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A Data-Driven Approach to Mitigating ESG Risks in Rare Earth Mineral Supply Chains

AKASH KUMAR
MBA Business Analytics, CHRIST (Deemed to be University), Pune, India

Abstract- The global shift toward clean energy and digital technology has made rare earth minerals critical to modern supply chains. Despite their importance, existing ESG assessment tools remain inadequate: corporate sustainability reports systematically underreport negative incidents, and major ESG rating agencies exhibit an average inter-agency correlation of only 0.54. This paper develops and validates a data-driven analytical framework using machine learning (ML) and natural language processing (NLP) to automatically detect, classify, and score ESG risks in rare earth mineral supply chains. Applied to a corpus of approximately 840 documents from five major rare earth producers across Australia, the USA, and China (2015–2025), the fine-tuned BERT classifier achieves an F1-score of 0.84. The framework detects ESG controversies an average of 127 days earlier than rating agency updates, reveals a 23.5-point composite ESG risk score gap between Chinese and Western producers, and confirms financial materiality with −3.2% average abnormal returns following controversy disclosure. All four research hypotheses are statistically supported. The study contributes a validated, sector-specific framework for investors, procurement managers, and regulators seeking improved ESG transparency in critical mineral supply chains.

Index Terms-Rare earth minerals; ESG risk; machine learning; natural language processing; supply chain transparency; BERT; critical minerals; sustainable supply chain.

I. INTRODUCTION

Rare earth minerals are a group of 17 metallic elements essential to electric vehicle motors, wind turbine generators, smartphone displays, precision defence systems, and medical imaging equipment. As global economies accelerate the transition toward clean energy, demand for these critical minerals is projected to grow by up to 600% by 2040 under net-zero scenarios [1]. China currently accounts for approximately 60% of global rare earth mining output and over 85% of processing capacity [2], creating both geopolitical vulnerabilities and deep ESG challenges that remain largely invisible to investors and procurement managers who rely on corporate sustainability disclosures.

The ESG challenges across rare earth supply chains are severe. Environmental risks include radioactive waste contamination, acid mine drainage, and greenhouse gas emissions. Social risks encompass labour rights violations, community displacement, and occupational health hazards. Governance risks include regulatory opacity, export restriction leverage, and documented corruption in licensing systems. Yet the tools stakeholders use to assess these risks are fundamentally inadequate. ESG rating agencies produce contradictory assessments with an average inter-agency Spearman correlation of only 0.54, compared to 0.99 for credit rating agencies assessing the same firms [3]. Annual update cycles create temporal gaps of six to eighteen months in risk recognition.

This paper addresses these gaps by developing a multi-source, machine learning-based ESG risk detection framework explicitly designed for rare earth supply chains. The framework integrates corporate sustainability reports, government regulatory filings, NGO investigations, and global news media to produce ESG risk assessments that are more accurate, more comprehensive, and significantly more timely than existing methodologies allow.

II. LITERATURE REVIEW AND RESEARCH GAP

A. Inadequacy of Current ESG Assessment Methods

Frameworks such as GRI, SASB, and TCFD provide standardised templates for corporate ESG disclosure, but these are voluntary, self-reported, and unable to distinguish genuine performance from skilled impression management. Berg et al. [3] decomposed inter-agency divergence and found 56% attributable to measurement differences and 38% to scope differences. Cho et al. [4] documented "organised hypocrisy" across hundreds of corporations a systematic pattern where sustainability reports emphasise positive achievements while underreporting negative incidents. Marquis et al. [5] confirmed that negative social incidents are disproportionately obscured compared to environmental metrics, which benefit from greater regulatory standardisation.

B. AI and NLP in ESG Analysis

The application of ML and NLP to ESG analysis is a rapidly growing research area. Li et al. [6] showed that ML models can predict corporate ESG controversies from disclosure text with 73% accuracy. Bauer et al. [7] demonstrated that fine-tuned BERT classifiers outperform general-purpose models for ESG controversy classification, particularly for governance-related content. Luo et al. [8] found that environmental themes account for approximately 60% of sustainability report content, motivating the multi-source approach adopted here: AI systems trained only on corporate documents will amplify rather than correct disclosure bias. Despite this progress, no existing framework specifically addresses the ESG risk profile of rare earth supply chains, which differs significantly from other industries in its radioactive waste characteristics, geopolitical concentration, and multi-jurisdictional governance structure.

III. RESEARCH METHODOLOGY

A. Research Design and Scope

This study uses a mixed-methods design with a primarily quantitative focus, grounded in a post-positivist philosophical stance. The study covers five major rare earth producers across three regulatory jurisdictions over a ten-year period (January 2015–December 2025): Lynas Rare Earths (Australia, ASX:LYC), MP Materials (USA, NYSE:MP), China Northern RE Group (China, SHA:600111), Shenghe Resources (China, SHA:600392), and Iluka Resources (Australia, ASX:ILU). Together they represent 38–42% of global rare earth production capacity outside China's many smaller producers. The analytical focus is on upstream supply chain stages mining, beneficiation, and primary processing where ESG risks are most concentrated.

B. Data Sources and Credibility Weights

The framework integrates five secondary data source categories: corporate sustainability reports (credibility weight C=0.6; n=50 reports), regulatory filings from SEC, ASX, CSRC, and MEP (C=0.9; n=120–150 filings), news media via Factiva and LexisNexis (C=0.7; n=500–600 articles), NGO investigation reports (C=0.8; n=30–50 reports), and ESG rating databases (MSCI, Sustainalytics, Refinitiv) used for validation. The total corpus comprised approximately 840 documents. Credibility weights reflect source independence and legal accountability.

C. Data Preprocessing Pipeline

Raw documents were processed through a five-stage pipeline: (1) text extraction using PyPDF2 and pdfplumber with normalisation of company name variants; (2) language standardization Chinese-language documents translated via Google Translate API with manual verification of rare earth terminology; (3) Named Entity Recognition using spaCy to identify organisations, locations, dates, and monetary figures; (4) two-stage sentiment analysis using VADER followed by FinBERT [9]; and (5) feature engineering computing ESG keyword density, negative sentiment co-occurrence scores, source credibility scores, and temporal proximity weights.

D. Machine Learning Model Development

Five algorithms were trained on a 500-paragraph manually labelled dataset (150 Environmental, 150 Social, 100 Governance, 100 Neutral) using a stratified 70/15/15 train/validation/test split with five-fold cross-validation: Support Vector Machine (SVM), Random Forest, XGBoost, Long Short-Term Memory (LSTM), and fine-tuned BERT. Inter-rater reliability for labelling was verified at Cohen's $\kappa = 0.74$ (substantial agreement). The target classification threshold was F1-score > 0.80, following [6] and [7].

E. ESG Risk Scoring Formula

The composite ESG risk score for each incident is computed as:

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ESG Risk Score = S × F × C × R

where S = Severity (1–5 ordinal scale), F = Frequency (1.0/1.5/2.0 for single/2–5/6+ occurrences), C = source credibility weight (Table I), and R = exponential recency decay R = e^(−0.1 × months ago). Raw scores are aggregated per company and normalised to a 0–100 composite scale for cross-company comparison.

IV. RESULTS AND ANALYSIS

A. ESG Risk Taxonomy: Frequency and Severity

Systematic analysis of the 840-document corpus identified 740 substantive ESG incidents across the five sample companies. Environmental incidents accounted for the largest share at 47% (n=348), driven primarily by radioactive and toxic waste management failures (20.0%, avg. severity 3.9/5) and water and soil contamination (17.8%, avg. severity 3.7/5). Social incidents accounted for 34% (n=251), with labour rights violations the most frequent sub-category (16.8%, n=124). Governance incidents constituted 19% (n=141), but corruption and business ethics incidents carried the highest average severity of any sub-category (4.2/5.0), indicating that while governance failures occur less frequently, they tend to be more materially serious. All three ESG dimensions showed an equal grand mean severity of 3.5/5.0.

B. Machine Learning Model Performance

Table I presents model performance results across five-fold cross-validation. The fine-tuned BERT model achieved the best overall performance (F1=0.84, Accuracy=92.1%), exceeding the research target of F1>0.80. LSTM ranked second (F1=0.81), followed by XGBoost (F1=0.78), SVM (F1=0.76), and Random Forest (F1=0.72). Feature importance analysis revealed that source type is the single most powerful predictor of ESG risk classification: regulatory filing sources consistently generate higher predicted risk scores than corporate report sources for equivalent incident content, directly validating the legitimacy theory prediction [4].

Table I Ml model performance (5-fold cross-validation)

Algorithm	Precision	Recall	F1-Score	Accuracy
BERT (Fine-Tuned)	0.86	0.83	0.84	92.1%
LSTM	0.83	0.80	0.81	89.4%
XGBoost	0.80	0.76	0.78	87.2%
SVM	0.78	0.74	0.76	85.8%
Random Forest	0.75	0.70	0.72	83.6%

C. Correlation Analysis

Spearman correlation analysis of 50 company-year observations (all significant at $p < 0.01$) revealed that environmental risk shows the strongest correlation with composite ESG scores ($\rho = 0.81$), followed by social risk ($\rho = 0.54$) and governance risk ($\rho = 0.48$). Fisher's Z-transformation confirmed that the environmental correlation significantly exceeds social and governance correlations ($Z = 4.17$, $p < 0.001$), supporting H2. Environmental risk also showed the strongest association with supply disruption risk ($\rho = 0.73$), though governance risk demonstrated a notably elevated correlation ($\rho = 0.62$), reflecting the role of regulatory enforcement actions in triggering operational disruptions.

D. Company-Level ESG Risk Scores

China Northern RE Group received the highest composite ESG risk score (66.9/100), with elevated readings across all three dimensions particularly social risk (62.8) and governance risk (58.1). MP Materials (USA) received the lowest composite score (37.2), reflecting the stronger regulatory transparency framework of US-listed companies. The average composite ESG risk score gap between Chinese producers (64.2) and Western producers (40.7) is 23.5 points statistically significant (ANOVA: $F=14.8$, $p<0.001$) and practically meaningful for supply chain risk management. Chinese companies scored 18.0 points higher on environmental risk, 25.7 points higher on social risk, and 29.6 points higher on governance risk than their Western peers. Validation against established rating agencies showed Spearman correlations of $\rho=0.65$–0.71 with MSCI ESG ratings and $\rho=0.61$–0.66 with Sustainalytics for Western companies, exceeding the convergent validity target of $|\rho| > 0.60$. Critically, AI scores were consistently higher for Chinese companies (16–19 points above agency scores), confirming that established rating

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agencies systematically underestimate ESG risk in jurisdictions where English-language disclosure is limited.

E. Hypothesis Testing Results

All four research hypotheses were supported by statistically significant evidence. H1 (Temporal Advantage): The framework detected ESG controversies an average of 127 days before corresponding rating agency score adjustments (paired t-test: $t=8.43$, $p<0.001$), exceeding the 90-day threshold and achieving a 91% controversy detection rate vs. ~62% for agency reviews. H2 (Disclosure Bias): Environmental risk indicators showed significantly stronger correlation with composite ESG scores than social or governance indicators (Fisher's $Z=4.17$, $p<0.001$). H3 (Financial Materiality): Event study analysis across 22 major controversy events found a mean abnormal stock return of −3.2% in the 30-day post-disclosure window ($t=2.67$, $p<0.05$). H4 (Geographic Transparency Gap): Chinese producers carried composite ESG risk scores 23.5 points higher than Western peers but with significantly lower transparency ratings (ANOVA $F=14.8$, $p<0.001$).

V. DISCUSSION

The finding that the data-driven framework detects 35–45% more ESG risk than corporate disclosures alone indicates is consistent with legitimacy theory [4]: organisations shape disclosures to maintain public trust rather than to achieve full transparency. What is significant here is the magnitude of the gap not a marginal measurement difference but a systematic underestimation large enough to mislead decision-makers with real financial, reputational, and operational consequences.

The environmental frequency dominance (47%) reflects two overlapping factors: environmental impacts from rare earth mining are genuinely severe and difficult to conceal, and environmental disclosure is more standardised and legally required than social or governance reporting. The result is that social risks labour violations, community displacement, health impacts and governance risks corruption, regulatory opacity, export restriction leverage are systematically underweighted in current ESG scores despite being, in many cases, equally or more serious per incident.

The 23.5-point composite ESG risk score gap between Chinese and Western producers is the most practically significant finding from a supply chain management perspective. Any organisation sourcing rare earth minerals from Chinese producers directly or through intermediaries is carrying a substantially higher ESG risk profile than standard rating agency assessments indicate. For companies subject to the EU CSDDD, US UFLPA, or Australia's Modern Slavery Act, this is not merely a reputational concern but a potential compliance liability.

VI. CONCLUSION

This paper developed, implemented, and validated a data-driven analytical framework for detecting, classifying, and mitigating ESG risks in rare earth mineral supply chains. All four research hypotheses were confirmed. The fine-tuned BERT classifier achieved F1=0.84. The framework provides a 127-day early warning advantage over rating agencies. Chinese producers carry 23.5 points higher composite ESG risk than Western peers but are systematically underestimated by agencies. Higher ESG risk scores predict −3.2% average abnormal returns following controversy disclosure.

Practical recommendations are: (1) Corporate procurement teams should adopt multi-source ESG monitoring and apply enhanced due diligence for Chinese suppliers; (2) Investors should integrate AI-generated risk scores alongside traditional ratings and leverage detection lead time for portfolio positioning; (3) Regulators should adopt AI-based monitoring for supply chain due diligence verification and extend mandatory ESG reporting to upstream extraction stages; (4) ESG rating agencies should increase weighting of non-corporate data sources and address geographic bias against non-English disclosure.

Future research should extend this framework to other critical minerals (lithium, cobalt, nickel), develop multilingual NLP models for Mandarin and Bahasa Indonesia, integrate real-time satellite and social media data streams, and apply blockchain-based traceability for tier-level ESG risk mapping.

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