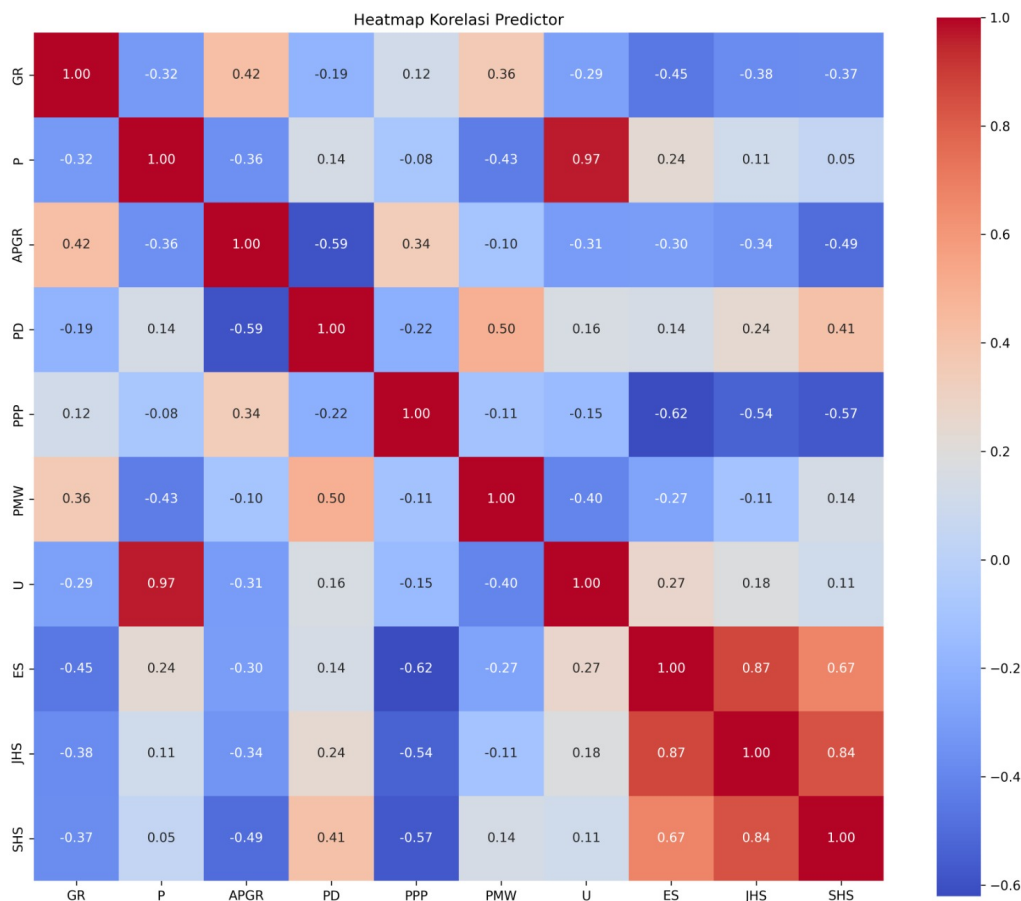


Figure 2. *Heatmap of Matrix Correlation*

The heatmap uses the following abbreviations: GR = Gender Ratio (2024); P = Population (Thousand); APGR = Annual Population Growth Rate (%); PD = Population Density (per km²); PPP = Percentage of Poor Population; PMW = Provincial Minimum Wage (Rp); U = Unemployment (Thousand); ES = Elementary School / Equivalent (%); JHS = Junior High School / Equivalent (%); SHS = Senior High School / Equivalent (%). While bivariate correlations show the individual linear relationships, multiple linear regression allows us to examine the unique contribution of each predictor while controlling for all others.

Table 4. *Linear Regression Validation for Machine Learning Results*

FACTORS		ESTIMATE	SE	t	p
Gender Ratio (2024)		-24.64344	154.94357	-0.1590	0.875
Population (Thousand)		-0.14683	2.90368	-0.0506	0.960
Annual Growth (Percentage)	Population Rate	1074.65915	1523.48770	0.7054	0.488
Population Density per square kilometer (km²)		0.64053	0.18828	3.4019	0.002
Percentage Population	of Poor	84.26274	92.44514	0.9115	0.371
Provincial Wage (Rp)	Minimum	0.00104	9.26e-4	1.1208	0.274
Unemployment (Thousand)		0.00451	0.00108	4.1696	<.001
Elementary School / Equivalent (Percentage)		299.01937	251.87623	1.1872	0.247
Junior High School / Equivalent (Percentage)		-190.60024	177.34477	-1.0747	0.294
Senior High School / Equivalent (Percentage)		64.06220	69.42319	0.9228	0.366

Note. Model fit: $R = 0.871$, $R^2 = 0.758$, Adjusted $R^2 = 0.653$, $F(10,23) = 7.21$, $p < .001$.

The overall regression model was statistically significant, $F(10,23) = 7.21$, $p < .001$, with $R = 0.871$, $R^2 = 0.758$, and Adjusted $R^2 = 0.653$, indicating that the predictor variables collectively explained approximately 75.8% of the variance in burglary rates, while 65.3% remained explained after adjusting for model complexity. As shown in Table 4, Population Density per square kilometer (km²) and Unemployment (Thousand) emerged

as statistically significant positive predictors of burglary rates, suggesting that densely populated provinces and regions with higher unemployment levels tend to experience greater burglary incidence.

Table 5. *Collinearity Statistics*

FACTORS	VIF	Tolerance
Gender Ratio (2024)	2.29	0.438
Population (Thousand)	1.31	0.763
Annual Population Growth Rate (%)	2.17	0.460
Population Density (per km ²)	2.70	0.371
Percentage of Poor Population	2.31	0.433
Provincial Minimum Wage (Rp)	3.13	0.320
Unemployment (Thousand)	1.58	0.633
Elementary School / Equivalent (%)	7.31	0.137
Junior High School / Equivalent (%)	9.41	0.106
Senior High School / Equivalent (%)	5.54	0.181

Multicollinearity occurs when two or more predictor variables are highly correlated with each other, which can inflate standard errors, reduce statistical power, and make it difficult to isolate the unique effect of each predictor. To diagnose multicollinearity among the predictors, we examined the Variance Inflation Factor (VIF) and Tolerance statistics (Table 5). A VIF exceeding 5 or 10 is often considered indicative of problematic collinearity. The results show that Junior High School (VIF = 9.41) and Elementary School (VIF = 7.31) have high VIF values, indicating substantial redundancy among education variables. Senior High School also shows moderate collinearity (VIF = 5.54). This explains why none of the education levels reached statistical significance in the linear regression (Table 4) and why they received zero importance in the machine learning feature importance (Table 6). In contrast, Population Density has a VIF of 2.70 which is well below conventional thresholds, confirming that its significant effect ($p = 0.002$ in Table 4) is not inflated by multicollinearity. Population (Thousand) has a very low VIF of 1.31, indicating it carries highly unique information, which helps explain why it becomes the most important predictor in the tree-based machine learning model (Table 6). Unemployment also has a low VIF of 1.58, yet it did not emerge as important in the ML model, suggesting its effect is linear and already captured by Population Density. Overall,

the only notable multicollinearity concerns involve the three education variables, which are conceptually related and were therefore considered together.

The Receiver Operating Characteristic (ROC) curve serves as a crucial analytical tool in evaluating how effectively each machine learning model differentiates between low and high burglary classifications. Because this study separates burglary incidents into two distinct groups based on severity, examining the ROC curve allows for a deeper understanding of each model's sensitivity and false-positive behavior within these specific contexts. By observing the shape of the ROC curve and the corresponding Area Under the Curve (AUC) values, we can assess which models maintain reliable discrimination across varying probability thresholds, making it possible to identify algorithms that are not only accurate but also robust in classifying levels of burglary.

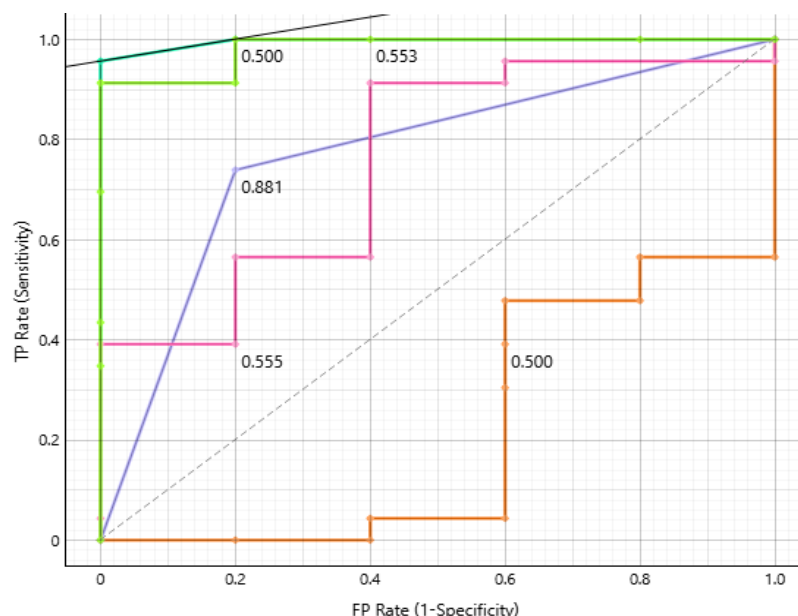


Figure 3. ROC Graph on Low Level of Burglaries

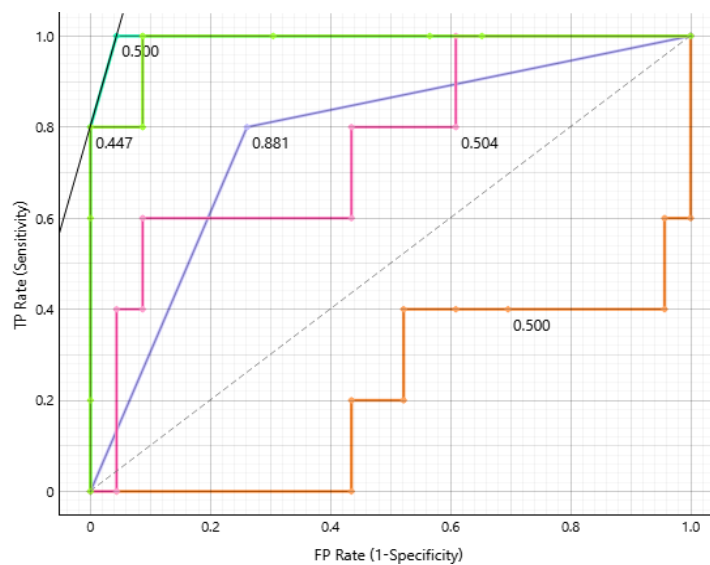


Figure 4. ROC Graph on High Level of Burglary

The ROC curves for both low- and high-burglary groups show nearly identical patterns. In both groups, the Decision Tree and Random Forest models consistently outperform all others, with their curves positioned near the upper-left corner indicating high sensitivity even at very low false-positive rates. Their AUC values remain near-perfect, 0.996 and 0.983 respectively, across both severity levels, demonstrating robust discriminative ability. AdaBoost and Neural Network produce moderate ROC curves, reaching true positive rates of approximately 0.80–0.88 at mid-range thresholds, but their shapes suggest instability in sensitivity. The SVM model continues to underperform, with a nearly diagonal curve and weak class separation. These results reinforce the superiority of tree-based algorithms for capturing non-linear patterns in burglary classification, though the near-perfect AUC values should be interpreted cautiously given the small dataset ($N = 34$).

Across both ROC analyses, the superiority of tree-based models is clear. Their ability to capture nonlinear patterns and interactively combined features makes them better suited for distinguishing provincial burglary levels, especially when socioeconomic and spatial characteristics vary widely across Indonesia. Meanwhile, the weaker performance of SVM and the instability of other models highlight the importance of selecting algorithms that can maintain sensitivity and specificity across changing probability thresholds.

Table 6. *Graph of Feature Importance*

Feature	Mean	Std
Population (Thousand)	0.415652	0.00325362
Percentage of Poor Population	0.225217	0.0690415
Gender Ratio	0.0226087	0.00325362
Senior High School / Equivalent (Percentage)	0	0
Junior High School / Equivalent (Percentage)	0	0
Elementary School / Equivalent (Percentage)	0	0
Unemployment (Thousand)	0	0
Provincial Minimum Wage (Rp)	0	0
Population Density per square kilometer (km ²)	0	0
Annual Population Growth Rate (Percentage)	0	0

Based on the feature importance measurement, the analysis shows that Population (Mean = 0.4157) is the most influential predictor in the model. This suggests that provinces with larger populations tend to exhibit clearer patterns of burglary variation, likely because higher population levels correspond to increased urbanization, greater housing density, and more opportunities for property-related crime. The relatively low standard deviation (Std = 0.0032) indicates that this feature contributes consistently across model iterations.

The second most influential feature is the Percentage of Poor Population (Mean = 0.2252), which reflects socioeconomic vulnerability within provinces. Its higher standard deviation (Std = 0.0690) suggests more variability in how poverty affects burglary rates across different regions. This aligns with criminological literature indicating that economic strain and limited access to resources can elevate property crime risk, particularly in areas where economic disparities are pronounced.

The Gender Ratio (Mean = 0.0223) appears as the third contributing factor, though with a substantially lower influence compared to population size and poverty level. This may indicate that demographic composition plays only a minor role in distinguishing burglary levels between provinces. The low variation (Std = 0.0032) suggests that the gender ratio has a consistent but limited impact.

All other variables such as education levels (Senior, Junior, and Elementary), unemployment, minimum wage, population density, and annual population growth, have zero measurable importance in the current model configuration. This does not

necessarily mean these factors are irrelevant in real-world settings; rather, within the context of this dataset and the algorithms used, these variables did not significantly enhance burglary prediction compared to the dominant structural indicators of population size and poverty levels.

Based on a tree regression analysis using demographic and socioeconomic predictors, the Burglary Potential Index (BPI) was developed by weighting three key features with non-zero importance scores: Population (41.57%, 0.415652), Poverty Rate (22.52%, 0.225217), and Gender Ratio (2.26%, 0.0226087). The BPI was calculated using a weighted formula derived from the feature importance scores of the Decision Tree model. The formula is as follows:

$$\text{Raw Index} = 0.415652 \cdot N_{\text{pop}} + 0.225217 \cdot N_{\text{poor}} + 0.0226087 \cdot N_{\text{gender}}$$

Figure 5. *The Burglary Potential Index (BPI) Formula*

The weights (0.416, 0.225, 0.023) correspond directly to the normalized feature importance means from the machine learning model, ensuring the index reflects the most salient predictive factors identified in the analysis. The index formula applies min-max normalization to each predictor and calculates a weighted sum, which is then rescaled to a 0–100 scale for comparative interpretation. West Java records the highest index score (100), primarily driven by its largest population size, which carries the greatest weight in the model. In contrast, Yogyakarta shows the lowest index (15.45), reflecting its smaller population and lower gender ratio, despite having a moderate poverty rate.

Table 7. *Burglary Index Based on Provinces in Indonesia*

Province	Home Burglary Potential Index
Jawa Barat	100.00
Jawa Timur	69.42
Jawa Tengah	65.67
Sumatera Utara	54.23
DKI Jakarta	53.12
Banten	45.89
Lampung	40.12
Sumatera Selatan	38.76
Papua	33.18
Nusa Tenggara Timur	32.15
Riau	30.09
Aceh	29.00
Kalimantan Barat	28.50
Sulawesi Selatan	27.88
Nusa Tenggara Barat	27.15
Kalimantan Selatan	26.45
Jambi	26.12
Sulawesi Tengah	25.89
Bengkulu	25.67
Kalimantan Timur	24.89
Sulawesi Utara	24.12
Gorontalo	23.78
Sulawesi Barat	23.45
Kalimantan Tengah	22.89
Kepulauan Riau	22.45
Sumatera Barat	21.89
Bali	21.23
Maluku	20.78
Maluku Utara	20.12
Papua Barat	19.89
Kepulauan Bangka Belitung	19.45
Sulawesi Tenggara	18.89
Kalimantan Utara	17.12
DI Yogyakarta	15.45

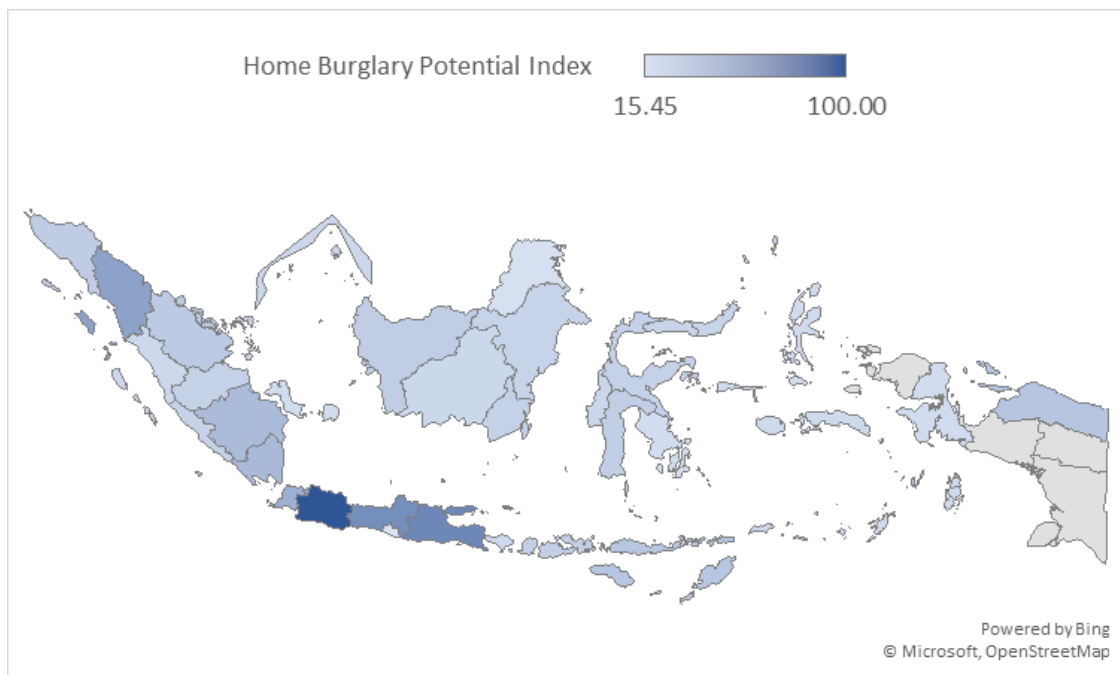


Figure 6. *Distribution of the Home Burglary Potential Index Map in Indonesia*

The provincial ranking derived from the index reveals a pronounced demographic bias, wherein densely populated provinces particularly those in Java and Sumatra dominate the upper quartile, irrespective of their relative poverty or gender ratio values. Conversely, provinces with extreme poverty rates, such as Papua (26.03%) and West Papua (20.49%), rank only 9th and 30th respectively, underscoring the model's overwhelming sensitivity to absolute population size rather than proportional socioeconomic disadvantage. This suggests that the model implicitly estimates the absolute volume of potential burglary incidents rather than the relative risk per capita, which may be more relevant for policy targeting.

It is important to emphasize that the Burglary Potential Index (BPI) remains exploratory and should not yet be used as an official predictive instrument. Because total population size dominates the feature importance, the BPI largely reflects population concentration rather than burglary risk per capita. Provinces with large populations (e.g., West Java) rank high primarily due to their population size, not necessarily because their per-capita burglary risk is proportionally higher. Future research with more refined indicators and external validation is needed before the BPI can be considered for operational use.

C. Qualitative Data Analysis

The qualitative aspect of this study was intended to examine how burglary is viewed and dealt with among people living in criminally vulnerable areas. Semi-structured interviews were done on four participants who had experience in residential burglaries or who knew someone involved. A thematic analysis was done on the collected data interviews using Braun and Clarke's six-stage approach (Braun & Clarke, 2006).

Four main themes were identified from recurring patterns across participants' experiences: (1) fear and insecurity after burglary, (2) environmental disorder, (3) skepticism on institutional support, and (4) adaptive coping. This research acknowledges that interpretation may be influenced by prior theoretical familiarity with criminology and social pathology literature. To reduce interpretive bias, interview transcripts were repeatedly reviewed and coded based on recurring participant meanings rather than solely theoretical assumptions.

1. Fear and Insecurity After Burglary

One dominant theme across interviews was the lingering fear, insecurity and hypervigilance following the burglary incidents. Participants described that it wasn't merely an experience of property loss, but also a violation of personal and domestic privacy. Nova explained that the incident felt particularly disturbing because the incident occurred quietly and unexpectedly, causing a sense of hypervigilance:

"Ternyata di depan itu udah rame, tetangga pada ngumpul dan ternyata ada yang kecolongan juga. Banyak yang bilang dari hape hilang, laptop, terus ada kayak perhiasan aksesoris gitu(...)Sekarang aku lebih hati-hati aja kalau keluar rumah harus inget kunci pintu, jaga barang bawaan, takut kemalingan lagi aja."

Similarly, Jolyne described intense emotional reactions immediately after discovering her house had been entered during the night:

"Ya awalnya panik sih... shock, terus sedih karena harta berharga semua kan...Jadi parno gitu, ya misalnya kayak bisa dibilang cemas. Kalau misalnya malam itu pasti, udah dikunci belum? Udah dikunci belum? Sampai kayak harus di-recheck lagi"

Zane, for example, explained that the burglary that affected his neighbor altered his habits and daily activities due to the reduced willingness of engaging in outdoor activities.

"I would cycle around with my friends around the complex but after that incident we barely go out"

These narratives show that burglary extends beyond material loss into the psychological domain of fear, vulnerability, and disrupted emotional security. Consistent with Ehlers and Clark's (2000) cognitive model of trauma and Janoff-Bulman's (1992) assumptive worlds theory, an unexpected intrusion shatters the belief that one's home is safe and predictable, leading to persistent hypervigilance and avoidance regardless of direct victimization. From a sociological standpoint of symbolic interactionism (Becker, 1963), the home loses its socially constructed meaning as a sanctuary and becomes reinterpreted as vulnerable and unpredictable. Thus, the emotional impact stems not only from financial loss but also from the symbolic destruction of trust attached to the home environment.

2. Environmental Disorder

Participants repeatedly associated burglary risk with environmental neglect, overcrowding, and weak neighborhood infrastructure. Nova described nearby residential areas as physically crowded and poorly maintained:

"Perumahannya lebih padet, dindingnya sampe tempel-tempel banget... sering banget kejadian perampokan."

Zane similarly emphasized how deteriorating infrastructure contributed to perceptions of danger:

"Potholes, missing lightbulbs, missing road signs... they have frequent incidents of criminality there."

Joan also highlighted the importance of environmental visibility and access control, particularly outside gated residential complexes:

"Komplek lebih aman karena ada security... yang rentan yang berada di luar komplek."

These accounts strongly reflect the assumptions of Social Disorganization Theory (Shaw & McKay, in McCaghy et al., 2016), which argues that neighborhoods characterized by instability, weak social cohesion, and environmental neglect experience weakened informal social control, thereby increasing vulnerability to crime. Simultaneously, they confirm Routine Activity Theory (Cohen & Felson, 1979): poor lighting, minimal surveillance, and

overcrowded housing create opportunities for motivated offenders in the absence of capable guardianship. Additionally, as Redfield (1947) argues, modernization and urban transformation weaken traditional communal bonds, making residents perceive environmental deterioration not merely as a physical issue but as a sign of declining social order.

3. Distrust Toward Institutional Protection

Another recurring theme involved skepticism regarding formal security systems and law enforcement effectiveness. Participants often perceived institutional responses as slow, inconsistent, or insufficient to prevent recurring burglary incidents. Joan explicitly criticized the limited responsiveness of local law enforcements:

"Jarang melihat ada polisi yang langsung ditindak... memakan banyak waktu."

Similarly, Zane questioned the effectiveness of local community management and infrastructure maintenance in preventing crime:

"...I don't think it's only about the space and infrastructures, I would also say that the head of the committee, and whoever may be responsible for maintaining the space is not doing their job properly."

"Regarding the lights, I simply do not understand how they can't just replace it?"

Nova likewise associated vulnerable neighborhoods with the absence of organized security systems and insufficient environmental maintenance:

"Di perumahan seperti itu... biasanya ga terawat, gaada keamanan... jadi lebih rawan aja kejadian hal seperti itu."

These findings reflect broader sociological discussions concerning weakened institutional trust and collective efficacy. According to Social Disorganization Theory, crime rates increase in communities where institutional coordination and informal social regulation are weak (McCaghy et al., 2016). Participants' descriptions of neglected infrastructure, insufficient lighting, and limited police visibility indicate that local institutions fail to maintain effective social control – aligning with Routine Activity Theory's concept of absent capable guardianship. Furthermore, such distrust contributes to secondary victimization (Orth, 2002): when

legal authorities are perceived as ineffective or dismissive, victims experience prolonged psychological distress, reinforcing ongoing fear and reliance on self-protective behaviors rather than formal protection mechanisms.

4. Adaptive Coping

Despite feelings of insecurity, participants also described various adaptive strategies used to manage burglary risk. These included strengthening household security, monitoring neighborhood activity, and relying on informal social support networks. oan explained that her family immediately implemented additional household protection measures after the burglary:

"Nah setelah kejadian itu baru kita pasang. Karena yaudah lesson learned gitu ya. Jadi kita pasang CCTV, terus tralisnya dipakein di jendelanya gitu"

Similarly, Nova explained that her neighborhood collectively increased physical security measures following the incident:

"Abis kejadian mamaku langsung bilang papaku kek eh tambahin beling sama kawat aja... biar lebih aman gitu. Dan beberapa orang juga ngelakuin itu gitu loh"

Zane's testimony described how residents collectively modified their routines after the burglary:

"Nobody would take their morning walks anymore and so much so they put curfew for themselves...Some people even added extra measure of security with adding more lights near their gates"

"The neighbors including my family offered a helping hand... We are a very closely knit community, everyone has each other's back..."

These adaptive strategies reflect collective efficacy (Sampson, Raudenbush & Earls, 1997): social cohesion and mutual trust enable informal social control, as seen when residents monitor each other's safety and share security measures. However, self-imposed restrictions on mobility, compulsive repeated checking, and persistent hypervigilance align with Ferraro's (1995) argument that fear of crime reshapes everyday routines. Following Janoff-Bulman (1992), such behaviors are compensatory attempts to restore a sense of control after a traumatic event. Moreover, as Scheper-Hughes and Bourgois (2004) note, communities exposed to persistent insecurity develop survival-oriented practices

that reshape social relations and everyday conduct. Thus, coping strategies are double-edged: they may enhance safety but also embed fear into daily life, transforming security into an organizing principle of social interaction.

DISCUSSION

This study employed a tripartite, mixed-methods design to construct a multidimensional analysis of burglary in Indonesia. By structurally reviewing global literature, applying machine learning to national socioeconomic data, and capturing the lived experiences of victims, we move beyond singular explanations to reveal burglary as a phenomenon situated at the intersection of structural pressure, fractured guardianship, and profound psychological violation.

The quantitative analysis reveals that burglary patterns across Indonesian provinces are strongly associated with structural demographic and socioeconomic conditions. Regression analysis identified population density and unemployment as significant predictors of burglary, while machine-learning models highlighted total population size and poverty as the most influential predictive factors.

However, these findings should be interpreted cautiously. The exceptionally high performance of the Decision Tree and Random Forest models may partially reflect overfitting due to the small provincial-level dataset ($N = 34$), limiting the generalizability of the predictive results. In this sense, the machine-learning component of the study should be understood primarily as exploratory rather than definitive predictive evidence. Moreover, the dominance of population size within the feature-importance analysis also suggests that the resulting burglary index may capture the concentration of population and urban activity more strongly than actual per-capita burglary risk. This limitation highlights the need for future studies to incorporate additional indicators such as housing density, migration instability, neighborhood infrastructure quality, and local governance capacity to produce more balanced predictive interpretations.

To explicitly integrate the qualitative and quantitative strands of this mixed-method study, Table 8 presents a joint display that maps each qualitative theme against its corresponding quantitative finding and provides an integrated interpretation.

Table 8. *Joint Display of Qualitative and Quantitative Findings*

Quantitative Evidence	Qualitative Evidence	Integrated Interpretation
Population Density significantly predicted burglary in regression analysis ($\beta = 0.641$, $p = .002$), while Population emerged as the most influential machine-learning predictor (importance = 0.416).	Participants repeatedly associated burglary with crowded residential areas, dense housing arrangements, poor visibility, inadequate surveillance, and neighborhoods perceived as overcrowded.	Across both analytical approaches, burglary appears more prevalent in environments characterized by high population concentration. Both findings suggest that demographic concentration increases opportunities for offending and weakens effective guardianship.
Unemployment significantly predicted burglary ($\beta = 0.005$, $p < .001$). Poverty was the second most influential predictor in the machine-learning model (importance = 0.225).	Participants frequently attributed burglary to financial hardship, economic pressure, and limited legitimate opportunities for income generation.	Economic vulnerability may function as a structural driver of burglary by increasing pressures that motivate property-related offending, particularly in communities facing limited socioeconomic resources.
The regression model explained 75.8% of burglary variance ($R^2 = .758$), indicating strong contributions from structural-level factors. Machine-learning models also identified demographic and socioeconomic variables as major predictors.	Participants consistently emphasized environmental disorder, weak neighborhood security, poor infrastructure, and inadequate guardianship rather than individual moral failure as explanations for burglary occurrence.	Both datasets indicate that burglary should be understood as a socially embedded phenomenon influenced by broader structural and environmental conditions rather than solely by individual deviance.

A central methodological insight from this study is the complementarity between classical statistical inference and machine learning. As shown in Table 4, regression analysis identified Population Density and Unemployment as the only statistically significant predictors of burglary after controlling for other demographic and socioeconomic variables. In contrast, the machine-learning feature importance analysis presented in Table 6 highlighted Population and Poverty Rate as the most influential predictors within non-linear predictive models. Rather than indicating contradictory results, these findings reflect the different purposes of each analytical approach. Regression analysis is designed to estimate the average linear effect of individual predictors, whereas machine learning prioritizes predictive accuracy and can capture

more complex interactions among variables. Additional support for this interpretation is provided by the collinearity diagnostics in Table 5, which demonstrate that Population carries relatively unique information compared to several other predictors. Taken together, the convergence of regression and machine-learning findings suggests that demographic concentration and socioeconomic vulnerability are key structural correlates of burglary in Indonesia. By combining inferential and predictive methods, the study provides a more comprehensive understanding of burglary patterns than either approach could offer independently.

Beyond structural indicators, the qualitative findings provide crucial insight into the lived consequences of burglary and the subjective meanings attached to it. Participants consistently described burglary as more than financial loss; it was experienced as a violation of domestic safety, trust, and emotional stability. These findings align with Ehlers and Clark's (2000) cognitive model of trauma and Janoff-Bulman's (1992) concept of disrupted assumptive worlds, which explain how traumatic events alter individuals' perceptions of safety and control. Victims reported persistent fear, hypervigilance, repeated checking behaviors, and changes in daily routines following burglary incidents. This is consistent with prior research showing that property damage, invasion of privacy, and inadequate institutional response amplify psychological distress among victims (Kunst & Hoek, 2024).

Participants also identified several contextual factors that they believed contributed to burglary in their communities, many of which resonate with criminological theories discussed in the first chapter. From the perspective of Strain Theory (Merton in Meehan et al., 2024), respondents frequently associated burglary with economic hardship, unemployment, and limited access to legitimate opportunities, noting that offenders in their areas were often driven by necessity rather than deliberate criminal strategy. Meanwhile, participants' descriptions of neighborhood conditions such as insufficient surveillance, poor lighting, low social cohesion, and frequent absence of residents reflect core elements of Routine Activity Theory (Cohen & Felson, 1979). Victims observed that burglaries typically occurred when motivated offenders could exploit vulnerable homes without capable guardianship, paralleling evidence from the literature showing that property cues, territoriality, and guardianship shape burglary risk (Montoya et al., 2016).

Additionally, respondents' concerns about community disorder, unstable residential patterns, and weak neighborhood cooperation strongly correspond to Social Disorganization Theory. As Shaw and McKay's framework suggests, communities marked by poverty, mobility, and low cohesion often struggle to enforce informal social controls, resulting in elevated crime risk. These observations correspond with national statistics showing higher burglary rates in provinces marked by socioeconomic instability and urbanization. Participants' perceptions reinforce that burglary in Indonesia is embedded in broader structural challenges that erode collective efficacy.

From a sociological perspective, the findings emphasize how structural environments shape burglary as a collective outcome. Prior studies, including Ardefa et al. (2025) and Ha et al. (2020), similarly found that poverty exerts the strongest influence on crime rates across Indonesian provinces, reinforcing that burglary reflects broader structural disparities rather than isolated deviant behavior.

Through a psychological perspective, burglary causes profound emotional and cognitive harm: victims report persistent anxiety, distrust, and vulnerability, especially when personal spaces are violated or institutional responses are inadequate (Kunst & Hoek, 2024). Offender motivations similarly involve strain, peer influence, and emotional dysregulation, with impulsivity and need driving offending when legitimate coping resources are scarce.

From an anthropological perspective, burglary must also be interpreted within the cultural and symbolic meanings of property, community relations, and local norms. Anthropological work demonstrates that cultural expectations, social cohesion, and historically embedded practices shape how communities interpret both offending and victimization (Snajdr, 2010). Specifically, a few participants repeatedly explained how there is a contrast between safer environments characterized by neighborhood cohesion and reciprocal monitoring with more anonymous and densely populated areas perceived as vulnerable to crime. This reflects broader anthropological discussions concerning the recession of communal ties in rapidly urbanizing societies (Redfield, 1947; Scheper-Hughes & Bourgois, 2004).

The findings also carry several practical implications for crime prevention policy in Indonesia. First, the strong relationship between environmental neglect and perceived insecurity suggests that urban planning interventions such as improved lighting,

infrastructure maintenance, and neighborhood accessibility control may help reduce burglary opportunities. These interventions require coordinated involvement from local governments, urban planners, law enforcement agencies, neighborhood administrations, and community organizations. Second, the importance of informal guardianship within participant narratives indicates that community-based policing and neighborhood watch systems may be more effective when combined with stronger resident participation and localized trust-building efforts. Third, the psychological consequences experienced by participants highlight the need for post-crime support mechanisms, including victim assistance services, trauma-informed counseling, and community recovery programs that address prolonged fear and social withdrawal after burglary incidents. Police victim-assistance units and social service agencies (Dinas Sosial) can assist victims through hotlines by providing accessible psychosocial support and post-crime recovery programs for affected residents.

This study has several limitations. The quantitative analysis relied on a relatively small provincial-level dataset ($N = 34$), which may increase the possibility of model overfitting and limit the generalizability of the machine learning results. The qualitative component also involved a limited number of participants, meaning that the findings may not fully represent the diversity of burglary experiences across Indonesia. In addition, regional representation bias may exist because experiences from certain social and geographic contexts remain underrepresented. Furthermore, the Burglary Potential Index (BPI) is exploratory and heavily weighted by total population size, meaning it reflects population concentration more than per-capita burglary risk; it is not ready for official predictive use. Future research is therefore encouraged to use larger longitudinal datasets, broader regional coverage, and more quantity and diversity of participant groups to strengthen understanding of burglary patterns and their social consequences in Indonesia.

CONCLUSION

This study demonstrates that burglary in Indonesia is influenced by interconnected structural, environmental, and social factors. Population density and socioeconomic vulnerability are closely associated with burglary patterns, while qualitative findings show that burglary also produces psychological insecurity, behavioral change, and

weakened perceptions of safety. Theoretically, the findings support three criminological frameworks; Strain Theory, Routine Activity Theory, and Social Disorganization Theory by showing that economic hardship, weak guardianship, and community instability collectively drive burglary as a multidimensional social pathology rather than isolated individual deviance. Methodologically, the sequential exploratory mixed-method design reveals the complementarity of classical statistics and machine learning; linear regression identifies population density as the dominant linear predictor, while machine learning uncovers non-linear effects of total population, poverty, and gender ratio. In terms of policy, prevention should extend beyond law enforcement to include urban planning, community-based programs that strengthen collective efficacy, and victim support services alongside responsive policing to rebuild institutional trust.

DAFTAR PUSTAKA

- Aryanti, N. (2021). The impact of industrialization on deviant behavior among adolescents. *Socio Politica: Jurnal Ilmiah Jurusan Sosiologi*, 11(1), 31–40.
- Ardefa, S. P., Naeruz, M., & Apriandi, A. (2025). Analisis Pengaruh Kemiskinan, Pengangguran Dan Tingkat Pendidikan Terhadap Tingkat Kriminalitas Di Indonesia: Penelitian. *Jurnal Pengabdian Masyarakat dan Riset Pendidikan*, 3(4), 4173-4177.
- Bansal, A., Sharma, R., Sharma, V., Jain, A. K., & Kukreja, V. (2023, April). A deep learning approach to detect and classify wheat leaf spot using faster R-CNN and support vector machine. In *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)* (pp. 1-6). IEEE.
- Beaton, A., Cook, M., Kavanagh, M., & Herrington, C. (2000). The psychological impact of burglary. *Psychology, Crime & Law*, 6(1), 33–43.
- Becker, H. S. (1963). *Outsiders: Studies in the sociology of deviance*. Free Press Glencoe.
- Bernburg, J. G. (2003). Labeling, life chances, and adult crime: The direct and indirect effects of official intervention in adolescence on crime in early adulthood. *Criminology*, 41(4), 1287–1318. <https://doi.org/10.1111/j.1745-9125.2003.tb01020.x>
- Bulegenova, B. B., & Turemuratov, O. Z. (2023). Urbanization as a global trend: Causes and consequences. *Bulletin of the LN Gumilyov Eurasian National University. Political Science. Regional Studies. Oriental Studies. Turkology Series*, 142(1), 37–42.
- Badan Pusat Statistik. (2024). *Statistik Kriminal 2024 [Dataset]*. BPS Indonesia. <https://www.bps.go.id/id/publication/2024/12/12/13317138a55b2f7096589536/statistik-kriminal-2024.html>
- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Chainey, S. P. (2021). A comparison of burglary near repeat victimization between rural and urban areas using a target-based assessment of criminal opportunity. *Crime & Delinquency*, 68(2), 320–343. <https://doi.org/10.1177/10575677211041920>

- Chiew, L. S., Amerudin, S., & Yusof, Z. M. (2020). A spatial analysis of the relationship between socio-demographic characteristics with burglar behaviours on burglary crime. *IOP Conference Series: Earth and Environmental Science*, 540(1), 012050.
- Clinard, M. B., & Meier, R. F. (1963). *Sociology of deviant behavior*. Holt, Rinehart and Winston.
- Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 588–608.
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297. <https://doi.org/10.1007/BF00994018>
- Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). Sage.
- Durkheim, E. (2023). The rules of sociological method. In *Social theory re-wired* (pp. 9–14). Routledge.
- Ehlers, A., & Clark, D. M. (2000). A cognitive model of posttraumatic stress disorder. *Behaviour research and therapy*, 38(4), 319–345. [https://doi.org/10.1016/s0005-7967\(99\)00123-0](https://doi.org/10.1016/s0005-7967(99)00123-0)
- Farrell, G. (2022). Forty years of declining burglary in the United States: Explanation and evidence relating to the security hypothesis. *Security Journal*, 35(2), 444–462.
- Ferraro, K.F. (1995) *Fear of Crime: Interpreting Victimization Risk*. State University of New York Press, New York.
- Fox, B. H., & Farrington, D. P. (2016). Is the development of offenders related to crime scene behaviors for burglary? Including situational influences in developmental and life-course theories of crime. *International Journal of Offender Therapy and Comparative Criminology*, 60(16), 1897–1927. <https://doi.org/10.1177/0306624X15621982>
- Franzese, R. J. (2015). *The sociology of deviance*. Charles C Thomas Publisher.
- Frith, M. J., Bowers, K. J., & Johnson, S. D. (2022). Household occupancy and burglary: A case study using COVID-19 restrictions. *Journal of Criminal Justice*, 82, 101996. <https://doi.org/10.1016/j.jcrimjus.2022.101996>
- Ha, O. K., Andresen, M. A., & Davies, G. (2020). The temporal (in)stability of the unemployment and crime relationship. *International Journal of Offender Therapy and Comparative Criminology*, 64(8), 840–859. <https://doi.org/10.1177/0306624X19896454>
- Hagedorn, R. B., Miller, J. P., & Labovitz, S. (1971). Industrialization, urbanization and deviant behavior: Examination of some basic issues. *Pacific Sociological Review*, 14(2), 177–195.
- Janoff-Bulman, R. (1989). Assumptive worlds and the stress of traumatic events: Applications of the schema construct. *Social cognition*, 7(2), 113–136.
- Katz, J. (2025). Hot potato criminology: Ethnographers and the shame of poor people's crimes. *Annual Review of Criminology*, 16, 36. <https://doi.org/10.1146/annurev-criminol>
- Kunst, M., & Hoek, D. (2024). Psychological Distress Among Domestic Burglary Victims: A Systematic Review of Possible Risk and Protective Factors. *Trauma, violence & abuse*, 25(1), 430–447. <https://doi.org/10.1177/15248380231155525>
- Li, H., Wang, Y., & Liu, X. (2022). Examining the effect of housing density and composition on residential burglary in Wuhan, China. *Journal of Housing and the Built Environment*, 38, 399–417. <https://doi.org/10.1007/s10901-022-09951-3>

- Lithwick, N. H., & Paquet, G. (Eds.). (2017). *Urban studies: A Canadian perspective*. Routledge.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444. <https://doi.org/10.1038/nature14539>
- McCaghy, C., Capron, T., Jamieson, J. D., & Carey, S. H. (2016). *Deviant behavior: Crime, conflict, and interest groups*. Routledge.
- Meehan, T., Forrester, L., & Haaja, J. A. (2024). *Sociological theories of crime: Strain theories. Introduction to Criminology and Criminal Justice*.
- Mendlein, A. K. (2021). International differences in crime reporting: A multilevel exploration of burglary reporting in 35 countries. *International Criminal Justice Review*, 31(2), 140–160. <https://doi.org/10.1177/1057567720981625>
- Montoya, L., Junger, M., & Ongena, Y. (2016). The relation between residential property and its surroundings and day- and night-time residential burglary. *Environment and Behavior*, 48(4), 515–549. <https://doi.org/10.1177/0013916514551047>
- Park, S. Y., & Lee, K. H. (2017). Identification of Environmental Cues and Decision-Making Strategies of Residential Burglars. *International Journal of Architectural Engineering Technology*, 4, 33-42.
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, 372.
- Quinney, R. (1970). *The social reality of crime*. Little, Brown.
- Quinlan, J. R. (1986). Induction of decision trees. *Machine Learning*, 1(1), 81-106. <https://doi.org/10.1007/BF00116251>
- Rahman, D. M. A., Hossain, M. A., & MATIN, D. A. N. (2025). *Pattern and Practice of Criminal Behavior in Bangladesh; A Sociological Study*.
- Reiman, J., & Leighton, P. (2010). *The Rich Get Richer and the Poor Get Prison: A Reader (2-downloads) (1st ed.)*. Routledge. <https://doi.org/10.4324/9781315662848>
- Redfield, R. (1947). The folk society. *American Journal of Sociology*, 52, 293–308. <https://doi.org/10.1086/220015>
- Rock, S., Gately, N., McCue, J., & St Martin, N. (2023). Temptations, techniques and typologies: Insights from a Western Australian sample of young people who burgle. *Youth Justice*, 23(3), 311–331. <https://doi.org/10.1177/14732254221122617>
- Sanders, A. N., Kuhns, J. B., & Blevins, K. R. (2017). Exploring and understanding differences between deliberate and impulsive male and female burglars. *Crime and Delinquency*, 63(12), 1547–1571. <https://doi.org/10.1177/0011128716660519>
- Sahlins, M. (1972). *Stone Age Economics*. Chicago: Aldine-Atherton.
- Susanto, P. C., Arini, D. U., Marlita, D., Yuntina, L., & Saribanon, E. (2024). Mixed methods research design concepts: quantitative, qualitative, exploratory sequential, exploratory sequential, embedded and parallel convergent. *International Journal of Advance Multidisciplinary*, 3(3), 471-485.
- Snajdr, E. (2019). Culture and crime. *Cambridge international crime and justice*, 245-250.
- Scheper-Hughes, N., & Bourgois, P. I. (Eds.). (2004). *Violence in war and peace: An anthology (Vol. 5)*. Malden, MA: Blackwell Pub.
- Tavares, J. P., & Costa, A. C. (2021). Spatial modeling and analysis of the determinants of property crime in Portugal. *ISPRS International Journal of Geo-Information*, 10(11), 731. <https://doi.org/10.3390/ijgi10110731>

- Taylor, E. (2017). "I should have been a security consultant": The Good Lives Model and residential burglars. *European Journal of Criminology*, 14(4), 434–450. <https://doi.org/10.1177/1477370816661743>
- Vilalta, C., Fondevila, G., & Lopez-Ramirez, P. (2023). A quantile panel examination of the moderation effects of guardianship on residential burglary. *Journal of Housing and the Built Environment*, 38(3), 1915-1938.
- Van Gelder, J. L., Nee, C., Otte, M., Demetriou, A., Van Sintemaartensdijk, I., & Van Prooijen, J. W. (2017). Virtual burglary: Exploring the potential of virtual reality to study burglary in action. *Journal of Research in Crime and Delinquency*, 54(1), 29-62.
- Wollinger, G. R. (2017). Choice behavior after burglary victimization: Moving, safety precautions, and passivity. *European Journal of Criminology*, 14(3), 329–343. <https://doi.org/10.1177/1477370816661738>
- Yue, H., & Zhu, X. (2021). The influence of urban built environment on residential burglary in China: Testing the encounter and enclosure hypotheses. *Criminology and Criminal Justice*, 21(4), 508–528. <https://doi.org/10.1177/1748895819874868>