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Risk-Monitoring Signals for Mining Safety Governance in Peru: Aggregate Non-Causal Associations Between Economic Activity and Occupational Accident Indicators, 2015–2024

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ABSTRACT

The objective of this study was to identify non-causal risk-monitoring signals for mining safety governance by examining monthly associations between economic activity indicators and exposure-standardized occupational accident indicators in the Peruvian mining sector from 2015 to 2024. Official data on mining exports, investment categories, occupational accidents, lost days, and hours worked were analyzed using Mann–Kendall tests, Theil–Sen slopes, false discovery rate (FDR)-adjusted Spearman correlations, lagged associations from 0 to 6 months, interquartile range (IQR)-based sensitivity checks, and a risk-monitoring classification protocol. The results showed significant increasing trends in mining exports and selected investment categories, while incident frequency, minor accident frequency, fatal accident frequency, and accident severity decreased. Spearman analysis identified 11 significant aggregate associations, all negative and mainly concentrated in incident and minor-accident indicators. The strongest associations were mining exports–incident frequency index ($\rho = -0.799$), beneficiation plant investment–incident frequency index ($\rho = -0.560$), and mining exports–minor accident frequency index ($\rho = -0.521$). Eight Class A priority review signals and three Class B targeted severity or fatality review signals were identified, while the disabling accident frequency index remained under routine monitoring. The framework supports institutional review, safety dashboards, and adaptive monitoring under an aggregate, ecological, and non-causal interpretation.

1. INTRODUCTION

Occupational safety remains a major concern in mining because hazardous work environments, complex production systems, and severe accident consequences require continuous hazard identification, risk assessment, and safety-performance monitoring [1, 2]. In mining-dependent economies, national accident indicators can support safety governance by allowing institutions to observe sector-wide safety patterns alongside changes in mining activity. However, economic activity should be interpreted only as contextual information for aggregate risk-monitoring signals, not as evidence that it directly improves or worsens safety outcomes.

Safety-indicator literature emphasizes that accident data require cautious interpretation. Lagging indicators, including injuries, near misses, and fatal events, may have monitoring value when temporal relationships are observed, but they should not be treated as direct measures of underlying system safety or causal evidence [3, 4]. Similarly, leading-indicator frameworks define safety indicators as context-dependent signals for management review rather than universal predictors of future accidents [5, 6]. In mining, operational and administrative data may support institutional review when monitoring, prediction, and causation are clearly distinguished [7].

The relationship between economic activity and occupational accidents is therefore better framed as a safety-monitoring issue than as a direct growth–safety relationship. Changes in exports or investment may coincide with shifts in production intensity, work organization, workforce demand, contractor participation, reporting practices, and safety-management workload. These conditions may affect how aggregate accident indicators behave, particularly because incidents, minor accidents, disabling injuries, fatal events, and severity measures differ in frequency, reporting sensitivity, and governance relevance. Previous evidence also suggests that reductions in total or minor accident indicators may coexist with structural or high-consequence risks [8, 9], while underreporting, severity-related reporting differences, outsourcing, contract labor, and multi-employer arrangements may further affect the interpretation of aggregate injury indicators [10-13].

Peru is a relevant setting because mining is both economically important and high risk, and official monthly data are available for mining economic activity and occupational accident indicators [14]. Nevertheless, aggregate evidence remains insufficient to determine whether exports and investment are uniformly associated with exposure-standardized accident indicators or whether different accident domains show divergent monitoring behavior.

Based on this gap, the study addressed three research questions: (i) What temporal trends characterized mining economic activity indicators and exposure-standardized occupational accident indicators in Peru from 2015 to 2024? (ii) Which aggregate associations between economic activity indicators and occupational accident indicators remained statistically significant after false discovery rate (FDR) adjustment and robustness checks? (iii) Which retained associations could be classified as risk-monitoring signals for mining safety governance under an aggregate, ecological, and non-causal interpretation?

The objective of this study was to identify aggregate, non-causal risk-monitoring signals for mining safety governance by examining temporal patterns and associations between economic activity indicators and exposure-standardized occupational accident indicators in Peru from 2015 to 2024. Non-parametric trend analysis, FDR-adjusted association testing, lag and sensitivity analyses, and a Class A, Class B, and Class C classification protocol were applied. The study contributes a safety-governance tool for interpreting official sector-level data without making causal, predictive, or company-level claims.

2. CONCEPTUAL FRAMEWORK

This study is grounded in a non-causal safety-governance framework that treats economic activity indicators as contextual sector-level information rather than direct determinants of occupational accidents. In mining, safety conditions are shaped by hazardous work environments, production intensity, workforce organization, contractor participation, reporting practices, and the effectiveness of hazard identification and risk-control processes [1, 2, 12, 13]. Therefore, changes in exports or investment may coincide with changes in the safety-management environment, but these mechanisms cannot be directly inferred from aggregate national monthly data.

The framework also distinguishes between accident indicators as lagging measures and their possible use as governance-monitoring signals. Accident frequency, severity, and fatality indicators describe events that have already occurred; however, prior safety-management research suggests that such indicators may still support institutional monitoring when interpreted cautiously and without causal or predictive assumptions [4, 5]. In this study, exposure-standardized accident indicators are therefore used to identify aggregate co-occurrence patterns that may guide governance review. This interpretation is particularly important because high-frequency indicators, disabling injuries, fatal events, and severity measures differ in reporting sensitivity, statistical stability, and consequence relevance [9, 11].

3. METHODOLOGY

3.1 Study design and data sources

The research was conducted under an aggregate, ecological, descriptive, and non-causal monthly design, aimed at examining temporal patterns and sector-level associations between economic activity indicators and occupational accident indicators in the Peruvian mining sector. The study period covered January 2015 to December 2024. The unit of analysis was the national mining sector observed by month. Therefore, all findings were interpreted as aggregate risk-monitoring patterns and not as company-level, mine-level, contractor-level, worker-level, predictive, or causal estimates.

Economic activity was represented by mining exports and five categories of mining investment. Mining exports were obtained from the Central Reserve Bank of Peru [15], while mining investment, occupational accident records, lost days, and hours worked were obtained from the Ministry of Energy and Mines [16, 17]. Economic indicators were analyzed as officially reported current USD values and were used only as contextual nominal sector-level indicators. These indicators were not adjusted for inflation, exchange-rate movements, international metal-price cycles, or real production volume.

The coverage of accident counts, lost days, and hours worked followed the reporting scope of the official MINEM series. Because the available dataset was aggregated at the national monthly level, contractor status, temporary employment, mine type, and activity-specific coverage could not be disaggregated or independently verified. Therefore, these dimensions were considered interpretation limits rather than analytical strata.

3.2 Indicator construction

Economic activity indicators were analyzed as officially reported monthly values in current USD, while occupational accident indicators were standardized per 1 million hours worked to account for monthly differences in labor exposure. This standardization allowed comparison across accident domains, including incidents, minor accidents, disabling accidents, fatal accidents, and accident-related severity burden. The analytical scope was restricted to occupational accident indicators; therefore, occupational diseases were excluded from the revised analysis and no occupational disease indicator was constructed. The operational definitions, formulas, and measurement units of the indicators are summarized in Table 1.

3.3 Data quality screening and distributional assessment

The dataset was screened for temporal completeness, duplicated monthly records, missing values, and invalid exposure denominators. Hours worked were verified to ensure that no zero or negative denominators were used in the construction of the occupational accident indicators. Unusual monthly observations were identified using the interquartile range (IQR) method. Values below $Q1 - 1.5 \times IQR$ or above $Q3 + 1.5 \times IQR$ were flagged as outliers. These observations were retained in the main analysis because they belonged to the official monthly series and were subsequently evaluated through sensitivity checks.

The distribution of each indicator was assessed using the Shapiro–Wilk test. Since most indicators departed from normality after FDR adjustment, non-parametric procedures were used for the trend and association analyses.

3.4 Trend and association analyses

Temporal trends were evaluated using the Mann–Kendall test, and the magnitude of the trend was estimated using the Theil–Sen slope. The slopes were reported as annual changes to facilitate interpretation of the monthly series. FDR adjustment was applied to account for multiple comparisons. Trend results were considered as contextual information for safety monitoring and were not interpreted as causal effects.

Aggregate economic–safety associations were estimated using Spearman's rank correlation coefficient. Each economic activity indicator was paired with each occupational accident indicator. Associations were retained when they remained statistically significant after FDR adjustment. The sign and magnitude of the coefficients were interpreted as aggregate co-occurrence patterns. Therefore, negative coefficients were not considered evidence that economic activity reduced accident risk.

Table 1. Operational definition of economic activity and occupational accident indicators

Indicator	Formula	Measurement Unit
Mining exports	Reported monthly FOB value	Current USD million
Mining investment in development and preparation	Reported monthly investment value	Current USD million
Mining investment in equipment	Reported monthly investment value	Current USD million
Mining investment in exploration	Reported monthly investment value	Current USD million
Mining investment in infrastructure	Reported monthly investment value	Current USD million
Mining investment in beneficiation plant	Reported monthly investment value	Current USD million
Incident frequency index	(Incidents × 1,000,000) / Hours worked	Incidents per million hours worked
Minor accident frequency index	(Minor accidents × 1,000,000) / Hours worked	Minor accidents per million hours worked
Disabling accident frequency index	(Disabling accidents × 1,000,000) / Hours worked	Disabling accidents per million hours worked
Fatal accident frequency index	(Fatal accidents × 1,000,000) / Hours worked	Fatal accidents per million hours worked
Accident severity index	(Lost days × 1,000,000) / Hours worked	Lost days per million hours worked

Notes: Economic activity indicators were analyzed as reported monthly values in current US dollars. Accident frequency and severity indicators were standardized per million hours worked. Hours worked was used as the exposure denominator for all accident-based indices.

3.5 Robustness and sensitivity analyses

Robustness was evaluated through three procedures. First, FDR-significant economic–safety associations were re-estimated using lagged Spearman correlations from 0 to 6 months in order to assess their temporal stability. These lagged associations were used only as a robustness screening procedure and were not interpreted as predictive or causal evidence.

Second, pair-specific IQR-based outliers were excluded, and the corresponding Spearman correlations were re-estimated. Associations were considered sensitivity-robust when both their direction and FDR-adjusted statistical significance were maintained.

Third, COVID-period sensitivity analyses were performed by excluding 2020 and, separately, by excluding 2020–2021. These analyses were conducted to determine whether the main signal classifications were retained outside the most disrupted pandemic periods. They were not designed to estimate pandemic effects or to isolate COVID-specific mechanisms.

Because monthly administrative series may be affected by serial dependence, seasonality, and delayed co-movement between economic activity and accident indicators, the FDR-significant same-month associations were complemented with lagged Spearman correlations from 0 to 6 months. These lagged analyses were used as robustness screens to assess the directional and temporal stability of aggregate risk-monitoring signals under alternative temporal alignments. They were not interpreted as causal lag effects, forecasting models, or evidence of predictive validity. Formal seasonal Mann–Kendall testing and pre-whitening procedures were not applied because the study was designed as a descriptive governance-monitoring analysis rather than an autoregressive or causal time-series model; this constraint was explicitly considered in the interpretation of the findings.

3.6 Risk-monitoring signal classification protocol for mining safety governance

A risk-monitoring signal classification protocol was developed to translate statistical outputs into a safety-engineering framework for mining safety governance. The protocol did not introduce new variables, predictive algorithms, operational thresholds, or causal assumptions. It was based only on the empirical outputs of the previous analyses, including Mann–Kendall trend direction, Theil–Sen slopes, FDR-adjusted Spearman correlations, lagged correlations, outlier sensitivity analysis, and COVID-period sensitivity checks.

The protocol was supported by safety-indicator and mining-safety literature. Operational and safety data may support managerial monitoring when they identify where institutional review is required, although this study did not apply machine-learning or predictive procedures [7]. Lagging indicators may provide monitoring value when temporal relationships are empirically observed [4], while safety indicators should remain context-dependent and connected to accident-related situations, temporal behavior, and proactive safety-management needs [5, 6]. In mining, risk assessment should progress from risk identification toward monitoring and corrective or preventive review [1]. Since aggregate administrative data do not fully capture organizational and workforce-related conditions, the signal classes were interpreted as governance-support outputs rather than deterministic explanations of accident occurrence [18].

The protocol followed five screening stages: trend-context assessment, identification of FDR-significant candidate pairs, evaluation of lag persistence from 0 to 6 months, pair-specific IQR-outlier sensitivity analysis, and final assignment to governance-review categories according to robustness, temporal persistence, and safety-consequence relevance. The resulting engineering protocol for risk-monitoring signal classification is summarized in Table 2.

Class A signals were defined as priority review signals and required FDR-adjusted statistical significance at lag 0, persistence across lags 0–6, and maintenance of both direction and statistical significance after outlier sensitivity analysis. This class was restricted to robust associations involving high-frequency accident indicators, specifically the incident frequency index and the minor accident frequency index.

Class B signals were defined as targeted severity review signals and required FDR-adjusted significance at lag 0, partial or complete lag persistence, and robustness after outlier sensitivity analysis. This class was assigned to severity-related or low-frequency high-consequence indicators, including the accident severity index and the fatal accident frequency index.

Class C signals corresponded to indicators that remained relevant for surveillance but did not meet the robustness or temporal persistence criteria for Class A or Class B. These classification rules were study-specific and were not interpreted as universal risk thresholds. Persistent negative associations were interpreted as aggregate economic–safety decoupling patterns, in which higher nominal economic activity indicators co-occurred with lower exposure-standardized occupational accident indicators, without implying that economic activity caused accident reductions.

Table 2. Engineering protocol for risk-monitoring signal classification

Stage	Engineering Screen	Statistical Input	Engineering Rule	Safety-Engineering Output
1	Trend context screening	Mann–Kendall and Theil–Sen	Identify increasing, decreasing, or non-significant monotonic patterns	Contextual trend flag
2	Association screening	Spearman correlation with FDR adjustment	Retain only FDR-significant economic–safety associations	Candidate signal pair
3	Lag persistence check	Lagged Spearman correlations, 0–6 months	Determine whether the association persists across lag structures	Temporally persistent signal
4	Outlier sensitivity check	Pair-specific IQR-outlier exclusion	Verify retained direction and FDR significance after sensitivity analysis	Robust signal
5	Governance classification	Combined evidence from Stages 1–4	Assign review category according to robustness, lag persistence, and safety-consequence relevance	Class A, B, or C risk-monitoring category

Note: FDR = false discovery rate; IQR = interquartile range. Trend evidence was used only as contextual information and was not an independent escalation criterion.

4. RESULTS AND DISCUSSION

4.1 Analytical dataset and accident indicators

The analytical dataset included monthly official records of the Peruvian mining sector for the period 2015–2024. Economic activity was represented by mining exports and five mining investment categories, while safety outcomes were restricted to occupational accident indicators, lost days, and hours worked.

The occupational accident indicators were standardized per 1 million hours worked, allowing comparison across general incidents, low-severity accidents, severe non-fatal accidents, fatal accidents, and accident-related severity burden.

4.2 Data quality and unusual monthly observations

The analytical dataset showed complete monthly coverage for the period 2015–2024, with no duplicated records, missing values, or invalid exposure denominators. Table 3 summarizes the data quality checks and the unusual monthly observations identified before the main analyses.

One negative economic value was observed in development and preparation investment in December 2017. The highest minor accident frequency index was recorded in July 2016, while the highest accident severity index was observed in June 2021. The IQR-based screening identified 36 outlier observations across economic activity and occupational accident indicators. These observations were retained because they belonged to the official monthly series and were flagged for subsequent sensitivity analysis.

4.3 Descriptive profile of economic activity and occupational accident indicators

Descriptive statistics for the 120 monthly observations are presented in Table 4. Mining exports showed the highest magnitude among the economic activity indicators, with a mean value of USD 2,732.07 million and a broad minimum–maximum range. Among the investment categories, infrastructure investment and beneficiation plant investment recorded the highest average monthly values, whereas exploration investment showed the lowest mean and the narrowest dispersion.

Hours worked averaged 39.19 million per month. Among the occupational accident indicators, the incident frequency index showed the highest central tendency, while the fatal accident frequency index remained the lowest across the series. The minor accident frequency index and the accident severity index showed the widest upper-range variability, whereas the disabling accident frequency index showed comparatively limited variability.

4.4 Distributional assessment and non-parametric rationale

The distributional assessment showed that most analytical indicators departed from normality after FDR adjustment. All economic activity indicators rejected normality. Among the occupational accident indicators, the incident frequency index, minor accident frequency index, fatal accident frequency index, and accident severity index also rejected normality, whereas the disabling accident frequency index did not.

Based on this distributional pattern, non-parametric procedures were retained for the trend and association analyses, including the Mann–Kendall test, Theil–Sen slope estimation, and Spearman correlation. Full normality diagnostics are reported in Table A1.

4.5 Temporal trends in economic activity and occupational accident indicators

The Mann–Kendall tests identified significant upward trends in mining exports, development and preparation investment, equipment investment, and beneficiation plant investment after FDR adjustment. Exploration investment and infrastructure investment did not show significant monotonic trends. Mining exports showed the largest annual Theil–Sen slope among the economic activity indicators, with an estimated increase of USD 257.99 million per year.

Among the occupational accident indicators, the incident frequency index, minor accident frequency index, and fatal accident frequency index showed significant decreasing trends. The incident frequency index had the steepest decline, with an estimated annual reduction of 16.01 incidents per 1 million hours worked. The disabling accident frequency index did not show a significant monotonic trend. The accident severity index also decreased significantly, with an annual Theil–Sen slope of −40.91 lost days per 1 million hours worked. These temporal patterns are summarized in Table 5.

The upward trends observed in mining exports and selected investment categories corresponded to officially reported nominal current USD values. Therefore, the Theil–Sen slopes for the economic activity indicators described changes in reported monetary activity only and were not interpreted as inflation-adjusted, exchange-rate-adjusted, price-cycle-adjusted, or real-volume changes.

Table 3. Data quality assessment and unusual monthly observations

Screening Component	Empirical Finding	Treatment in the Analysis
Temporal coverage	120 monthly records; 120 unique months; January 2015–December 2024	Complete monthly sequence retained
Duplicated observations	No duplicated monthly records	No correction required
Missing values	No missing values in required analytical variables	No imputation required
Exposure denominator	No zero or negative values in hours worked	All records retained for index calculation
Negative economic value	One negative value in mining investment in development and preparation, December 2017	Retained as part of the official monthly series; flagged for sensitivity analysis
Peak minor accident frequency	267.83 minor accidents per million hours worked, July 2016	Retained; flagged for sensitivity analysis
Peak accident severity	3,989.98 lost days per million hours worked, June 2021	Retained; flagged for sensitivity analysis
IQR-based outlier screening	36 outlying observations across economic activity and accident indicators	Retained in the main analysis; assessed through sensitivity checks

Note: IQR = interquartile range. Outlier screening was used to identify unusual monthly observations and did not determine record exclusion.

Table 4. Descriptive statistics of economic activity and occupational accident indicators

Indicator	Mean (SD)	Median (IQR)	Min–Max
Mining exports	2,732.07 (849.51)	2,561.93 (1,356.70)	1,180.77–4,894.57
Mining investment in development and preparation	54.80 (27.83)	50.67 (37.32)	−23.06–153.37
Mining investment in equipment	60.47 (33.10)	53.67 (37.04)	15.78–206.20
Mining investment in exploration	34.78 (13.02)	33.98 (13.54)	12.66–114.12
Mining investment in infrastructure	100.30 (42.84)	93.03 (38.65)	36.46–322.79
Mining investment in beneficiation plant	85.31 (51.13)	87.93 (79.05)	2.19–230.07
Hours worked	39.19 (5.57)	39.96 (6.62)	15.80–48.96
Incident frequency index	94.42 (50.11)	80.01 (86.10)	20.95–201.80
Minor accident frequency index	9.05 (23.95)	6.46 (2.25)	3.66–267.83
Disabling accident frequency index	2.32 (0.34)	2.36 (0.52)	1.21–3.13
Fatal accident frequency index	0.07 (0.09)	0.05 (0.06)	0.00–0.66
Accident severity index	549.03 (537.20)	460.77 (449.64)	12.97–3,989.98

Note: SD = standard deviation; IQR = interquartile range. All indicators were calculated from 120 monthly observations. Hours worked is reported in million hours for readability.

Table 5. Mann–Kendall and Theil–Sen trend estimates

Indicator	τ	FDR p	Slope/Year (95% CI)	Trend
Mining exports	0.707	<0.001	257.99 (236.07 to 279.81)	Increasing
Mining investment in development and preparation	0.401	<0.001	4.58 (3.39 to 5.98)	Increasing
Mining investment in equipment	0.263	<0.001	3.31 (1.88 to 4.92)	Increasing
Mining investment in exploration	0.083	0.221	0.47 (−0.22 to 1.15)	No significant trend
Mining investment in infrastructure	0.028	0.648	0.52 (−1.56 to 2.58)	No significant trend
Mining investment in beneficiation plant	0.329	<0.001	9.16 (6.69 to 11.45)	Increasing
Incident frequency index	−0.776	<0.001	−16.01 (−17.24 to −14.75)	Decreasing
Minor accident frequency index	−0.500	<0.001	−0.40 (−0.50 to −0.31)	Decreasing
Disabling accident frequency index	−0.075	0.246	−0.01 (−0.04 to 0.01)	No significant trend
Fatal accident frequency index	−0.214	<0.001	−0.004 (−0.006 to −0.001)	Decreasing
Accident severity index	−0.251	<0.001	−40.91 (−61.03 to −23.17)	Decreasing

Note: CI = confidence interval; FDR = false discovery rate. Theil–Sen slopes are expressed per year.

4.6 Aggregate temporal associations between economic activity and occupational accident indicators

Spearman correlation analysis identified 11 aggregate economic–safety associations that remained statistically significant after FDR adjustment. All significant associations were negative. The strongest association was observed between mining exports and the incident frequency index ($\rho = -0.799$, FDR $p < 0.001$), followed by beneficiation plant investment and the incident frequency index ($\rho = -0.560$, FDR $p < 0.001$), and mining exports and the minor accident frequency index ($\rho = -0.521$, FDR $p < 0.001$).

Significant inverse associations were mainly concentrated in the incident frequency index and the minor accident frequency index. No FDR-significant association was observed for the disabling accident frequency index. These associations are summarized in Table 6, and the complete correlation matrix is shown in Figure 1.

Table 6. Spearman correlations that remained significant after FDR adjustment

Economic Activity Indicator	Occupational Accident Indicators	ρ	Raw p	FDR p
Mining exports	Incident frequency index	−0.799	<0.001	<0.001
Mining investment in beneficiation plant	Incident frequency index	−0.560	<0.001	<0.001
Mining exports	Minor accident frequency index	−0.521	<0.001	<0.001
Mining investment in development and preparation	Minor accident frequency index	−0.461	<0.001	<0.001
Mining investment in development and preparation	Incident frequency index	−0.430	<0.001	<0.001
Mining investment in beneficiation plant	Minor accident frequency index	−0.399	<0.001	<0.001
Mining investment in equipment	Incident frequency index	−0.395	<0.001	<0.001
Mining investment in equipment	Minor accident frequency index	−0.379	<0.001	<0.001
Mining investment in beneficiation plant	Accident severity index	−0.266	0.003	0.011
Mining investment in beneficiation plant	Fatal accident frequency index	−0.227	0.012	0.035
Mining exports	Accident severity index	−0.227	0.013	0.035

Note: ρ = Spearman correlation coefficient; FDR = false discovery rate. All correlations were estimated using 120 monthly observations. Only associations with FDR-adjusted $p < 0.05$ are shown.

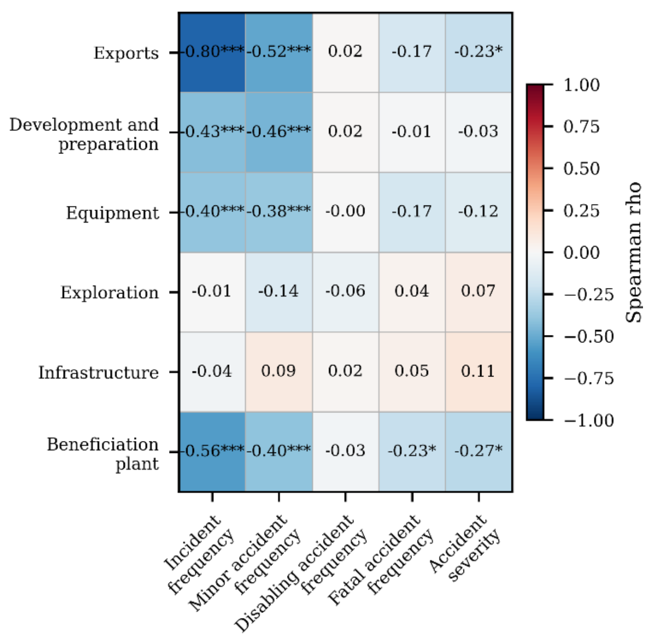

Figure 1. Heatmap of FDR-adjusted aggregate associations
Note: Cells show Spearman correlation coefficients between economic activity indicators and occupational accident indicators. Asterisks denote false discovery rate (FDR)-adjusted statistical significance: $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

4.7 Robustness checks: Lagged associations and sensitivity analysis

Lagged Spearman analyses showed that the FDR-significant same-month associations remained directionally consistent across the evaluated lag structures. All 11 associations identified at lag 0 retained negative coefficients in the robustness assessment. For the main inverse associations involving the incident frequency index and the minor accident frequency index, FDR-significant correlations persisted across lags from 0 to 6 months.

The strongest lagged coefficients were observed for mining exports and the incident frequency index at lag 0 ($\rho = -0.799$), mining exports and the minor accident frequency index at lag 6 ($\rho = -0.714$), and development and preparation investment and the minor accident frequency index at lag 6 ($\rho = -0.598$). The sensitivity analysis excluding IQR-based outliers preserved the direction of all associations and retained FDR-adjusted statistical significance for each pair summarized in Table 7. These results were interpreted as evidence of temporal and sensitivity robustness, and not as predictive or causal evidence.

4.8 Risk-monitoring signal classification for mining safety governance

The risk-monitoring signal classification protocol translated the statistical findings into three safety-governance review categories based on FDR-adjusted same-month associations, lag persistence from 0 to 6 months, and robustness after pair-specific IQR-based outlier exclusion. Trend evidence was used only as contextual information and did not determine the signal class assignment. Therefore, the retained signals were interpreted as aggregate monitoring outputs and not as causal or predictive estimates.

The classification was interpreted against a background of increasing nominal economic activity and decreasing exposure-standardized accident indicators. Mining exports, development and preparation investment, equipment investment, and beneficiation plant investment showed significant increasing trends, while the incident frequency index, minor accident frequency index, fatal accident frequency index, and accident severity index showed significant decreasing trends. All retained economic–safety signal pairs were negative and were therefore interpreted as aggregate economic–safety decoupling patterns, without implying that economic activity caused accident reductions.

Class A priority review signals were concentrated in the incident frequency index and the minor accident frequency index. The strongest Class A signal was observed between mining exports and the incident frequency index ($\rho0 = -0.799$, FDR $p < 0.001$), with significance across lags 0–6 and retained robustness after outlier exclusion. Additional Class A signals involved beneficiation plant investment, development and preparation investment, equipment investment, and mining exports in relation to high-frequency accident indicators. Overall, Class A findings indicated that the most consistent monitoring outputs were concentrated in frequent accident-prevention indicators.

Class B targeted severity review signals were identified for severity-related and low-frequency high-consequence outcomes. Mining exports and beneficiation plant investment were associated with the accident severity index, while beneficiation plant investment was also associated with the fatal accident frequency index. These signals were retained because of their consequence relevance, despite lower aggregate statistical strength. The disabling accident frequency index did not show FDR-significant economic–safety associations and was therefore retained as a Class C routine monitoring signal.

The classification matrix in Table 8 shows that the strongest risk-monitoring outputs were concentrated in high-frequency accident-prevention indicators, particularly the incident frequency index and the minor accident frequency index. Severity- and fatality-related signals were fewer and had smaller coefficients, but were retained for targeted review because of their consequence relevance. The disabling accident frequency index remained under routine monitoring, without escalation to Class A or Class B.

COVID-period sensitivity checks confirmed the stability of all Class A accident-prevention signals after excluding 2020 and 2020–2021, as shown in Table A2. Severity-related signals were largely retained; however, the beneficiation plant investment–fatal accident frequency index signal lost lag persistence after excluding 2020–2021 and was downgraded to routine monitoring, as detailed in Table A3. These findings support the robustness of the main accident-prevention signals while indicating lower temporal stability for the fatality-related signal.

Table 7. Robustness checks: lagged correlations and sensitivity analysis

Economic Activity Indicator	Occupational Accident Indicators	ρ0 (FDR p)	Sig. Lags	Max ρ (lag)	Sens. ρ (FDR p)
ME	IFI	−0.799 (<0.001)	0–6	−0.799 (0)	−0.799 (<0.001)
MIBP	IFI	−0.560 (<0.001)	0–6	−0.574 (6)	−0.560 (<0.001)
ME	MAFI	−0.521 (<0.001)	0–6	−0.714 (6)	−0.491 (<0.001)
MIDP	MAFI	−0.461 (<0.001)	0–6	−0.598 (6)	−0.380 (<0.001)
MIDP	IFI	−0.430 (<0.001)	0–6	−0.494 (6)	−0.397 (<0.001)
MIBP	MAFI	−0.399 (<0.001)	0–6	−0.520 (5)	−0.301 (0.004)
MIEQ	IFI	−0.395 (<0.001)	0–6	−0.395 (0)	−0.344 (<0.001)
MIEQ	MAFI	−0.379 (<0.001)	0–6	−0.408 (1)	−0.296 (0.006)
MIBP	ASI	−0.266 (0.011)	0–6	−0.374 (5)	−0.310 (0.003)
MIBP	FFI	−0.227 (0.036)	0, 2–6	−0.305 (5)	−0.262 (0.013)
ME	ASI	−0.227 (0.037)	0, 1, 4–6	−0.268 (6)	−0.281 (0.006)

Note: ρ_0 = same-month Spearman correlation coefficient; FDR = false discovery rate; Significant lags = FDR-significant lagged correlations across the 0–6 month period; Maximum lagged ρ = strongest lagged Spearman correlation coefficient and corresponding lag; Sensitivity ρ = correlation coefficient estimated after pair-specific interquartile range (IQR)-based outlier exclusion. ME = mining exports; MIDP = mining investment in development and preparation; MIEQ = mining investment in equipment; MIBP = mining investment in beneficiation plant; IFI = incident frequency index; MAFI = minor accident frequency index; FFI = fatal accident frequency index; ASI = accident severity index.

Table 8. Classification of risk-monitoring signals for adaptive mining safety governance

Class	Safety Domain	Indicator Pair	Statistical Evidence	Governance Response
A	Accident prevention	ME–IFI	$\rho_0 = -0.799$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIBP–IFI	$\rho_0 = -0.560$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	ME–MAFI	$\rho_0 = -0.521$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIDP–MAFI	$\rho_0 = -0.461$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIDP–IFI	$\rho_0 = -0.430$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIBP–MAFI	$\rho_0 = -0.399$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIEQ–IFI	$\rho_0 = -0.395$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
A	Accident prevention	MIEQ–MAFI	$\rho_0 = -0.379$; FDR $p < 0.001$; significant at lags 0–6	Priority institutional review
B	Severity burden	MIBP–ASI	$\rho_0 = -0.266$; FDR $p = 0.011$; significant at lags 0–6	Targeted severity review
B	Fatality surveillance	MIBP–FFI	$\rho_0 = -0.227$; FDR $p = 0.036$; significant at lags 0 and 2–6	Targeted fatality review
B	Severity burden	ME–ASI	$\rho_0 = -0.227$; FDR $p = 0.037$; significant at lags 0, 1 and 4–6	Targeted severity review
C	Severe non-fatal accidents	DAFI	No FDR-significant economic–safety association identified	Routine monitoring

Note: ME = mining exports; MIDP = mining investment in development and preparation; MIEQ = mining investment in equipment; MIBP = mining investment in beneficiation plant; IFI = incident frequency index; MAFI = minor accident frequency index; DAFI = disabling accident frequency index; FFI = fatal accident frequency index; ASI = accident severity index. FDR = false discovery rate. Class A = priority review signal; Class B = targeted severity review signal; Class C = routine monitoring signal. Priority review refers to institutional analytical review of aggregate patterns and does not imply automatic operational intervention.

4.9 Interpretation of divergent occupational accident patterns

The aggregate findings should not be interpreted as uniform evidence of safety improvement across all accident domains. Although the incident frequency index, minor accident frequency index, fatal accident frequency index, and accident severity index decreased during 2015–2024, the disabling accident frequency index showed no significant monotonic trend and no FDR-significant economic–safety association. This indicates divergent signal behavior across accident strata: high-frequency indicators generated the most robust monitoring signals, severity- and fatality-related indicators generated weaker but consequence-relevant signals, and disabling accidents remained under routine monitoring. Similar patterns have been reported in mining contexts where reductions in total accident counts may coexist with persistent structural risks and high-consequence hazards [8].

This divergence may reflect differences in event frequency, reporting sensitivity, and classification stability. Incident and minor-accident indicators are more frequent and may respond more visibly to reporting practices or safety routines, whereas disabling, fatal, and severity-related outcomes are less frequent and more vulnerable to monthly instability. Since underreporting remains a persistent problem in occupational safety research [9], reductions in frequent indicators should not be assumed to indicate equivalent reductions in severe or disabling risk.

Operational factors may also distribute risk unevenly across the workforce. Production pressure, subcontracting, and multi-employer arrangements can concentrate hazardous tasks among groups not identifiable in national aggregate data. Contract labor has been associated with poorer occupational health and safety outcomes in mining [12], while broader labor-market pressures may influence severe occupational events [19]. Therefore, the absence of company-, mine-, contractor-, and worker-level data limited direct interpretation of these mechanisms.

From a governance perspective, the Class A, Class B, and Class C categories reflect different levels of aggregate statistical stability and monitoring use, not a hierarchy of safety importance. Thus, reductions in frequent indicators are compatible with, but do not demonstrate, equivalent improvement in severe, disabling, or fatal risk, consistent with prior work emphasizing association rather than causation in mining safety and economic contexts [20].

4.10 Implications for mining safety governance

The proposed risk-monitoring signal framework translates aggregate statistical results into structured safety-governance review categories. It was not designed to predict accidents, establish causal effects, or activate automatic enforcement actions, but to support institutional review, adaptive monitoring, and safety-management decision support. Class A signals indicate priority institutional review, Class B signals indicate targeted severity or fatality review, and Class C signals indicate routine monitoring. This interpretation is consistent with safety-indicator approaches in which indicators are used as guiding signals rather than absolute measures of safety performance [5].

From a practical perspective, the framework may support an aggregate mining safety dashboard. Class A signals may prioritize review of frequent accident-control routines, reporting completeness, and inspection planning, whereas Class B signals may guide verification of severity- and fatality-related controls. Class C indicators should remain visible to detect future changes in trend direction, lag persistence, or sensitivity behavior. This approach is aligned with safety-management models emphasizing hazard identification, control verification, and continuous monitoring [2, 6].

The framework may also guide inspection prioritization and contractor-risk monitoring. Since mining safety governance is shaped by outsourcing, subcontracting, and multi-employer arrangements [13], and the aggregate data did not identify contractor status, subcontracting intensity, mine-level exposure, or worker-level conditions, the signals should be interpreted as prompts for further review rather than definitive evidence of risk concentration. Persistent high-frequency signals may justify review of reporting systems and preventive controls, whereas severity or fatality signals may justify verification of critical controls, emergency preparedness, contractor supervision, and high-consequence hazard management [21, 22].

Economic indicators should be incorporated cautiously. Mining exports and investment categories were analyzed as nominal current-USD sector-level indicators, not as real production measures or causal determinants of safety outcomes. Thus, inverse aggregate associations should be interpreted as economic–safety co-occurrence patterns that contextualize monitoring, not as evidence that economic growth, exports, or investment reduced occupational accidents [23, 24].

4.11 Limitations of aggregate risk-monitoring interpretation

Several limitations define the scope of this study. First, the design was ecological, aggregate, descriptive, and non-causal. The unit of analysis was the national mining sector observed by month; therefore, the findings cannot be attributed to mines, companies, contractors, supervisors, or workers. No multivariable causal model was estimated, and the analysis did not adjust for company-level factors, mine type, contractor status, inspection intensity, workforce composition, subcontracting intensity, or price- and volume-adjusted economic activity. Economic indicators were analyzed as officially reported current USD values rather than as real production or investment measures. This is relevant because economic–safety relationships may be complex, non-linear, and influenced by mechanisms not captured in aggregate administrative data [25].

Second, occupational accident indicators were derived from administrative records, which may be affected by underreporting, reporting culture, classification rules, and changes in recording practices. Mining injury information may be under-reported [26], and the magnitude of underreporting may vary according to the measurement approach [11] and injury severity [10]. Accordingly, incident and minor-accident indicators may be more sensitive to reporting variation than fatality indicators.

Third, the official databases were not designed as an integrated safety-governance dataset. Their completeness, comparability, and classification consistency over time could not be independently audited. In addition, lagging indicators capture realized outcomes and should not be treated as direct measures of underlying system safety [3]. Although lagged correlations from 0 to 6 months were used to examine the temporal stability of the retained aggregate associations, the analysis did not formally remove serial dependence or seasonal structure through pre-whitening, seasonal Mann–Kendall testing, or autoregressive modelling. Consequently, the reported associations should be interpreted as descriptive risk-monitoring signals rather than independent time-series effects, causal lag structures, or predictive relationships.

Finally, COVID-period sensitivity checks supported the stability of the main Class A signals; however, they were not designed to identify pandemic-specific mechanisms. Overall, the results should be interpreted as aggregate risk-monitoring signals for governance review, not as causal explanations or comprehensive measures of safety-system performance.

5. CONCLUSIONS

This study examined aggregate monthly associations between mining economic activity indicators and exposure-standardized occupational accident indicators in Peru from 2015 to 2024 under an ecological, descriptive, and non-causal framework. Its main contribution was the development of a risk-monitoring classification framework that translates national-level statistical patterns into governance-oriented review categories.

The most consistent monitoring signals were concentrated in the incident frequency index and the minor accident frequency index, whereas severity- and fatality-related indicators generated fewer but still governance-relevant signals. The disabling accident frequency index did not meet escalation criteria and remained under routine monitoring. Therefore, reductions in frequent accident indicators should not be interpreted as uniform improvement across all accident-severity domains.

The proposed Class A, Class B, and Class C framework may support aggregate safety dashboards, institutional review, inspection planning, reporting-quality audits, and severity surveillance. Economic indicators were used only as contextual nominal sector-level information, and the inverse associations observed should be interpreted as aggregate co-occurrence patterns, not as evidence that exports, investment, or economic expansion reduced occupational accidents. Future research should apply this framework to disaggregated mine-, company-, contractor-, geographic-, and workforce-exposure data, incorporating price-adjusted economic measures, inspection and enforcement indicators, reporting-quality metrics, and multivariable time-series approaches.

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APPENDIX

Table A1. Normality diagnostics for economic activity and occupational accident indicators

Indicator	Skewness	Kurtosis	Shapiro–Wilk W	FDR-Adjusted p-Value
Mining exports	0.32	−0.76	0.973	0.016
Mining investment in development and preparation	0.72	1	0.956	0.001
Mining investment in equipment	1.69	4.04	0.869	<0.001
Mining investment in exploration	2.16	11.2	0.859	<0.001
Mining investment in infrastructure	1.9	6.15	0.864	<0.001
Mining investment in beneficiation plant	0.41	−0.06	0.957	0.001
Incident frequency index	0.52	−1.10	0.907	<0.001
Minor accident frequency index	10.78	117.38	0.116	<0.001
Disabling accident frequency index	−0.36	0.64	0.981	0.096
Fatal accident frequency index	4.66	28.12	0.575	<0.001
Accident severity index	3.87	21.48	0.671	<0.001

Note: Normality was assessed using the Shapiro–Wilk test with false discovery rate (FDR) adjustment. All indicators were assessed using 120 monthly observations. FDR-adjusted p-values below 0.05 indicate evidence of departure from normality.

Table A2. COVID-period sensitivity of risk-monitoring signal classes

Scenario	n	Trend Flag	Class A	Class B	Class C
Full	120	Main retained	8	3	0
Excl. 2020	108	Main retained	8	3	0
Excl. 2020–2021	96	Main retained; exploration ↑	8	2	1

Note: Class A = priority review signal; Class B = targeted severity review signal; Class C = routine monitoring signal. Trend flag summarizes whether the main trend pattern was retained after excluding the COVID-19 period.

Table A3. Sensitivity of severity-related risk-monitoring signals

Signal Pair	Full	Excl. 2020	Excl. 2020–2021	Interpretation
MIBP–ASI	B	B	B	Retained
ME–ASI	B	B	B	Retained
MIBP–FFI	B	B	C	Less stable

Note: ME = mining exports; MIBP = mining investment in beneficiation plant; ASI = accident severity index; FFI = fatal accident frequency index. A = Class A; B = Class B; C = Class C.