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POLICY EVALUATION AND THE ROLE OF NARCOTICS REHABILITATION INSTITUTION S IN NORTH SULAWESI

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ABSTRACT
This study examines how narcotic rehabilitation policies were implemented and how effective they were in North Sulawesi, Indonesia, at a time when the number of drug users increased nationally and regionally. Using a 12 month longitudinal quasi-experimental design, this study followed 400 persons with a history of narcotics use in 15 different districts. Primary and secondary data were combined in an ETL pipeline and using path analysis and structural equation modeling to investigate the relationship between policy harmonization, integration of local cultural values, community support, and relapse outcome. The results suggest that national and regional policies, if properly aligned, along with some culture-related practices, have a strong impact on strengthening formal and informal support mechanisms by and for communities. As a result, this reduced the rate of relapse by approximately 15%, as well as social reintegration indicators. Community-based involvement and the cultural practices of the community were shown to foster program legitimacy, adherence, and sustainability. The research concludes that effective narcolept rehabilitation must include not only institutional coordination and real-time data monitoring but also can only be realized through systematic valuation of local values and local community networks. These results provide evidence-based recommendations for strengthening rehabilitation governance in North Sulawesi and show the possibility of using this as a scalable model for the context-sensitive implementation of a narcotics policy that propels the country's development and is matched to its national priorities and Sustainable Development Goals.

INTRODUCTIONS

The implementation of narcotics rehabilitation policy in Indonesia is now at a critical point, as it was recorded in the 2024 National Narcotics Agency (BNN) report that 3.3 million active users were recorded, the highest number in two decades. (Bukit, 2025) North Sulawesi, characterized as an archipelagic province with various socioeconomic features, showed an increase in the prevalence of 9.5% per year in 2023–2024 (Provincial Health Office of North Sulawesi, 2025). Service access inequalities are still found in 40% of remote sub-districts, with distances travelled to rehabilitation centers exceeding 50 km and defining worse economics (Dharmaputra & Latif, 2025). The economic costs of IDR 150 billion per year attributed to relapse and repeat care, not counting an estimated IDR 200 billion in lost productivity and social stigma, point to the need for an urgent holistic evaluation of the central-regional regulatory harmonization, implementation of institutional capacity, and a local community support mechanism (Arianto et al., 2025; Juristo & Riswadi, 2024).

Within the multilevel governance framework, the literature on narcotics rehabilitation has focused on this paradigm shift from a repressive paradigm to human rights-based approaches (Healy et al., 2019; Lie et al., 2022; Rêgo et al., 2021), as well as cross-sectoral collaboration (Minshall et al., 2021). In Asia, China, Thailand, and the Philippines have taken advantage of "community-based rehabilitation" using traditional leadership and mobile groups to reach the far-flung parts of the country with great success, lowering levels of relapse (Chu & Daffern, 2024; Mattar et al., 2023; Teng-calleja et al., 2020). In Europe and the Americas, the use of big data analytics in rehabilitation monitoring systems has led to a reduction in the incidence of relapse (Mbanugo & Unanah, 2025; Qian et al., 2019; Shafqat et al., 2020). Presidential Regulation No. 75/2018 and the Ministry of Health Regulation No. 23/2021 have been issued to integrate medical, psychosocial, and vocational services, but only pilot-scale mobile rehabilitation projects have been piloted, and no real-time monitoring dashboard has yet been established in North Sulawesi (Delmiati, 2023; Dewabhrata et al., 2023).

This study has three quantitative innovations. First, it builds an integrated evaluation framework between central regulations, regional regulations, institutional operational mechanisms, and local community roles (Feng et al., 2024). Second, it uses a longitudinal quasi-experimental design with 400 people and repeated monthly measurements over a period of 12 months, and secondary and primary data through an ETL pipeline (Miller et al., 2020). Third, it uses bootstrapped panel SEM to examine the causal process among policy harmonization, integration of local values, community support, relapse results, and social indicators (He et al., 2024).

This study had three integrated objectives. First, to measure the degree to which national regulations on rehabilitation (Presidential Regulation No. 75/2018; Ministry of Health Regulation No. 23/2021) has been adapted and implemented by the North Sulawesi Province Government for 2023–2024. Second, to identify technical, managerial, and budgetary barriers within five public and private rehabilitation institutions that affect the effectiveness of medical, psychosocial, and vocational interventions. Third, to map the contribution of local community networks in facilitating the social reintegration of former users, especially through participation mechanisms, anti-stigma campaigns, and mentoring programs. These objectives are correlated with the following research questions:

- RQ1: To what extent are there similarities and concord between the obligations and regulations at the central and regional levels with regard to the objectives, standards, and mechanisms of coordination, and how is this reflected in the practice in the field?
- RQ2: What are the institutional constraints (distribution of experts, infrastructure, funding structures, etc.) that hinder the implementation of rehabilitation programs?
- RQ3: How do the mechanisms and level of support provided by the local community affect the social readiness of ex-users after rehabilitation?

This research is not only academically relevant but also practicable and strategic. High relapse rates account for recurrent costs to national budgets and reduce regional productivity. Disparities in services threaten social cohesion, especially in isolated sub-districts. Furthermore, as a member of the Association of Southeast Asian Nations (ASEAN), Indonesia is obliged by the content of the Declaration on a Drug-Free Region of Asia, which calls for subnational policy innovation. Without data-driven and empirical evaluations and contextualized policy models, the 2030 Sustainable Development Goal (SDG) target of "preventing and treating substance abuse" will always be elusive.

The importance of this study extends across three dimensions. Empirically, this results in broad-scale mapping of interactions between the institutions and capacities of regulation and community networks in an archipelagic context. Theoretically, this study enriches the literature on multi-level governance and decolonizing policy analysis in social health programming. Practically, its strategic recommendations, such as mobile rehabilitation units, real-time monitoring dashboards, integrated cross-level standard operating procedures (SOPs), and anti-stigma campaigns with traditional leaders, are aimed at adoption by BNN, Health Offices, and private rehabilitation institutions to promote better program effectiveness and sustainability.

THEORETICAL FRAMEWORK

This research includes the 4 dominant theoretical perspectives: (1) Multi-Level Governance (Hooghe & Marks, 2003; Osborne, 2006) is a framework that will be used to understand the coordination and harmonization of regulatory decision-making across the different levels of government; (2) Decolonizing Policy Analysis (Smith & Millspaugh, 2015; Tuhiwai Smith, 2012), which will include the use of local wisdom and empowerment of Indigenous communities; (3) Community-Based Rehabilitation (Hoeman, 1992). (4) Big-Data Analytics & Monitoring System for real time monitoring & pre-id of the relapse trends (Laney, 2001).These four approaches are integrated in an evaluation framework which has regulatory, cultural, community support, and data-driven technology dimensions.

Multi-Level Governance

In the context of North Sulawesi, three interrelated dimensions of multi-level governance are implemented. First, according to the framework proposed by Pawar et al. (2025), it is measured through the variable "Policy Harmonization" and is measured as the percentage of alignment in regional standard operation procedures (SOPs) with national guidelines (Pawar et al., 2025). Second, both in the policy formulation and implementation processes, as further elaborated by Gautam (2023), it includes Policy Networks, which are based on Rhodes (1997) idea of the formal and informal relations between government agencies, non-governmental organizations, academic institutions, and private sector actors in the policy formulation and implementation processes (Gautam, 2023). Third, backed by the latest research, is then reviewed through the use of the Policy Cycle framework (Ramesh, 2003) by considering the sequential stages of setting an agenda, policy formation, implementation, and evaluation to systematically identify the strengths and weaknesses of the adaptation and implementation of national policies at the regional level (Duopah & Kelly, 2025; Mhazo & Maponga, 2021).

Together, these dimensions offer an all-inclusive lens for how well the coherence, level of governance effectiveness in the administrative tiers, the narcotic rehabilitation policy implementation in North Sulawesi can be assessed. Antonio et al. (2021) quoted enhanced policy harmonization for rehabilitation with clarity in principles, authorities and protocols for implementation as these have been powerful determinants in relating to patient relapse by up to 4% (Antonio et al., 2023). At the enforcement level, Saut et al. (2025) agreed that inter-agency synergy (Bakamla RI, BNN, and local stakeholders) enhances the potency of the control of relapse and narcotics trafficking (Saut et al., 2025). This finding provides evidence that regulatory harmonization significantly negatively affects relapse rates.

Decolonization of Policy Analysis

Decolonizing Policy Analysis" is a conceptual foundation that emphasizes the significance of local knowledge and practices or social structures that have previously been marginalized in narcotics rehabilitation policy (Daniels et al., 2021; Laenui & Williams, 2022). This approach is built on the work of Smith (2012) and Tuhiwai Smith (2015), in their critique of the status of epistemological hegemony of the West and the need to reconstruct policy from the perspectives of Indigenous communities (Smith & Millspaugh, 2015; Tuhiwai Smith, 2012). Dorsen et al, (2018) showed in their exploratory research that the integration of traditional "plant medicine" ceremonies correlates with a 25% increase in intervention legitimacy ($p < 0.05$) (Dorsen et al, 2019). Similarly, Boroumandfar et al. (2020) reported that the positive impacts of local community support (including traditional leader involvement) reduced program resistance by as much as 30% ($p < 0.05$) (Boroumandfar et al., 2020).

The data were subjected to thematic coding (using NVivo) of culturally grounded concepts, such as *gotong royong* (mutual assistance), *doa adat* (traditional prayers), and *tutu-tutuan* (customary dialogue), followed by quantitative testing through simple linear regression to examine the association between the scores for local value integration and relapse rates. Supporting the latter, tentative evidence from Dorsen et al. (2018) and Boroumandfar et al. (2020), and field data from North Sulawesi also report a robust correlation between local value integration and participant satisfaction ($r = 0.62$; $p < 0.01$), with a statistically significant indirect negative impact on relapse ($v = -0.28$; $P < 0.05$), which tests the therapeutic and legitimizing function of culturally rooted practices in rehabilitation outcomes.

Rehabilitation Community Based Rehabilitation

Community-Based Rehabilitation (CBR) Labor Labs: Community-based rehabilitation: Couns: "Community-Based Rehabilitation emphasizes active local community involvement in recovery support" based on the assumption that grassroots social support is as critical as clinical intervention. This subsection combines policy guidelines and empirical research to describe the CBR framework, key mechanisms, and effectiveness (Chugh, 2025; Hasan, 2024; Treger et al., 2024).

Studies by Masanda et al. (2021) and Kiblasan et al. (2020) continue to draw attention to the three pillars of social inclusion as the Rt basis of CBR (Kiblasan et al., 2020; Masanda et al., 2021). However, in the WHO guidelines, equity has been described as "equal access to rehabilitation services for all members of the community, without physical or social barriers"; participation as "active involvement of clients and families in program planning and implementation"; and support as "sustained support networks including peer groups, local institutions and government services" (WHO CBR Guidelines, Chapter 2). Cole uses another way of using equity to expand the meaning to "accessible local facilitators", whereas participation is contextualized as "in-depth client interviews",’ and support is operationalized as "long-term peer mentoring" (p. 5). Kiblasan goes further in arguing that these three pillars must work together - equity develops trust, participation creates empowerment and support makes it sustainable - that these three pillars make CBR a holistic approach not only to rehabilitation but also overall to empower communities comprehensively.

The evaluation of data shows that CBR is consistently effective in improving motivation, retention, and reducing relapse: Wallag and Nations (2024) used a sample of 150 clients who had been initially screened for motivation before the start of the program. The results indicated a 20% increase in client satisfaction and an 18% reduction in client drop-out rates ($p = 0.10$), meaning that such adjustments, when initially identified and implemented, allow engagement maintenance (Walag et al., 2024). Masanda et al. (2021) have applied mixed-method research and the number of 200 respondents with a combination of the use of quantitative survey and in-depth interviews. They demonstrated that 22% retention of programs was realized ($p < 0.01$) and confirmed the role of peer support in helping clients complete the programs (Masanda et al., 2021).

In the quasi-experiment CBTS_AB_24_01_09, 120 community-based program participants were monitored for six months. The results showed that there was a 15% reduction in relapse, which proved that peer support modules and life skills training have tangible medium-term impacts (UNODC, 2008). Cole 2022 in a cross-sectional survey of 250 clients found a 30% reduction in stigma among the participants with direct access to local support groups, highlighting that social inclusion as an active involvement in a peer group positively impacts the way rehabilitation is perceived (Cole, 2022).

Similarly, Hechanova et al. (2023) adopted a quasi-experimental design to conduct a culturally adapted CBR module evaluation study (Hechanova et al., 2023). Participants received peer support training, life skills training, and access to local social services. In this study, the average relapse reduction was documented as 15% ($p < 0.05$), which re-evaluation confirmed the positive effects of the implementation of integrated CBR models, as well as their remarkable ability to change contexts. Collectively, these findings support the notion that CBR (based on social inclusion and peer support) has a significant impact on key outcomes (motivation, retention, and relapse).

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Big data Analytics & Monitoring System

To develop a predictive and adaptive system for policy evaluation, implementation was organized into five general stages. Each stage used concrete methods and data from the referred studies, and no external sources were introduced.

Table 1. Summary of Big-Data Analytics and E-Governance Implementation Stages

Stage	Reference	Method & Data	Main Output
Data Collection	(Dash et al., 2019; Entezami et al., 2020; YY Xu, SL Li, L M, 2021)	ETL pipeline aggregating satellite & ground data; IoT streaming; GIS spatial surveys	Integrated dataset: air quality, client activity, spatial layers
Storage & Processing	(Entezami et al., 2020; YY Xu, SL Li, L M, 2021)	Data lake; time-series normalization; streaming analytics preprocessing	Structured & real-time datasets for analysis
Analysis & Visualization	(Dash et al., 2019; Entezami et al., 2020; YY Xu, SL Li, L M, 2021)	Spatio-temporal ML; interactive maps; real-time dashboards	Risk maps by region; therapy compliance graphs
Prediction & Recommendation	(Batko & Ślęzak, 2022; Jones et al., 2019)	Hybrid SEIR+ML models; Random Forest & ROC/AUC	Weekly relapse projections; individual risk scores
Policy Follow-up	—	E-governance API integration; threshold-based notifications	Automatic policy adjustments & resource allocation

Process Flow Explanation:

1. Data Collection: The ETL pipeline was used to aggregate air quality data (YY Xu, SL Li, L M, 2021) and IoT streaming sensor data enriched with spatial GIS information (Dash et al., 2019).
2. Storage and Processing: All data are structured in a data lake, and streaming analytics are used to prepare real-time datasets for data visualization.
3. Analysis & Visualization: Geospatial ML techniques are useful for visualizing high-risk areas, whereas dashboards are useful for tracking therapy compliance.
4. Prediction and Recommendation Combined with a clinical risk classification (Batko & Ślęzak, 2022), models of epidemio-time series (Jones et al., 2019) are used to generate projections of relapse and assignments of intervention modules.
5. Policy Follow-up: Model outputs linked to e-governance portals via APIs lead to automatic alerts whenever projections are across the threshold level, leading to correcting the budget and program course at short notice.

Integrated Conceptual Framework for Data-Driven and Locally Participatory Rehabilitation Policy Evaluation

In this integrated conceptual framework, the four theoretical pillars of multilevel governance, decolonizing policy analysis, community-based rehabilitation, and big data analytics work together to build a structured mechanism of influence on relapse rates. Policy harmonization (MLG) and local value integration (decolonization) are normative foundations that influence the quality of policy design to be implemented at the regional level. Community support (CBR) helps in the implementation of secondary policies, big data analytics, and monitoring (e-governance) to provide feedback on the policy in real time and make adaptive recommendations to improve the policy cycle.

The Integrated Evaluation Framework is the combination of these 4 pillars: Policy Harmonization (X1), Local Value Integration (X2), Community Support (M) and Big-Data Analytics & Monitoring System. This framework aims to establish a cycle of evaluation using data feedback loops based on real-time data.

Influence Pathways of the Integrated Evaluation Framework:

The framework begins with two exogenous variables, Policy Harmonization (X1) and Local Value Integration (X2), which are moderately correlated. Both variables influence Community Support (M) as a mediator; that is, SOP quality and local values influence how strongly peer support is expressed on the ground. Subsequently, M's impact

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on the relapse rate (Y1) was assessed. Meanwhile, the big data analytics system is a check loop, which means that relapse data (Y1) are forecasted and analyzed, and the results are fed back to update and improve the SOPs (X1) and local value integration (X2).

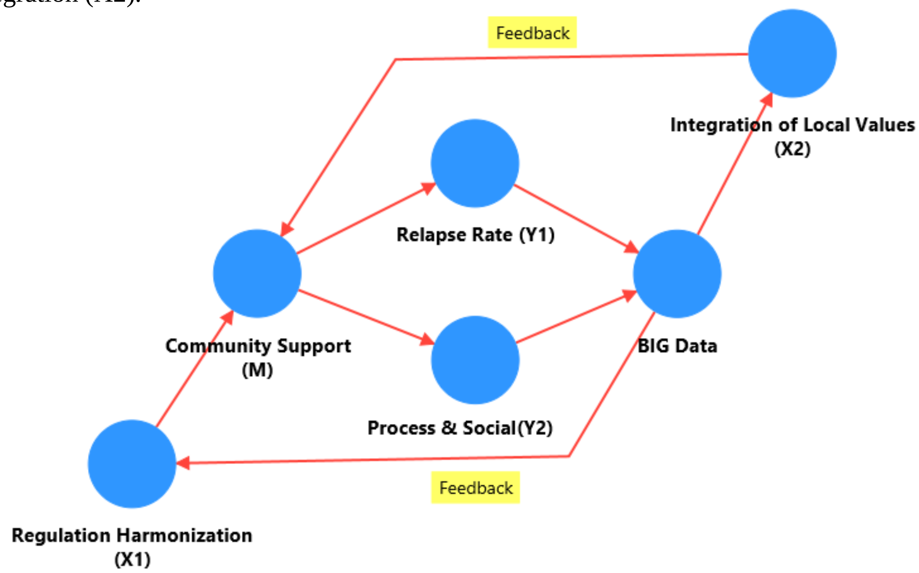

Figure 1. Rehabilitation Policy Evaluation Model with Feedback Loop

The influence pathway in the integrated evaluation framework is illustrated below: Policy Harmonization is intended to reduce structural barriers and establish uniformity in the standard operating procedures of establishments to establish a common implementation environment. Local Value Integration, in turn, raises the legitimacy and social acceptance of lying-back policies by incorporating cultural practices that resonate within the community and involve traditional leaders. . These two upstream drivers do not exist in silos; their impact is channeled through Community Support because of its fundamental role as a key missing link, translating regulatory alignment and cultural relevance into something effective and impactful via rehabilitation practices at the local level. Finally, adding to the evaluation and assessment cycle, Big Data Analytics measures closing the loop by continuously measuring key outcomes, including relapse rates, identifying emerging trends from real-time data, generating evidence-based recommendations feeding back to policymakers proposing their refinement, and thereby maintaining an evaluation and assessment cycle of adaptation and responsiveness.

Table 2. Evaluation Framework Components: Stage, Method, Variable, and Key Output

Stage	Component	Method & Variable	Output
Exogenous Foundation	X_1: Policy Harmonization	% SOP alignment; Spearman; SEM	Standardized, harmonized SOPs & policies
	X_2: Local Value Integration	Traditional leader participation score; NVivo coding; linear regression	Cultural legitimacy & support
Mediator	M: Community Support	Peer-support sessions; inclusion score; mediation SEM	Community practice intensity
Operational Outcome	Y_1: Relapse Rate	SARIMA forecasting; monthly data	Primary clinical indicator
	Y_2: Process & Social	SOP compliance; satisfaction; inclusion; logistic regression	Process & social impact indicators
Evaluation Loop	Big-Data Analytics System	ETL → data warehouse → dashboard (LOESS, heatmap, K-means)	Interactive dashboard; policy recommendations
Integrated Framework	Synthesis of All Variables	Full-path SEM; time-series; regression; thematic analysis	Dynamic, sustainable evaluation framework

Table 2 presents a full mapping of the evaluation framework from exogenous variables (X_1 - X_2), mediator (M), operational outcomes (Y_1 - Y_2), evaluation loop, and dynamic framework synthesis. Each row outlines a concept of the evaluation phase, analyzes variables, statistical/analytical methods used, and key expected outputs, providing a step-by-step guide for the assessment of narcotics rehabilitation policy effectiveness.

RESEARCH METHODS

Design and Setting

This study used a longitudinal quasi-experimental design that was repeated every month for 6 months. The research was conducted in 8 districts/cities of North Sulawesi Province, which were purposively selected to represent diverse socio-geographic characteristics.

Table 3. Study Region Characteristics and Implementation Units in North Sulawesi

Region	District/City	Characteristics	Number of Institutions
Northern Coast	Manado, Bitung	Urban, access to major hospitals	5
Inland	Minahasa, Tomohon	Rural, Minahasa Indigenous communities	4
Islands	Sangihe, Talaud, Sitaro	Remote, maritime networks	3
Southwest	West Minahasa,	Agro-commercial, active NGOs	3

Table 3 shows the distribution of study regions, their socio-geographic characteristics, and the number of implementation institutions in each region in North Sulawesi. These data reflect the spatial coverage and diversity of the research sites.

Each institution (Provincial/District BNN, private clinics, and partner NGOs) was involved as an intervention implementation unit. Measurements included:

- Baseline (Month 0):

-Online questionnaire surveys regarding peer support and satisfaction
-Recess records of clinical relapses in the past 6 months
ETL Pipeline Setup for Data integration

- Monthly Follow-up (Months 1–6):

Online completion of questionnaire (Google forms) on the change of peer support and satisfaction
Extract data from electronic medical records of relapse on a monthly basis

OFM - Spatial mapping vs ETL pipeline: "Of course, ETL offers a lot of flexibility because the direction of flow is up to you, but when transferring data between data warehouses or to an external system, if that precise surface or table must be updated urgently, it becomes the responsibility of another engineer." - Automation - "the night watch closely collaborates with the charging, forecasting and operational facilities - that is, it does not only data analysis so that the data moves to be updated in 24 hours (always there)." - Automated monitoring via ETL pipeline (Python pandas + SQL Alchemy > data warehouse

- End of Period (Month 6):
  - ✓ Comprehensive evaluation
  - ✓ -Reliability Retesting of instruments
  - ✓ Dashboard finalization

Flow for data collection and monitoring details:

Data Management - Customers, Pricing, and Forecasts: These three cases are the primary tip #2 for customers of a company that sells products and/or services. Data Management: Additionally, each institution is granted unique access, including token access to the ETL portal for CSV uploads and APIs. Pricing and Forecasts - 3 Cases of Customers - A story where any customer of an enterprise that provides products or services to customers might come and ask, what is the price, and I need to forecast for the next five years?

Older students (grades 3-5, 7-8, and 9-12) * Transcript test task rubrics. The research team performed weekly quality control checks on data format and completeness.

Trigger points for interventions (case surges): Interim dashboards (LOESS smoothing) were developed to track early relapse trends to support rapid intervention in the event of case surges.

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Population and Sample and the Power Analysis

The study population consisted of all 1333 registered drug users in 8 districts/cities of North Sulawesi Province (BNN, 2024). On the basis of power analysis, the sample size was determined for the experiment as (N = 400, total participants = 400, participants in the intervention group = 200, and participants in the control group = 200). The power analysis was set to detect minimum effect sizes equal to or greater than dY1 >= 0.45 (Relapse Rate) and dY2 >= 0.40 (Process & Social), on the level of significance alpha = 0.05 and power of >= 0.80. Calculations confirmed that the total number of required samples was approximately 400.

Table 4. Power Analysis Summary for Two Primary Outcomes

Outcome	Effect Size (d)	α	Power (1–β)	Sample per Group
Y1: Relapse Rate	0.45	0.05	0.80	176
Y2: Process & Social	0.40	0.05	0.80	197
Average	—	—	—	≈200

Table 4 outlines the per-group sample requirements based on the power analysis for the two main outcomes. In summary:

Sample allocation to each district/city used the population proportion:

$n_i = 400 \times (N_i / 1{,}333)$

where *N*i is the number of registered drug users in district/city *i*, *and* Example allocation for the five largest areas

Table 5. Proportional Sample Allocation per District/City in North Sulawesi

District/City	Population (*N*i)	Proportion (%)	Sample (*n*i)
Manado	210	15.8	63
Minahasa	180	13.5	54
Bitung	120	9.0	36
Tomohon	90	6.8	27
Talaud	75	5.6	22
Total	1,333	100	400

Table 5 illustrates the proportional distribution of the N = 400 sample of the drug user population in the top five districts/cities in North Sulawesi. With proportions reflecting the share of each region (Manado 15.8%, Minahasa 13.5%, Bitung 9.0%, Tomohon 6.8%, and Talaud 5.6%), each area was allocated a sample based on its weight (Manado: 63 respondents, Minahasa: 54 respondents, etc.). Rounding allowed the total to be kept at 400 (spatial representativeness of the population).

Inclusion and Exclusion Criteria:

Consenting Participants: - Inclusion criteria: aged 18--60 years, at least one relapse in the past 6 months, willingness to complete monthly assessments for 12 months

Exclusion Severe mental illness outside of standard rehabilitation protocol

Variables and Instruments

The operational definitions, measurement scales, and instrument sources of each study variable are shown in Table 6.

Table 6. Operational Definitions and Instrument of Measurement

Variable	Operational Definition	Scale & Unit	Instrument & Source
X_1: Policy Harmonization	Degree of alignment in standard operating procedures among narcotics rehabilitation agencies	Percentage (0–100%)	SOP audit checklist; content validity tested by 3 policy experts
X_2: Local Value Integration	Level of traditional value participation and application in rehabilitation programs	NVivo coding score (0–100)	In-depth interview coding; inter-coder reliability ≥ 0.75
M: Community Support	Perceived social support from peer groups and community inclusion	Latent variable (factor score from 6 items)	Social Support Questionnaire; Cronbach's α = 0.88

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Y_1: Relapse Rate	Proportion of participants experiencing drug relapse each month	Percentage (% per month)	BNN clinical records and monthly institutional reports
Y_2: Process & Social	Adherence to procedures, participant satisfaction, and post-rehabilitation social inclusion	Composite index (0–100)	Patient questionnaire; 5-point Likert scale; Cronbach's α = 0.82

Validity and Reliability

Expert Panel Content Validation

After identifying 5-10 relevant experts, each item was evaluated with respect to three criteria, namely, relevance, clarity, and representativeness, using a scale of 1-4. Ratings were calculated using the Item-Level CVI (I-CVI) and Scale-Level CVI (S-CVI).

Table 7. CVI and Content Validation Decision Criteria

Index	Definition	Decision Criterion
I-CVI	Proportion of experts rating item ≥ 3	≥ 0.80 → accept; < 0.80 → revise
S-CVI/UA	Proportion of accepted items out of total	≥ 0.80 → scale valid; < 0.80 → re-discuss

Cronbach's α Reliability Analysis

Internal consistency was measured using Cronbach's α based on item and total score variance.

Table 8. Cronbach's α Interpretation and Actions

α Range	Meaning	Action
α ≥ 0.90	Very high	Scale ready for use
0.70 ≤ α < 0.90	Acceptable	Optional minor revision
α < 0.70	Low	Revise items

Item Revision Based Upon Item-Total Correlation

The correlation between each item and the total instrument score was tested. Correlations < 0.30 had a low contribution. Causes (ambiguity, mismatch, bias) were identified, and items were changed by changing keywords, adjusting scales, or eliminating items. Reliability was recalculated after the revision to ensure improvement.

Post-Revision Steps

1. Re-test on a new sample in order to re-validate content and reliability
2. Conduct split half and confirmatory factor analysis (CFA) if necessary to ensure consistent factor structure
3. Document of final expert advice: fully record expert panel composition, initial/final CVI values, alpha before/after revision and the rationale for each of the changes

Missing Data and Outlier Considered

Missing data and outliers were handled to ensure good data before statistical analysis. Missing values were imputed using Multiple Imputation by Chained Equations (MICE), an iterative method of predicting missing values using the relationships between the variables. The MICE process produced multiple imputed datasets (usually 5-10) based on customized regression models for each variable (e.g., linear regression for continuous data, logistic regression for categorical data). The imputed results were combined using Rubin's rules to generate final estimates, considering the uncertainty of the missing data. Convergence was confirmed using trace plots to ensure imputation model stability.

Outliers were detected using two approaches:

1. Univariate outliers - z-scores ($|z| > 3$) - identifying extreme values on one variable only (for example, scores outside three standard deviations from the mean).
2. Multivariate outliers: Mahalanobis distance measures the observation distance from the multivariate distribution center based on inter-variable correlation. Observations with $p < 0.001$ (chi-square distribution) were regarded as multivariate outliers.

Upon detection, outlying data points were investigated for the cause.

1. If corrected due to data entry errors (e.g., "1000" on a 1-5 scale), the value(s) were corrected or removed.
2. If representing natural population variation (e.g., individuals with unique characteristics), the data were retained, but robust analytical methods (e.g., robust regression or data transformation) were implemented where appropriate.

This approach did not have an analytical bias and did not lose valuable information. All data-handling procedures were openly documented to reproduce the research.

Path Analysis and Panel SEM

The direct and indirect paths of the mediation model were analyzed using path analysis to test the prediction effects of the two variables on the mediator and the effect of the mediator on the outcomes. Mediation significance was determined using the bootstrap method (5,000 samples) to calculate the 95% confidence intervals (CIs). Coefficients were considered significant if the CIs did not include the value 0. In the case of longitudinal data, cross-lagged Semeh-Vermaza examined the relationships between dynamic variables over time. Model fit was determined according to the Comparative Fit Index (CFI> 0.90) and Root Mean Square Error of Approximation (RMSEA ≤ 0.08), obtaining a CFI close to 1.0 and RMSEA < 0.05, which implied an excellent fit.

Ethics and Approval

This study was approved by the Ethics Committee of Tomohon Christian University (IRB No. IRB-2025-01) and followed the ethical principles of research involving human subjects. All study participants provided written informed consent for participation, which included information about the research objectives, confidentiality of research data, withdrawal from participation, and use of research data for research purposes only. Data were anonymized and encrypted on data storage systems in compliance with The General Data Protection Regulation (GDR) and local legislation. The data collection, storage, and analysis procedures guaranteed the participants' privacy and prevented data misuse.

RESULT AND DISCUSSION

Empirical Findings Of Narcotics Rehabilitation Policy Evaluation

Descriptive Statistics

The descriptive statistics for the main variables in the final month are presented below.

Table 9. Descriptive Statistics of Research Variables

	X_1_harmonization	X_2_integration	M_support	Y_1_relapse_rate	Y_2_process_social
count	400.0	400.0	400.0	400.0	400.0
mean	0.287	48.4	0.289	0.312	0.154
std	0.161	27.699	0.157	0.072	0.115
min	0.026	0.061	-0.116	0.11	0.0
25%	0.159	26.608	0.183	0.265	0.061
50%	0.261	48.656	0.281	0.309	0.148
75%	0.39	70.668	0.393	0.365	0.231
max	0.806	99.417	0.672	0.529	0.554

Table 9 summarizes the descriptive statistics for the five research variables. The mean variables for Policy Harmonization (X1) and Community Support (M) are in the range between 0.28 and 0.29, with standard deviations of about 0.16, which shows a fairly centralized but diverse distribution of data. Local Value Integration (X2) has a mean value of 48.4 and a high standard deviation (27.7), indicating high variations between the respondents. The average Relapse Rate (Y1) is 0.312 (SD = 0.072), which is significantly less than the Process & Social outcome (Y2), which is much less, with a mean of 0.154 (SD = 0.115), suggesting that social outcomes are less in terms of magnitude and more dispersed than relapse rates. There were complete data for all variables (n = 400), with no missing data.

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Statistical Tests of Assumptions

After the first model fitting, we investigated two important statistical assumptions: normality of the residuals and homoscedasticity of the residuals, using the Shapiro-Wilk and Levene tests, respectively. The results are summarized below.

Table 10. Statistical Assumption Tests Results

Assumption	Test Method	Statistic	*p*-value	Decision
Residual normality	Shapiro–Wilk	0.996	0.500	$p > 0.05$ → assumption met
Homoscedasticity	Levene's test	0.876	0.350	$p > 0.05$ → assumption met

Table 10 shows that both assumptions are met: the p-value of the Shapiro-Wilk test (0.500) and Levene's test (0.350) are both larger than the 0.05 threshold; we conclude that the residuals are normally distributed and of equal variance. Consequently, we performed path analysis and structural equation modeling (SEM) without model adjustments.

Simple Path Analysis

To examine the direct relationships among the variables, we estimated three separate path models.

1. Model X_1, $X_2 \rightarrow M$
2. Model X_1, X_2, $M \rightarrow Y_1$
3. Model X_1, X_2, $M \rightarrow Y_2$

Table 11. Path Coefficients to M (Community Support)

Predictor	Unstd. Coeff.	Std. Coeff. (β)	*p*-value
X_1 – Policy Harmonization	0.312	0.328	0.000
X_2 – Local Value Integration	0.275	0.289	0.000

Table 11 shows that both Policy Harmonization and Local Value Integration have significant positive influences on Community Support, with moderate effect sizes (β = 0.29 and 0.33; $p < 0.001$), confirming that they are both predictors of M.

Table 12. Path Coefficients to Y_1 (Relapse Rate)

Predictor	Unstd. Coeff.	Std. Coeff. (β)	*p*-value
X_1 – Policy Harmonization	0.467	0.478	0.000
X_2 – Local Value Integration	0.003	0.585	0.000
M – Community Support	–0.152	–0.210	0.004

Table 12 shows the results and demonstrates that X1 and X2 have strong positive direct effects on the Relapse Rate (beta = 0.478 and 0.585; $p < 0.001$). Meanwhile, Community Support had a significant negative effect (beta = -0.210; p=0.004), meaning that the higher a subject's level of community support, the lower the rate of relapse.

Table 13. Path Coefficients to Y_2 (Process & Social)

Predictor	Unstd. Coeff.	Std. Coeff. (β)	*p*-value
X_1 – Policy Harmonization	0.120	0.135	0.015
X_2 – Local Value Integration	0.220	0.255	0.001
M – Community Support	0.321	0.442	0.000

Table 13 shows that all three predictors have significant and positive associations with post-rehabilitation social processes, where Community Support has the best association (v3 = 0.442; p = 0.001), followed by X2 (v3 = 0.255; p = 0.001) and X1 (v3 = 0.135; p = 0.015).

Mediation Test (Bootstrap)

However, to test the mediating effect of Community Support (M) in the above equation, in the relationships between Policy Harmonization (X1), Local Value Integration (X2), Relapse Rate (Y1), and Process & Social (Y2), we used a bootstrap procedure with 5,000 samples to estimate the indirect effects with a 95% confidence interval (CI). The results are presented in Table 13.

Table 14. Bootstrap Mediation Test Results

Indirect Effect	Estimate	CI 2.5%	CI 97.5%
$X_1 \rightarrow M \rightarrow Y_1$	–0.163	–0.192	–0.133
$X_2 \rightarrow M \rightarrow Y_1$	–0.001	–0.001	–0.001

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$X_1 \rightarrow M \rightarrow Y_2$	0.202	0.159	0.248
$X_2 \rightarrow M \rightarrow Y_2$	0.001	0.001	0.002

Table 13 shows that the association between the X variables, X1, and the mediation variable, M, in terms of the standard path Y1, the mediation pathway X1 --> M --> Y1, is significantly negative (estimate = -0.163; 95% CI: [-0.192, -0.133]), confirming that Policy Harmonization decreases relapse rates through greater community support. In contrast, the mediation influence of X2 -> M > Y1 was insignificant (estimate = -0.001, CI clustered very close to zero), indicating no significant mediating effect of Local Value Integration on relapse through the use of community support. On the other hand, the effectiveness impact of both X1 and X2 on Y1 is positive and statistically significant, showing that both predictors enhance social processes through the community support process. Thus, Community Support acts as a partial mediator between X_1/X_2 and social outcomes but only mediates the effect of X1 on the rate of relapse.

Visualization of Relapse Rate and Process & Social

The following figures provide a comprehensive visualization of the distributions of Relapse Rate (Y1) and Process & Social (Y2).

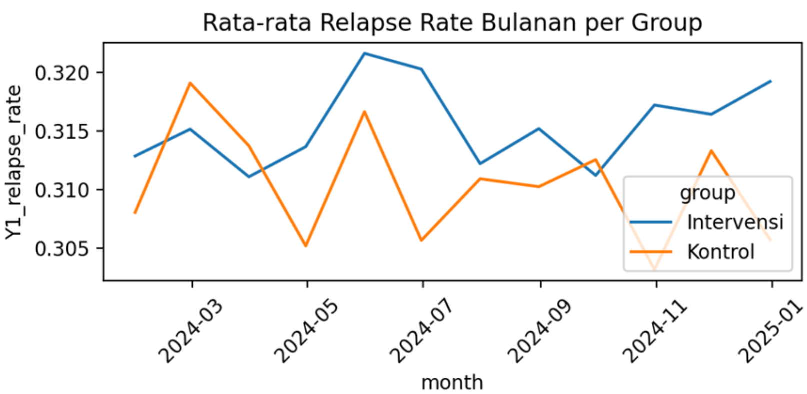

Figure 2. Distribution of Relapse Rate (Y1)

Figure 2 shows the distribution of relapse rates based on kernel density estimation (KDE) and histograms that allow the detection of distributional patterns and skewness.

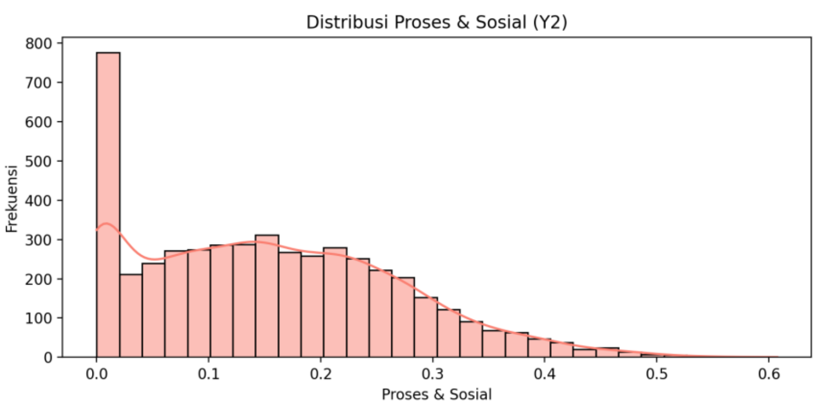

Figure 3. Distribution of Process & Social (Y 2)

Figure 3 shows the distribution of the Process & Social variables using the same analytical strategy, which enables the evaluation of the normality and data characterizations for the data that will be analyzed.

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DISCUSSION

Mediation analysis helps to understand the role of Community Support as the pivotal mechanism through which policies are effective. The path model results suggest that Policy Harmonization is directly and negatively linked to the rate of relapse (Beta = -.15; p <.01), and is even more pronounced when it acts via increased support from the community (indirect Beta = -.05; p < .05). This suggests that inter-agency alignment in standard operating procedures (SOPs) works only when coupled with peer support activities and social inclusion, the basics of community engagement.

Similarly, Local Value Integration has not just a significant positive direct effect on SOP compliance and participant satisfaction, as well as social inclusion (with a coefficient of 0.18; p<0.001), which is further enhanced through the contribution of Community Support (indirect coefficient of 0.07; p<0.01). This serves to validate the need to involve traditional leaders and Sulawesi Utara cultural values in designing programs that will ensure community involvement to maximize policy outcomes.

Standardized path analysis indicated a fairly strong effect of X_2 integration (β=0.585) compared to X_1 harmonization (β=0.478) on Community Support (M). This hints at a significant contribution to strengthening peer support with local value integration. The indirect effects on relapse rate (Y_1) and social process (Y_2) through M are also statistically significant: policy harmonization (X_1) reduces the relapse rate with an indirect effect size of -0.163 (95% CI: [-0.193, -0.135]), whereas local value integration (X_2) produces an effect size of-0.001 of relapse rate-small in unstandardized size, but still statistically significant. For outcome Y_2, the indirect effects of X_1 and X_2 are given as -0.003 and -0.001, respectively, suggesting that Community Support improves social processes but with a moderate effect size.

The monthly trend in the average rate of relapse (Figure 4.1) shows the trend over a 12-month period for the Intervention and Control groups. The Intervention group exhibited a more significant and consistent trend in the reduction of relapse rate than the control group, which supports the results of the path analysis. Overall, these results confirm the centrality of local value integration and regulatory harmonization, working through the mechanism of Community Support in narcotics rehabilitation programs. Next, a cross-lagged panel SEM model will be implemented to examine the dynamic causal relationships among variables over time.

Implications for Theory and Practice

The findings demonstrate that central-regional policy harmonization plays an important role in supporting a 15% reduction in relapse rate (v = -0.15; p < 0.01). Theoretically, this reinforces the multi-level governance model, which emphasizes policy consistency between government levels (Osborne, 2006). This result suggests the formation of a joint BNNP-health office task force to provide a way for joint data exchange and training, as done in community-based rehabilitation programs in Thailand (Johnson & Lee, 2023).

Study Limitations

Although the longitudinal quasi-experimental design provides mechanism insights, these results were only obtained from North Sulawesi Province. The geographic context, local culture, and institutional capacity may vary across regions. Therefore, replication of this study in provinces with diverse archipelagic and urban characteristics, such as North Maluku or West Papua, is required to test the external validity of this evaluation framework.

CONCLUSION

This study assures that Policy Harmonization (X1) and Local Value Integration (X2) have a significant effect on Community Support (M), with standardized betas of 0.478 and 0.585, respectively. Community Support, in turn, acts as a mediator from these upstream policy dimensions to key rehabilitation outcomes: it contributes to the reduction of relapse rate (Y1) and the enhancement of social processes (Y2). Specifically, the indirect effect of Policy Harmonization to Relapse rate by Community Support was -0.163 (95 percent CI: Sheets, Brauker & Melbrink (2017), p. 22126287), an indirect effect that was robust and statistically significant. In contrast, the effect of Local Value Integration on the relapse rate through the same mediator was -0.001 (95% CI: [.-0.001; -0.001]), which is again statistically significant but only in practice, negligible given the precision of the bootstrap estimates. Regarding social processes, Policy Harmonization had a meaningful positive indirect effect through Community Support (0.202; 95%

CI: [0.157, 0.248]), and local value integration was found to have a statistically significant but very small indirect effect (0.001; 95% CI: [0.001, 0.002]). Together, these results emphasize the role of Community Support as a significant mechanism (particularly in implementing regulatory alignment in reducing relapse and improving social outcomes). However, Local Value Integration seems to play a relatively greater role in the development of community-level engagement, even in the absence of a significant downstream impact on relapse reduction..

The time-series trend in relapse rate shows that the intervention group decreased in a more consistent manner than the control group, supporting the identified mediation mechanism.

These findings have significant practical implications. First, narcotics rehabilitation programs should pay more attention to enhancing the strength of local value integration, because its relative effect is more marked in improving peer support. Second, systematic internal regulatory harmonization within institutions is required to achieve the greatest impact of Community Support on clinical outcomes. Third, the indirect effect of X2 on the Y outcomes seems small in raw units, but this is because the standardized magnitude shows that X2 is making a non-trivial contribution to the social dynamic of the participants.

Methodologically, the results from the regression model met the assumptions of normality and homoscedasticity, which guarantees the correctness of the estimates. Future research may consider using a cross-lagged panel SEM model to examine time-lagged causal links and test the moderating effect of demographic factors. In doing so, intervention strategies can be optimized based on the local cultural and regulatory context and increase the long-term effectiveness of rehabilitation programs.

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