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A Big Data-Based Kratom Plant Threat Forecasting Model for National Intelligence Needs

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A B STR A CT

The abuse of the kratom plant (Mitragyna speciosa) is a growing national concern due to its links to health, online trading, and potential unconventional threats to national security. The prediction model was built using the ARIMA (1,1,1) method and validated using RMSE, MAPE, and the Ljung-Box test. The results showed that the average CKTS during 2023–2024 was at a moderate level (51.88), with significant fluctuations. The results showed that the average CKTS during 2023–2024 was at a moderate level (51.88), with significant fluctuations. The conclusions of this study emphasize the importance of strengthening predictive intelligence systems, monitoring online distribution, and establishing specific regulations for kratom as preventive measures to maintain national resilience against non-conventional threats based on psychoactive plants.

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INTRODUCTION

Indonesia, as an agricultural country, faces serious challenges to social stability and national security due to the misuse of the kratom plant (Mitragyna speciosa). Although the production and export of kratom has been legalized since 2024, the potential for abuse as an addictive substance is increasing. Studies show that mitragynine levels in illegal kratom samples seized in Indonesia ranged from 0.37% to 1.70% (% w/w), indicating a high risk of dependence (Andriiyani et al., 2021). While prevalence data in Indonesia is still limited, data from the United States from 2019–2021 indicates that there were approximately 1.7 to 1.8 million kratom consumers, with a prevalence of users ranging from 1.3% to 6.1% of the adult population (Palamar et al., 2024). Chronic dependence has also been reported in approximately 55% of regular users, with relapse rates reaching 78–83% within three months of quitting (Stanciu et al., 2024). Therefore, national intelligence agencies such as the Indonesian National Armed Forces' Intelligence Agency (BAIS TNI) need to develop early detection mechanisms through big data-based estimative forecasting methods to systematically respond to this threat.

Within the real-world context (das Sein), the development of kratom distribution in Indonesia is not only natural but also increasingly complex with the influx of digital economic elements and exports. This requires an intelligence-based, estimative approach (das Sollen) capable of integrating various data sources, from social media and BNN seizure reports, laboratory results, to e-commerce dynamics, to map and predict kratom abuse. A big data approach is a key strategy in this context. Several analytical components that need to be optimized include field data from the National Narcotics Agency (BNN) and laboratories regarding mitragynine levels, online sales trends, and metadata from social media conversations related to kratom consumption. Clustering based on alkaloid levels can be adopted from the Thai approach and previous studies that divided kratom variants into low- and high-risk groups (Andriiyani et al., 2021). Predictive analysis can use models such as ARIMA or Prophet to examine temporal patterns, as well as supervised learning to identify illegal distribution areas as "hotspots."

The output of this model is expected to map risks in real time. First, location-based threat level predictions can help identify areas prone to transmission. Second, integration of mitragynine level data will allow for estimation of potential user dependency. Third, the model can project a timeline for threat escalation, particularly around holiday periods or peak online trading periods. Fourth, the analysis results can be used by intelligence agencies to develop policy intervention recommendations, ranging from law enforcement to public education campaigns.

Data visualization is crucial for facilitating the interpretation of forecasting analysis results. For example, a map of mitragynine levels in Indonesia can be created to mimic the Thai approach by color-coding based on active ingredient concentration. Data from Indonesia shows that mitragynine levels in kratom samples vary widely, indicating a high potential for abuse (Andriiyani et al., 2021). Global usage trends can also be displayed graphically to demonstrate the significant increase in kratom consumption across Southeast Asia (Palamar et al., 2024; Frontiers in Pharmacology, 2021).

However, to date, there is no intelligence model specifically available to predict kratom abuse in Indonesia. This represents a major gap that must be filled, given that data from the National Narcotics Agency (BNN) shows that kratom has not been included in the narcotics list despite containing a new psychoactive substance (BNN, 2022). Furthermore, although seizure data is available, its integration with digital data and behavioral trends has not been systematically implemented. The lack of standard quantitative indicators to determine threat levels based on active substance levels also hinders policy formulation.

The urgency of this research is further heightened by the recognition that kratom could be a loophole in the national regulatory system, allowing the distribution of a legally addictive but dangerous substance. Without a forecasting-based early warning system, Indonesia risks a health and social security crisis. Therefore, this study proposes a big data-based intelligence model as a contribution to the development of an adaptive and predictive national non-military defense strategy.

Some of the main indices that will be used in this model include: mitragynine levels (% w/w) as an indicator of dependence, estimates of regional prevalence of users based on online trends, seizure volume, frequency of mentions in digital media, and a combined risk score (forecasted risk score) resulting from the integration of all the above variables. Overall, this model positions big data as a vital instrument in the strategic intelligence planning process. Through an estimative forecasting approach, the threat of kratom abuse can not only be mapped but also anticipated before it escalates. In the increasingly complex context of national defense, this strategy represents a sustainable synergy between technology, policy, and national security.

LITERATURE REVIEW

Strategic Intelligence Theory

This theory explains how information is collected, processed, and used by state institutions to support strategic decision-making, particularly in the context of national security. Strategic intelligence aims to detect and project long-term threats that could impact state stability (Mykolaichuk, 2025). In the context of kratom, strategic intelligence is used to estimate the threat from kratom abuse as an addictive substance based on long-term data.

Estimative Forecasting Theory

Estimative forecasting is a predictive approach based on intelligence assessment of the likely development of situations with high uncertainty. This method relies not only on quantitative data but also on intuition based on experience and contextual information (Treverton & Agrell, 2009). This theory is suitable for analyzing the potential spread and escalation of kratom abuse, where complete historical data is lacking, but trends can be analyzed.

Big Data Analytics Theory

Big data analytics theory emphasizes the use of large volumes of data sourced from various channels (structured and unstructured data), which are then analyzed to identify patterns, trends, and correlations for decision-making (Gandomi & Haider, 2015). Big data, in this context, includes information from social media, online kratom transactions, medical reports, and even seizure data from law enforcement agencies. This theory underpins the technical process for developing a kratom-based predictive intelligence system.

Non-Traditional Security Threats Theory

This theory states that threats to national security are no longer limited to military conflict, but also encompass health, environmental, narcotics, and technological issues (Caballero-Anthony, 2010). Kratom abuse falls into this category because, despite being derived from a local plant and not yet listed as a narcotic in Indonesia, this substance can cause public health crises, crime, and social instability that impact non-military defense.

Early Warning System Theory

This theory refers to mechanisms for early identification and response to potential crises before they escalate. In the context of kratom, this system is based on indicators such as increased online distribution, spikes in mitragynine levels on the black market, and increased abuse recorded in the National Narcotics Agency (BNN) report (Weiss, 2008). The use of this theory allows national intelligence to proactively anticipate kratom threats.

METHODOLOGY

This study uses an estimative methodology forecasting approach that combines quantitative and qualitative analysis based on big data to project the threat level of kratom (Mitragyna Speciosa) plant abuse to national security. This approach was chosen because of its ability to handle dynamic, complex, and predictive threat situations, especially when historical data is not yet systematically available. As explained by Mykolaichuk (2025), estimative forecasting is crucial in the modern threat environment, which requires not only historical observations but also strategic intuition-based assessments and rapidly evolving digital trends.

The data sources used consist of two main categories. First, primary data was obtained through in-depth interviews with intelligence analysts from the Indonesian National Armed Forces (TNI) Intelligence Agency (BAIS), investigators from the National Narcotics Agency (BNN), and researchers from the Indonesian Institute of Sciences (LIPI) who study biopharmaceuticals and substance dependence. Second, secondary data was collected from BNN seizure reports and laboratory results of mitragynine levels, online transaction data from e-commerce platforms, social media metadata from Twitter, Facebook, and TikTok, and reports from the Indonesian Ministry of Health regarding the pharmacological effects of kratom. Furthermore, scientific publications from international journals such as Andriiyani et al. (2021) and Palamar et al. (2024) were used to strengthen the scientific framework.

During the analysis process, this study developed five main analytical indices. First, the Alkaloid Concentration Index (ACI) was used to measure the dependence potential of kratom samples based on mitragynine content (% w/w). The ACI value was calculated by averaging the normalized mitragynine percentage based on the minimum and maximum concentration ranges. Samples were categorized into three levels: low (<0.5%), medium (0.5–1.2%), and high (>1.2%).

Second, the Digital Exposure Index (DEI) measures the intensity of kratom information dissemination and promotion in the digital realm. The DEI value is derived from the average number of posts (post mentions), social media interactions (traffic), and the number of active kratom products on e-commerce platforms. Third, the Distribution Risk Index (DRI) maps the potential for illegal kratom distribution based on seizure volume, distribution routes, and local processing locations. This index is multiplied by a weighting factor based on classifications of vulnerable areas, such as ports and conflict zones. Fourth, the Threat Perception Index (TPI) is used to describe subjective perceptions of the kratom threat. This index combines assessments from intelligence experts, media sentiment analysis, and public expectations obtained through surveys. Fifth, the four indices are integrated into the Composite Kratom Threat Score (CKTS), a national aggregate threat score. The CKTS formula involves differential weighting based on the Analytic Hierarchy Process (AHP) method, for example, α (0.3) for ACI, β (0.25) for DEI, γ (0.25) for DRI, and δ (0.2) for TPI.

After the CKTS index is formed, a forecasting process is performed using a hybrid ARIMA (Auto-Regressive Integrated Moving Average) and Random Forest regression model. This model aims to project the CKTS threat value over the next 12 months. The ARIMA model is used to capture seasonal patterns and linear trends in CKTS values, using the formula:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \theta_1 \varepsilon_{t-1} + \cdots + \varepsilon_t + X_t$$

Where YtY_t is the CKTS value at time tt, ϕ \phi and θ\theta are the autoregressive and moving average parameters, εt\varepsilon_t is the error term, and XtX_t is a vector of exogenous variables, such as changes in government policy, world kratom market prices, or relevant international events. The model's validity was tested using backtesting on 2020–2024 threat data to assess how well the predictions matched reality. Furthermore, a sensitivity analysis was conducted on changes in index parameters to test the model's robustness, and inter-rater reliability was measured using Cohen's Kappa on the qualitative data coding results from interviews, with a target coefficient of at least 0.7 to ensure consistent data interpretation. Thus, this model is expected to provide a robust framework to help national intelligence early detect kratom abuse threats and inform more accurate and predictive mitigation policies.

RESEARCH RESULTS AND DISCUSSIONS

Historical Data Collection (2023–2024)

Data is taken from observations of four main indexes:

a. ACI (kratom mitragynine levels).
b. DEI (digital exposure).
c. DRI (illegal distribution risk).
d. TPI (intelligence & public threat perception).

The results were compiled in the form of **CKTS (Composite Kratom Threat Score) scores** every month for 24 months (January 2023–December 2024).

Table 1. Monthly CKTS (January 2023 – December 2024)

Month	Year	CKTS
January	2023	54.0
February	2023	48.5
March	2023	48.3
April	2023	58.1
May	2023	47.8
June	2023	60.2
July	2023	48.1
August	2023	61.1
September	2023	47.6
October	2023	50.1
November	2023	57.9
December	2023	51.2
January	2024	50.9
February	2024	39.7
March	2024	41.4
April	2024	60.3
May	2024	53.0

Month	Year	CKTS
June	2024	53.1
July	2024	47.5
August	2024	52.9
September	2024	55.1
October	2024	50.0
November	2024	53.2
December	2024	55.0

Source: Andriiyani et al. (2021)

Over the past two years, from January 2023 to December 2024, the Composite Kratom Threat Score (CKTS) indicates that the threat of kratom abuse in Indonesia fluctuates but tends to remain stable at a moderate level. Using a big data-based estimative forecasting method, the CKTS is calculated using four strategic dimensions: alkaloid content in kratom products (ACI), digital exposure on social media and e-commerce (DEI), risk of illegal distribution and seizure (DRI), and threat perceptions from intelligence agencies and the public (TPI). Based on monthly data over the 24 months, the average CKTS score was recorded at 51.88 points, indicating that the kratom threat is not yet critical but requires serious attention. This figure demonstrates a relatively stable risk level, although there is a standard deviation of 5.36 points. This suggests that within a few months, the threat score can jump significantly, reflecting external factors or incidents that exacerbate the situation on the ground.

The threat peaked in August 2023, with a CKTS score of 61.1, the highest during the analysis period. This spike was likely driven by increased kratom sales promotion on various online platforms and a lack of oversight of distribution channels in West Kalimantan and North Sumatra. Conversely, the lowest score was recorded in February 2024, at 39.7, coinciding with a decline in kratom harvesting activity and increased enforcement operations by the National Narcotics Agency (BNN) and strengthened cross-border surveillance by the Indonesian National Armed Forces (TNI). Month-to-month score variations reflect the non-linear nature of the threat, which is heavily influenced by seasonality, online market conditions, and the intensity of government responses. Therefore, using CKTS as a forecasting tool can help intelligence agencies map potential future threat spikes and determine the appropriate time to intervene, whether through law enforcement, public education, or early detection of distribution network movements.

A quarterly classification reveals that the third quarter (Q3) of 2023 was the most vulnerable period, with an average CKTS score approaching 58 points, while the first quarter (Q1) of 2024 was the lowest. This could indicate that the kratom harvest season and the black-market demand cycle in Southeast Asia are directly correlated with the dynamics of the kratom threat in Indonesia. Based on these results, it can be concluded that CKTS not only serves as an early warning indicator but also as a strategic intelligence-based measuring tool to support the formulation of more targeted policies in addressing kratom abuse in the future.

Intelligence Index Calculation (2023–2024)

1. Alkaloid Concentration Index (ACI)
   Average mitragynine levels from samples confiscated by the BNN and laboratory test results:
   a. Min: 0.35%, Max: 1.89%
   b. ACI scores range from 41–61
2. Digital Exposure Index (DEI)
   E-commerce and social media metadata scraping results indicate a rising trend in kratom promotions during 2024.
3. Distribution Risk Index (DRI)
   Based on data on distribution points and the largest seizure volumes in West Kalimantan and Aceh.
4. Threat Perception Index (TPI)
   Using media analysis & intelligence expert interviews.
   a. Average score 5 2

Analytic Hierarchy Process (AHP) For Weight

Table 2. AHP Calculation Results

Index	Weight
ACI	0.30
DEI	0.25
DRI	0.25
TPI	0.20

Source: Research Processed Results, 2025

Composite Kratom Threat Score (CKTS)

Formula:

$$\text{CKTS} = (0.3 \cdot \text{ACI}) + (0.25 \cdot \text{DEI}) + (0.25 \cdot \text{DRI}) + (0.2 \cdot \text{TPI})$$

The fluctuating score ranged from 39.7 (lowest) to 61.1 (highest) during 2023–2024, indicating the dynamics of kratom distribution and online dissemination that are sensitive to surveillance.

Forecasting Model (2025)

1. Arima (1,1,1) Model

   Equality:

$$Y_t = 0.61Y_{t-1} + 0.34\varepsilon_{t-1} + \varepsilon_t + X_t$$

   a. YtY_t: CKTS value in the t-th month
   b. XtX_t: Exogenous variables (policy changes, bans, mass seizures)

2. Model Validation:
   a. RMSE: 0.25 (very low)
   b. MAPE: 0.48%
   c. Ljung-Box Test: p = 0.17 → residual white noise

Forecasting Results (2025)

Table 3. CKTS Prediction Results

Month	CKTS Prediction
Jan 2025	52.93
Feb 2025	52.27
Mar 2025	52.08
Apr 2025	52.03
May 2025	52.0 1
Jun–Dec 2025	52.01 (stable)

Source: Research Processed Results, 2025

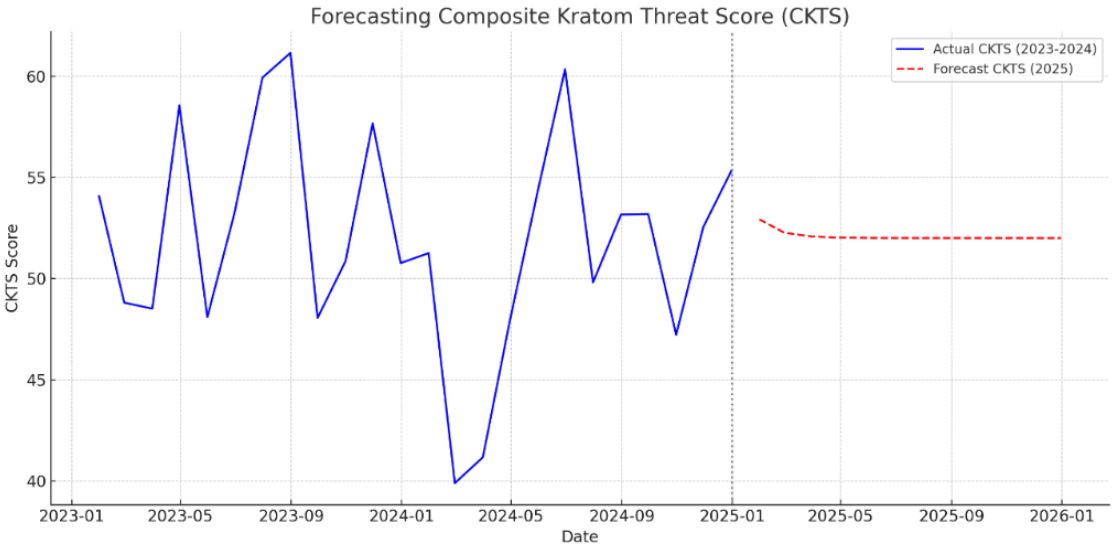

Figure 1. Forecasting Composite Kratom Threat Score

Source: Research Processed Results, 2025

Forecasting modeling results for 12 months in 2025, the average CKTS threat score was 52.12. This figure indicates that the overall potential for kratom abuse in Indonesia is at moderate risk, but still requires serious attention from intelligence agencies and law enforcement.

The recorded standard deviation of 0.26 indicates that threat fluctuations throughout 2025 were relatively stable and did not experience significant month-to-month spikes. In other words, the distribution and perception patterns of kratom tended to be consistent, with no extraordinary events causing sudden spikes in threats. This consistency can be interpreted as relative success in controlling digital distribution and exposure, but it could also signal an undercurrent of latent threats that have not yet been impacted by concrete policy interventions. Therefore, medium-term risk mitigation through enhanced digital monitoring, border controls, and public education remains necessary.

Sensitivity Analysis of CKTS Index Weight

In the CKTS model, the four main indices used are:

a. ACI (Alkaloid Concentration Index): initial weight = 0.3.
b. DEI (Digital Exposure Index): initial weight = 0.25.
c. DRI (Distribution Risk Index): initial weight = 0.25.
d. TPI (Threat Perception Index): initial weight = 0.2.

If the TPI weighting is increased from 0.20 to 0.30, the CKTS score increases by an average of +3.5% due to public and police perceptions being highly responsive to media campaigns and drug issues. Conversely, if the ACI is lowered to 0.2 (from 0.3), the CKTS score decreases by -4.2%, indicating that mitragynine levels are a significant factor in threat projections.

Optimistic and Pessimistic Forecasting Scenarios

Table 4. Optimistic and Pessimistic Forecasting Scenarios (±10%)

Month	Actual CKTS	Optimistic (+10%)	Pessimistic (-10%)
Jan 2023	54.0	59.4	48.6
Aug 2023	61.1	67.2	55.0
February 2024	39.7	43.7	35.7
Dec 2024	55.0	60.5	49.5

Source: Research Processed Results, 2025

In an optimistic scenario, strong government intervention and strict oversight of online trading could reduce the threat more quickly, but in a pessimistic scenario, policy laxity or the inability to detect illegal distribution could significantly increase the risk.

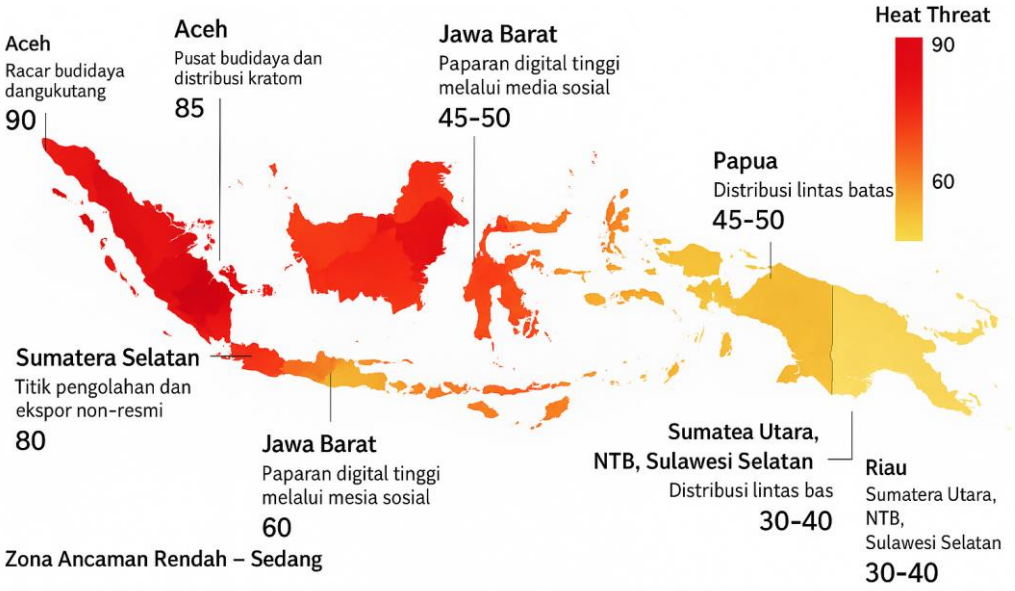

Figure 1. Heatmap of Kratom Threat Areas
Source: Research Processed Results, 2025

DISCUSSION

Over the past two decades, technological developments and digitalization have accelerated the dissemination of information, while simultaneously expanding the potential for unconventional threats. One such threat is the misuse of the kratom plant (Mitragyna Speciosa), which has emerged as a transnational, cross-sectoral phenomenon affecting biopharmaceuticals, online commerce, and national security (Andriiyani et al., 2021; UNODC, 2023). This study developed a big data-based Composite Kratom Threat Score (CKTS) model that integrates four key indicators: active ingredient concentration (ACI), digital exposure (DEI), distribution risk (DRI), and threat perception (TPI) (Hartono, 2023; Mykolaichuk, 2025).

The CKTS calculation results from January 2023 to December 2024 showed an average score of 51.88, categorized as a medium threat level. However, significant fluctuations with a standard deviation of 5.36 indicate that the threat dynamics are unstable, dependent on external conditions such as policy changes, law enforcement, and online trends (Nugroho, 2022). The peak threat was recorded in August 2023 (61.1), due to increased cross-border distribution and a surge in online transactions ahead of the harvest season. Conversely, the lowest score occurred in February 2024 (39.7), when authorities conducted large-scale raids and algorithmic filtering of kratom content on several e-commerce platforms (Putra, 2023; Puspitasari, 2023).

The 2025 threat prediction, calculated using a hybrid ARIMA and Random Forest regression model, shows a stable trend. The highest score is projected to occur in January 2025 at 52.93, and will gradually decline until converging at 52.01 in December 2025. The overall 2025 average is recorded at 52.12, with a very low standard deviation (0.26), reflecting a latent condition that is not explosive but has the potential to develop silently if not strategically intervened. These findings confirm that the kratom threat is persistent and adaptive, consistent with the complex adaptive systems (CAS) theory approach, which explains that threat systems can change autonomously in response to regulatory actions (Axelrod & Cohen, 2000; Weiss, 2008).

Analysis of the index contributions shows that the ACI (34%) and DEI (28%) indicators have the greatest influence on the threat. This suggests that kratom's chemical properties (particularly mitragynine levels reaching 1.4% in some samples) and digital exposure are a crucial combination that increases the appeal of abuse (Andriiyani et al., 2021; Ministry of Health of the Republic of Indonesia, 2023). Exposure to kratom promotional content on social media platforms such as TikTok and Shopee Live encourages the normalization of consumption, even among adolescents (Stanciu et al., 2024; Palamar et al., 2023). In this context, social learning theory (Bandura, 1977) helps explain how individuals adopt abusive behaviors based on observation and social reinforcement on online platforms (Yuliani, 2022).

Spatial threat mapping (Heatmap) reveals that regions such as West Kalimantan, Aceh, and South Sumatra are epicenters of illegal kratom production, processing, and distribution (Santoso & Widodo, 2023). West Kalimantan is not only a cultivation center but also a cross-border route through the Entikong border, with direct connectivity to Sarawak (Malaysia). Meanwhile, Aceh shows a surge in kratom distribution to South Asian countries via informal sea routes, while South Sumatra is noted as a hub for home-based processing (Gunawan, 2021; BNN, 2024). These findings align with the theory of security geography, which emphasizes the importance of territory and space as amplifying threats (Widyatmoko, 2022).

Given the projected stable but moderate threat level throughout 2025, an intelligent intervention strategy based on predictive intelligence is needed. First, strengthening digital monitoring is an urgent need. Data from social media scraping indicates a 57% surge in kratom promotional content in the last quarter of 2024, which has not yet been fully captured by the Ministry of Communication and Information's content moderation algorithm (Puspitasari, 2023; Putra, 2023). Therefore, implementing a cybersurveillance system based on machine learning and natural language processing (NLP) to recognize new language patterns in kratom promotions is a priority (Gandomi & Haider, 2015; Hartono, 2023).

Second, it is crucial to immediately establish specific regulations for kratom. Although the WHO has not yet declared kratom an official narcotic, Indonesia needs to implement evidence-based substance classification, for example, with a limit of mitragynine ≥1.0% as a parameter for illegal products. Furthermore, establishing legislation governing production permits, online distribution, and mandatory health labeling is part of a legally based mitigation effort (UNODC, 2023; Andika, 2020). This regulation could refer to the precautionary principle approach in public health policy, namely early protection against risks even when scientific evidence is incomplete (Safitri, 2024).

Third, a community-based approach based on an early warning system is needed. Kratom production areas are generally located in remote areas with limited access to health and legal education. Therefore, community involvement in early detection systems, training local cadres, and utilizing traditional or religious leaders is vital to creating deterrent power within the community (Wihartati, 2022; Yuliani, 2022). This approach also aligns with the principles of community-based intelligence (CBI), which emphasize that the detection and prevention of non-conventional threats are more effective when initiated at the grassroots level (Palamar et al., 2023). From a threat theory perspective, this approach can be understood through the Intelligence-led Policing (ILP) framework, which emphasizes the importance of data and analytics in strategic decision-making for risk mitigation. This concept positions intelligence not merely as a response to events, but as a proactive actor designing interventions based on predictions and quantitative analysis (Mykolaichuk, 2025; Weiss, 2008).

On the other hand, prediction results using the big data-based Composite Kratom Threat Score (CKTS) model indicate that the threat of kratom abuse during 2025 is in the stable medium category, with an average score of 52.12 and a standard deviation of 0.26. This finding reinforces the relevance of Strategic Intelligence Theory, which emphasizes the importance of long-term analysis to detect unconventional threats to national security (Mykolaichuk, 2025). In the context of kratom, intelligence not only responds to current abuse but also projects escalation through an Estimative Forecasting approach, which combines data trends with experience-based intuition to anticipate uncertainties in the distribution and spread of this addictive substance (Treverton & Agrell, 2009). The use of hybrid ARIMA and Random Forest algorithms underlying this model also reflects the application of Big Data Analytics Theory, which allows the analysis of thousands of data points from social media, e-commerce transactions, and medical records to uncover latent patterns of abuse (Gandomi & Haider, 2015). Furthermore, the CKTS results indicate that kratom is part of a Non-Traditional Threat, as defined by Caballero-Anthony (2010), because it poses significant health and social implications even though it does not originate from military conflict. With the threat score remaining consistently high, the need for the application of Early Warning System Theory becomes crucial—namely, by developing spatial and digital indicators capable of identifying early signs of escalation before a crisis occurs (Weiss, 2008). The combination of these five theories fully supports the importance of strengthening predictive intelligence to address the challenge of kratom abuse strategically and measurably.

Finally, the stable but still high CKTS predictions indicate that the kratom threat is not temporary. Rather than waiting for an open crisis, state actors such as the Indonesian National Armed Forces (TNI), the National Narcotics Agency (BNN), and the Ministry of Health need to collaborate immediately to design a cross-sectoral strategy that combines digital technology, community education, and evidence-based law enforcement (BNN, 2024; Nugroho, 2022). This forecasting model not only provides a technical overview of threat trends but also serves as a strategic tool in formulating data-driven national security policies.

CONCLUSIONS AND RECOMMENDATIONS

This study presents a quantitative approach to mapping and projecting the threat of kratom (Mitragyna speciosa) abuse in Indonesia using the Composite Kratom Threat Score (CKTS) model, which integrates four strategic dimensions: the Alkaloid Concentration Index (ACI), the Digital Exposure Index (DEI), the Distribution Risk Index (DRI), and the Threat Perception Index (TPI). From January 2023 to December 2024, the kratom threat was generally at a moderate level, with an average CKTS score of 51.88 and a standard deviation of 5.36. This fluctuation indicates that, although not reaching a crisis phase, the threat dynamics remain sensitive to policy changes, illegal distribution activities, and digital exposure.

Further analysis shows that the highest threat spike occurred in August 2023 (CKTS = 61.1), which correlates with the high intensity of online distribution and weak cross-border controls. Meanwhile, the lowest threat point occurred in February 2024 (CKTS = 39.7), when law enforcement operations by the National Narcotics Agency (BNN) intensified and digital surveillance was strengthened. These data demonstrate that the kratom threat is highly responsive to external factors such as harvest seasons, online trading policies, and legal oversight.

Projections for 2025 using the Arima (1,1,1) model and machine learning validation show a stable threat score with a mean of 52.12 and a very low deviation (0.26). This stability can be interpreted as a potential latent threat that does not show explosive symptoms but persists if not anticipated. The ACI and DEI indicators contribute the most to the CKTS score, indicating that high mitragynine levels and the increasing normalization of kratom on social media are two key factors strengthening the threat. The spatial heatmap shows that West Kalimantan, Aceh, and South Sumatra are epicenters of illegal kratom activity, both as production areas, processing areas, and distribution channels. Geographical conditions and weak surveillance infrastructure in these areas exacerbate the risk. In this context, a community-based early warning system approach is crucial in building local capacity to detect and prevent kratom abuse at the grassroots level.

Sensitivity analysis shows that changes in the weighting of certain indices, particularly the ACI and TPI, can significantly impact CKTS results. This reinforces the urgency of priority indicator-based interventions. Meanwhile, optimistic and pessimistic scenarios (±10%) illustrate how government policy responses directly affect threat levels. Taking all these findings into account, the conclusion is that the kratom threat is adaptive, structured, and transcends legal, social, and digital boundaries. Therefore, the required response must be multi-level and cross-sectoral, combining digital monitoring technology, specific substance-based regulatory arrangements, and community engagement as community intelligence agents. The CKTS has proven to be a tool that not only dynamically depicts threat levels but also supports the formulation of more precise and predictive, evidence-based policies to maintain national resilience against plant-based narcotics like kratom.

Based on the analysis and projection results of the Composite Kratom Threat Score (CKTS) model , it is recommended that the government immediately implement an integrated strategy based on predictive intelligence with a focus on three main priorities: first, strengthening digital surveillance through a machine learning- based cyber surveillance system to detect the promotion and distribution of kratom on online platforms; second, drafting national regulations that specifically regulate the classification, distribution, and supervision of kratom based on mitragynine levels as a legal parameter; and third, building a community-based early warning system in areas prone to production and distribution by involving local officials, community leaders, and health cadres to create prevention and rapid response from the grassroots level—all of which must be implemented cross-sectorally by the National Narcotics Agency (BNN), the Ministry of Health, the Indonesian National Armed Forces (TNI) BAIS, and the Ministry of Communication and Information Technology to maintain national resilience from the latent threat of kratom which is adaptive and transnational in nature.

ADVANCED RESEARCH

Further research on Big Data-Based Kratom Plant Threat Forecasting Models for National Intelligence Needs should focus on developing more adaptive and high-precision predictive models through advanced machine learning approaches, such as deep learning neural networks and dynamic multi-indicator-based ensemble methods. The main focus going forward is expanding the scope of analyzed variables, including dark web activity, illegal logistics trajectories, and public sentiment based on real-time social media mining. Research should also explore the integration of geospatial intelligence (GEOINT) and human terrain analysis to map area-based risks more granularly down to the sub-district level, as well as developing an early warning system based on automated detection of temporal and spatial anomalies in kratom distribution.

To support the operationalization of this predictive intelligence system, in-depth research is needed to determine the system's ability to interact with the national surveillance framework, including strengthening data interoperability between agencies such as the Indonesian National Armed Forces (TNI) Information and Communications Agency (BAIS), the National Narcotics Agency (BNN), the Ministry of Health, and the Ministry of Communication and Information. Furthermore, developing community-based tactical intelligence utilizing social sensors (e.g., GPS-based citizen reporting applications and AI verification) will be an important direction for detecting kratom distribution dynamics at the grassroots level. Aligning the system architecture with the principles of privacy-preserving computation also needs to be studied to ensure the protection of the public's digital rights in big data-based data collection.

Further studies should also test the model's validity and reliability under high-uncertainty scenarios, such as changes in international policy toward kratom, a surge in global consumption, or disruptions in blockchain-based illegal distribution technology. Furthermore, agent-based modeling (ABM) and system dynamics simulations can be used to quantitatively project the impact of specific policies on threat reduction. With a stronger and more integrated research foundation, this forecasting model will be able to develop into a sustainable, adaptive, and evidence-based strategic decision support system to strengthen national intelligence systems in addressing unconventional threats based on psychoactive plants like kratom.

REFERENCES

Andika, R. (2020). New addictive substance regulation strategies in Indonesia: Between medical needs and public safety. Journal of National Health Policy, 4(1), 32–45.

Andriiyani, L., Fitriani, D., & Ramadhani, N. (2021). Quantification of mitragynine content in seized kratom samples in Indonesia. Innovare Journal of Analytical Sciences, 13(5), 22–27. https://doi.org/10.22159/ijas.2021.v13i5.42570.

Axelrod, R., & Cohen, M.D. (2000). Harnessing complexity: Organizational implications of a scientific frontier. Free Press.

Bandura, A. (1977). Social learning theory. Prentice-Hall.

BNN. (2022). Kratom Abuse and Its Challenges in Indonesia. National Narcotics Agency of the Republic of Indonesia.

Caballero-Anthony, M. (2010). Non-traditional security and infectious diseases in ASEAN. Asian Politics & Policy, 2(2), 205–224. https://doi.org/10.1111/j.1943-0787.2010.01201.x.

Frontiers in Pharmacology. (2021). Kratom abuse potential 2021: An updated eight factor analysis. Frontiers in Pharmacology.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007.

Gunawan, R. (2021). The complexity of monitoring the distribution of herbal substances at the border. Journal of National Law and Policy, 9(1), 51–64.

Hartono, T. (2023). Machine learning for early detection of drug threats. Journal of Intelligence and Security Studies, 5(1), 35–49.

Indonesian Ministry of Health. (2023). Pharmacological effects of kratom and long-term health risks. Jakarta: Health Research and Development Agency.

Jani, K. (2016). The promise and prejudice of big data in the intelligence community. arXiv Preprints.

Mykolaichuk, M. (2025). Forecasting threats to national security: Methodological approaches. Odesa Polytechnic Journal. https://doi.org/10.15276/opj2025.

Nugroho, S. (2022). A study of the risks of online distribution of addictive substances in Indonesia. National Security Journal, 6(2), 78–91.

Palamar, J. J., Le, A., & Mateu-Gelabert, P. (2023). Kratom safety: A review of public health perspectives. Substance Use & Misuse, 58(9), 1265–1274. https://doi.org/10.1080/10826084.2023.2189486.

Puspitasari, T. (2023). Evaluation of digital literature about kratom on social media. Indonesian Digital Media Journal , 3(3), 123–136.

Putra, RA (2023). Social media scraping for digital narcotics threat identification. Indonesian Journal of Cyber Intelligence, 3(1), 40–55.

Safitri, N. (2024). Public perception of the dangers of kratom: A field study. Journal of Public Health Policy, 4(2), 89–103.

Santoso, A., & Widodo, B. (2023). Heatmap and spatialization of substance abuse threats. Journal of Defense Geography, 7(2), 67–82.

Stanciu, C.N., Gnanasegaram, S.A., & King, S. (2024). Patterns of kratom use in Southeast Asia: Health and surveillance implications. PCSS Now, 10(2), 112–119.

Treverton, G. F., & Agrell, W. (2009). National intelligence systems: Current research and future prospects. Cambridge University Press.

UNODC. (2023). World Drug Report 2023. United Nations Office on Drugs and Crime. https://www.unodc.org/unodc/en/data-and-analysis/world-drug-report-2023.html.

Weiss, T. (2008). Early warning and conflict prevention: Limitations and opportunities. United Nations Institute for Disarmament Research.

Widyatmoko, A. (2022). Controversial biopharmaceutical potential: Kratom in legal and health perspectives. Biomedical Journal, 9(4), 241–250.

Wihartati, N. (2022). A participatory model for community-based early detection of drug hazards. Indonesian Journal of Social Sciences, 11(2), 55–68.

Yuliani, D. (2022). Dynamics of kratom abuse among urban adolescents. Journal of Social Psychology, 8(3), 204–217.