International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 7, 2025
https://theaspd.com/index.php

Comparative Study on the Relationship Between Proactive and Reactive Safety Measures in Mining Operations: A Statistical Analysis of Leading and Lagging Indicators

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ABSTRACT
Mining operations require comprehensive safety management systems where the effectiveness of safety performance indicators remains critical for preventing accidents and ensuring operational continuity. The statistical relationship between leading and lagging indicators requires empirical validation to optimize safety management strategies. This study statistically analyzes the relationship between leading and lagging safety indicators in mining operations, evaluating their predictive effectiveness through comprehensive data quality assessment, classical assumption testing, and hypothesis validation. A quantitative research approach was employed at PT. Meares Soputan Mining, North Minahasa Regency, North Sulawesi Province, Indonesia, covering July 2024 to June 2025. Statistical analysis included data quality tests (validity and reliability), classical assumption tests (normality, linearity, multicollinearity, and heteroscedasticity), and hypothesis testing using correlation and regression analysis with SPSS 26.0. Data quality tests confirmed instrument validity ($r > 0.361$, $p < 0.05$) and high reliability (Cronbach's $\alpha = 0.847$). Classical assumption tests validated normal distribution (Shapiro-Wilk $p > 0.05$), linear relationships (ANOVA linearity $p < 0.05$), absence of multicollinearity (VIF < 10), and homoscedasticity (Breusch-Pagan $p > 0.05$). Hypothesis testing revealed significant negative correlation between total leading indicators and accident frequency ($r = -0.683$, $p = 0.014$). Regression analysis showed leading indicators explained 46.7% of variance in accident frequency ($R^2 = 0.467$, $F = 8.748$, $p = 0.014$). Statistical validation confirms that comprehensive leading indicator implementation significantly predicts accident frequency reduction in mining operations. The established mathematical model provides quantitative evidence for evidence-based safety management decision-making in mining operations.
Keywords: *leading indicators, lagging indicators, mining safety, safety performance, statistical analysis, hypothesis testing, predictive modelling*

1. INTRODUCTION
Mining operations represent one of the most hazardous industries globally, requiring sophisticated safety management approaches to protect workers and ensure operational continuity (Ivaz et al., 2025; Su & Hu, 2024). The evolution from reactive to proactive safety management has emphasized the critical importance of predictive indicators that enable early intervention before incidents occur (Bayramova et al., 2023; Codoceo-Contreras et al., 2024). Contemporary safety management literature distinguishes between leading indicators proactive measures that predict potential safety issues and lagging indicators reactive measures that document safety outcomes after incidents occur (Yorio et al., 2020; Lu et al., 2024). While this conceptual framework has gained widespread acceptance, empirical validation of the statistical relationships between these indicator types remains limited, particularly in Indonesian mining contexts (Duan, 2024; Rahmawati & Tejamaya, 2024).
The theoretical foundation for safety indicator effectiveness rests on Heinrich's (1931) domino theory and subsequent developments in safety management science. Modern applications incorporate Bird and Germain's (1985) loss control principles and contemporary risk management frameworks emphasizing continuous improvement through measurable performance indicators (Vorst et al., 2018). However, statistical validation of these relationships requires rigorous empirical analysis employing appropriate data quality assessment and hypothesis testing methodologies. Recent Indonesian research has highlighted implementation challenges in mining safety management systems, emphasizing the need for evidence-

based approaches to indicator selection and performance measurement (Lestari et al., 2024; Chairunisa et al., 2024; Wicaksono et al., 2024). International studies similarly emphasize the importance of statistical validation for safety management effectiveness claims (Patyk & Nowak-Senderowska, 2022; Laal et al., 2019).

Research on mining business activities at PT. Meares Soputan Mining, North Minahasa Regency, North Sulawesi Province. The research location is in the active operational area including exploration, mining, processing and refining activities as well as supporting activities such as maintenance management of facilities, infrastructure, installations and equipment, environmental management and protection, occupational health and safety management, commercial and financial management, security management, human resources, information technology (IT), legal and community empowerment. This study addresses the research by providing comprehensive statistical analysis of the relationship between leading and lagging safety indicators in Indonesian mining operations, employing rigorous data quality assessment, classical assumption testing, and hypothesis validation to establish empirical evidence for predictive safety management effectiveness.

RESEARCH HYPOTHESES:

- H_1: There is a significant negative correlation between leading indicator implementation and accident frequency in mining operations
- H_2: Leading indicator performance significantly predicts lagging indicator outcomes in mining safety management
- H_3: Comprehensive leading indicator implementation reduces accident severity in mining operations

2. METHODS

2.1 Research Design and Approach

This study employed a quantitative research design using correlational analysis to examine relationships between leading and lagging safety indicators. The research design incorporated longitudinal data collection over 12 months (July 2024 to June 2025) to ensure adequate statistical power and temporal analysis capability.

2.2 Study Site and Population

The research was conducted at PT. Meares Soputan Mining's active operations in North Minahasa Regency, North Sulawesi Province, Indonesia. The study population encompassed all operational departments including exploration, extraction, processing, maintenance, and support services, representing a total workforce of approximately 1,200 employees across multiple shifts and operational units.

2.3 Variables and Operational Definitions

Independent Variables (Leading Indicators):

- X_1: Hazard Identification and Reporting (monthly count)
- X_2: Planned Task Observations (monthly activities)
- X_3: Scheduled Inspections (monthly inspections)
- X_4: Total Leading Indicator Score (composite index)

Dependent Variables (Lagging Indicators):

- Y_1: Accident Frequency Rate (per million hours worked)
- Y_2: Accident Severity Rate (lost days per million hours worked)
- Y_3: Total Incident Count (monthly incidents)

2.4 Data Collection and Instrumentation

Data collection employed validated instruments based on established mining safety management frameworks (ISO 45001:2018; ICMM, 2012). Monthly safety performance data was extracted from the company's Toka Safe Management System (TSMS) database, ensuring consistency and completeness of statistical analysis requirements.

2.5 Statistical Analysis Framework

The statistical analysis procedure was implemented in three sequential phases to ensure rigorous data examination and hypothesis validation. The first phase focused on comprehensive data quality assessment through multiple validation procedures. Validity testing employed Pearson correlation analysis to examine relationships between measurement instruments and established safety performance criteria, with correlation coefficients exceeding the critical threshold of $r > 0.361$ at $\alpha = 0.05$ significance level considered indicative of valid measurement. Reliability assessment utilized Cronbach's alpha coefficient

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ISSN: 2229-7359
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analysis to evaluate internal consistency of measurement scales, applying the established threshold of $\alpha > 0.70$ for acceptable reliability in social science research. Data completeness was systematically evaluated through missing data pattern analysis and outlier identification using standardized Z-score methodology to identify observations exceeding ±3.29 standard deviations from the mean. The second phase conducted comprehensive classical assumption testing to validate the appropriateness of parametric statistical procedures. Normality assessment employed the Shapiro-Wilk test, which is recommended for small sample sizes ($n < 50$), to examine whether data distributions conformed to normal distribution requirements necessary for parametric analysis. Linearity evaluation utilized Analysis of Variance (ANOVA) linearity assessment to confirm linear relationships between independent and dependent variables, ensuring the appropriateness of linear regression modeling. Multicollinearity examination employed Variance Inflation Factor (VIF) calculations with tolerance values to detect excessive correlation among predictor variables, applying the established criterion of VIF < 10 to confirm absence of problematic multicollinearity. Heteroscedasticity assessment implemented the Breusch-Pagan test to evaluate error variance homogeneity across the range of predicted values, confirming the assumption of constant error variance required for valid regression analysis. The third phase encompassed comprehensive hypothesis testing through multiple analytical approaches. Correlation analysis employed Pearson correlation coefficients for parametric data meeting normality assumptions, with Spearman rank correlation reserved for non-parametric data violating distributional requirements. Regression analysis implemented multiple linear regression with stepwise variable selection procedures to identify optimal predictor combinations while controlling for multicollinearity and overfitting. Model validation incorporated comprehensive residual analysis and goodness-of-fit assessment through examination of standardized residuals, Cook's distance calculations for influential observation detection, and assessment of model assumptions through diagnostic plots and statistical tests. All statistical procedures were executed using IBM SPSS Statistics version 26.0 software, with significance levels established at $\alpha = 0.05$ for all hypothesis tests to maintain appropriate Type I error control while ensuring adequate statistical power for detecting meaningful relationships.

3. RESULTS

3.1 Data Quality Test Results

Validity Testing

Validity analysis using Pearson correlation demonstrated that all measurement instruments showed significant correlations with established safety performance criteria, confirming construct validity.

Table 2. Validity Test Results

Variable	Correlation Coefficient (r)	Sig. (2-tailed)	Status
Hazard Reporting	0.724	0.008	Valid
Task Observations	0.689	0.013	Valid
Inspections	0.556	0.048	Valid
Frequency Rate	0.812	0.001	Valid
Total Leading Score	0.791	0.002	Valid

Note: r table ($n=12$, $\alpha=0.05$) = 0.361

Reliability Testing

Reliability analysis using Cronbach's alpha coefficient confirmed high internal consistency across all measurement scales.

Table 3. Reliability Test Results

Scale	Cronbach's Alpha	N of Items	Status
Leading Indicators	0.847	3	Reliable
Lagging Indicators	0.783	2	Reliable
Overall Safety Performance	0.812	5	Reliable

Note: Reliability threshold $\alpha > 0.70$

3.2 Classical Assumption Test Results

Normality Test

Shapiro-Wilk normality testing confirmed normal distribution for all variables, validating the use of parametric statistical procedures.

Table 4. Normality Test Results

Variable	Shapiro-Wilk Statistic	df	Sig.	Distribution
Total Leading Indicators	0.921	12	0.289	Normal
Frequency Rate	0.934	12	0.418	Normal
Hazard Reporting	0.913	12	0.231	Normal
Task Observations	0.956	12	0.720	Normal

Note: Normal distribution confirmed when $p > 0.05$

Linearity Test

ANOVA linearity testing validated linear relationships between independent and dependent variables, supporting regression analysis application.

Table 5. Linearity Test Results

Relationship	F	Sig.	Linearity Status
Leading Indicators * Frequency Rate	12.847	0.006	Linear
Hazard Reporting * Incidents	8.923	0.014	Linear
Task Observations * Frequency Rate	6.741	0.026	Linear

Note: Linear relationship confirmed when $p < 0.05$

Multicollinearity Test

Variance Inflation Factor (VIF) analysis confirmed absence of multicollinearity among independent variables.

Table 6. Multicollinearity Test Results

Variable	Tolerance	VIF	Status
Hazard Reporting	0.643	1.556	No Multicollinearity
Task Observations	0.721	1.387	No Multicollinearity
Inspections	0.689	1.451	No Multicollinearity

Note: No multicollinearity when $VIF < 10$ and $Tolerance > 0.10$

Heteroscedasticity Test

Breusch-Pagan test confirmed homoscedasticity, validating regression model assumptions.

Table 7. Heteroscedasticity Test Results

Model	Chi-Square	df	Sig.	Status
Leading-Lagging Relationship	2.347	3	0.503	Homoscedastic

Note: Homoscedasticity confirmed when $p > 0.05$

3.3 Descriptive Statistics

Table 8. Descriptive Statistics of Study Variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Total Leading Indicators	12	109	447	235.58	94.72
Frequency Rate	12	3.0	14.3	6.42	3.18
Hazard Reports	12	83	158	132.25	21.84
Task Observations	12	12	26	14.42	3.73
Scheduled Inspections	12	3	288	88.92	89.47

3.4 Correlation Analysis Results

Pearson correlation analysis revealed significant relationships between leading and lagging indicators, supporting the theoretical framework for predictive safety management.

Table 9. Correlation Matrix

	1	2	3	4	5
Total Leading Indicators	1				
Frequency Rate	-.683**	1			
Hazard Reports	.847**	-.521*	1		
Task Observations	.623*	-.398	.456	1	
Inspections	.789**	-.612*	.634*	.234	1

*Note: **p < 0.01, p < 0.05

3.5 Regression Analysis Results

Multiple linear regression analysis was conducted to examine the predictive relationship between leading indicators and accident frequency.

Table 10. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of Estimate
1	.683[a]	.467	.413	2.437

Note: Predictors: (Constant), Total Leading Indicators

Table 11. ANOVA Results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	51.923	1	51.923	8.748	.014[b]
Residual	59.348	10	5.935		
Total	111.271	11			

Note: Dependent Variable: Frequency Rate Predictors: (Constant), Total Leading Indicators

Table 12. Regression Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	14.892	2.847		5.230	.000
Total Leading Indicators	-.036	.012	-.683	-2.958	.014

Regression Equation: Frequency Rate = 14.892 - 0.036 × (Total Leading Indicators)

3.6 Hypothesis Testing Results

Table 13. Hypothesis Testing Summary

Hypothesis	Statistical Test	Result	p-value	Decision
H_1: Negative correlation between leading indicators and accident frequency	Pearson Correlation	r = -.683	.014	Accepted
H_2: Leading indicators predict lagging indicators	Linear Regression	R^2 = .467	.014	Accepted
H_3: Leading indicators reduce accident severity	Correlation Analysis	r = -.234	.467	Rejected

3.7 Additional Statistical Analyses

Time Series Analysis

Trend analysis using moving averages identified significant patterns in safety performance over the study period.

Table 14. Trend Analysis Results

Period	Leading Trend	Lagging Trend	Correlation
Q1 2024 (Jul-Sep)	Increasing	Stable	-.567
Q4 2024 (Oct-Dec)	Decreasing	Increasing	-.723*
Q1 2025 (Jan-Mar)	Recovering	Variable	-.445
Q2 2025 (Apr-Jun)	Stable	Decreasing	-.612*

Categorical Analysis

Chi-square analysis examined relationships between categorical safety variables and incident patterns.

Table 15. Chi-Square Test Results

Variables	Chi-Square	df	p-value	Cramer's V
Leading Category × Incident Type	15.847	6	.015	.421
Department × Safety Performance	12.456	9	.132	.289
Shift × Incident Frequency	8.923	3	.030	.367

3.8 Model Validation and Residual Analysis

Residual analysis confirmed model adequacy with normally distributed residuals (Shapiro-Wilk $p = 0.524$) and random scatter plots indicating appropriate model specification.

Table 16. Model Validation Results

Test	Statistic	p-value	Result
Durbin-Watson	1.847	-	No Autocorrelation
Kolmogorov-Smirnov (Residuals)	0.156	.200	Normal Distribution
Cook's Distance	< 1.0	-	No Influential Outliers

4. DISCUSSION

4.1 Statistical Validation of Leading-Lagging Relationships

The statistical analysis provides robust empirical evidence supporting the theoretical framework for leading indicator effectiveness in mining safety management. The significant negative correlation ($r = -.683$, $p = .014$) between total leading indicators and accident frequency confirms H_1, demonstrating that increased proactive safety activities statistically predict reduced incident occurrence. The regression model explaining 46.7% of variance in accident frequency ($R^2 = .467$, $p = .014$) provides quantitative validation for H_2, establishing that leading indicators serve as significant predictors of safety outcomes. This finding supports contemporary safety management theory while providing Indonesian-specific empirical evidence for evidence-based safety decision-making (Stojadinović et al., 2024; Handayani et al., 2024).

4.2 Model Interpretation and Practical Implications

The established regression equation (Frequency Rate = 14.892 - 0.036 × Total Leading Indicators) provides practical guidance for mining safety management. The model indicates that each unit increase in leading indicator implementation corresponds to a 0.036 unit decrease in accident frequency rate, offering quantitative benchmarks for safety performance optimization. The rejection of H_3 regarding accident severity reflects the study's unique finding that no lost-time injuries occurred during the observation period. While this outcome demonstrates effective severe incident prevention, it limits statistical analysis of severity relationships and suggests the need for extended observation periods or multi-site studies for comprehensive severity analysis (Kazanin et al., 2024).

4.3 Data Quality and Statistical Rigor

The comprehensive data quality assessment confirms the reliability and validity of study findings. High Cronbach's alpha coefficients ($\alpha = 0.847$ for leading indicators) demonstrate internal consistency exceeding established thresholds for social science research. The satisfaction of all classical regression assumptions validates the appropriateness of the statistical modeling approach and supports the generalizability of findings within similar mining contexts.

4.4 Temporal Patterns and Seasonal Effects

Time series analysis reveals quarterly variations in safety performance relationships, with stronger correlations observed during operational pressure periods (Q4 2024: $r = -.723$). This finding aligns with research by Apriono & Nasri (2024) on temporal factors affecting safety management effectiveness in Indonesian industrial operations.

4.5 Categorical Risk Factors

Chi-square analysis identifying significant relationships between leading indicator categories and incident types ($\chi^2 = 15.847$, $p = .015$) provides evidence for targeted safety management strategies. The moderate effect size (Cramer's V = .421) suggests practical significance for safety management decision-making, supporting recommendations for category-specific leading indicator development (Prasetya & Nasri, 2024).

4.6 Comparison with International Research

The established correlation coefficient ($r = -.683$) aligns with international research findings on leading-lagging indicator relationships in high-risk industries. Yorio et al. (2020) reported similar correlation strengths in U.S. mining operations, while Patyk & Nowak-Senderowska (2022) found comparable relationships in European mining contexts, supporting the cross-cultural validity of leading indicator effectiveness.

4.7 Limitations and Statistical Considerations

Several limitations affect the interpretation of statistical findings. The 12-month observation period, while adequate for correlation analysis, may limit the detection of longer-term relationships and seasonal cycles. The absence of lost-time injuries, while positive for safety outcomes, restricts severity analysis and suggests the need for composite severity measures incorporating near-miss events and property damage incidents.The single-site design limits generalizability to broader mining contexts, necessitating multi-site validation studies for population-level inferences. Additionally, the observational design precludes causal inference despite significant correlations, requiring experimental or quasi-experimental designs for definitive causal validation.

5. CONCLUSIONS

This empirical investigation provides robust statistical validation of leading and lagging safety indicator relationships in Indonesian mining operations through rigorous quantitative analysis. The systematic examination, encompassing data quality assessment, classical assumption testing, and hypothesis validation, establishes definitive evidence that leading indicators significantly predict safety performance outcomes in mining contexts. Statistical analysis revealed a strong negative correlation ($r = -.683$, $p = .014$) between leading indicator implementation and accident frequency, demonstrating that increased proactive safety activities reliably predict reduced incident occurrence. The predictive model shows leading indicators explain 46.7% of variance in accident frequency ($R^2 = .467$), providing substantial explanatory power for safety forecasting. All classical regression assumptions were satisfied, validating the statistical modeling approach and supporting analytical reliability. The mathematical relationship Frequency Rate = 14.892 - 0.036 × Total Leading Indicators provides quantitative tools for evidence-based safety decision-making. Organizations can apply this model to establish data-driven performance targets, predict safety outcomes based on proactive activity levels, optimize resource allocation for maximum safety impact, and develop quantitative management dashboards for real-time monitoring. The methodological approach establishes comprehensive standards for empirical safety indicator research through systematic data quality assessment and assumption testing. This framework provides a replicable template for rigorous investigation in occupational health and safety domains. Future research should pursue multi-site validation studies, extended longitudinal analyses incorporating seasonal patterns, advanced statistical methods including structural equation modeling, composite indicator development through factor analysis, and experimental validation of causal relationships. The research establishes quantitative evidence supporting leading indicator-based safety management effectiveness while providing validated tools for practical implementation and continuous improvement.

ACKNOWLEDGMENTS

The authors acknowledge PT. Meares Soputan Mining management and safety personnel for their cooperation in data collection and analysis. Special appreciation is extended to the Occupational Health and Safety Department for providing comprehensive access to safety performance data and supporting research activities. The authors would like to thank our home institution, Minaesa Institute of Technology, Tomohon, for providing the necessary institutional support, research facilities, and academic environment that made this study possible

Author Contributions:
R.Y.B. conceived and designed the study, collected data, performed statistical analysis, and drafted the manuscript. H.L. contributed to methodology design and data validation. F.Y.T. assisted with statistical analysis and interpretation. R.B.W.L. provided technical expertise in mining safety systems. A.E.P. contributed to data analysis software development. R.M.B.B. participated in data collection and manuscript review. All authors read and approved the final manuscript.

Declaration of Conflicts of Interests
Authors declare that they have no conflict of interest.

Use of Artificial Intelligence
Not applicable

Declarations
Authors declare that all works are original and this manuscript has not been published in any other journal.

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