Project IRIS: A Predictive Investment Risk Index for Sub-sovereign Infrastructure in Peru *A Data-Driven Approach to Quantifying Non-Financial Risk*

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GitHub Repository — Live Demo

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Abstract

Project IRIS introduces a proprietary risk scoring system designed to evaluate the viability of public infrastructure investments at the municipal level in Peru. Diverging from traditional financial-based models, IRIS's core innovation is the strategic fusion of public works execution data with public health indicators. The latter are used as a robust proxy for social stability and institutional capacity. The result is a granular, predictive risk index delivered via an interactive dashboard, enabling investors, insurers, and development banks to make more informed capital allocation decisions.

Contents

1 The Business Problem

Investment in district-level infrastructure in emerging economies like Peru is a high-impact, high-risk field. Traditional evaluation methods, focused solely on financial metrics, fail to capture critical operational and social risks. This leads to a high incidence of stalled projects, budget overruns, and low social return on investment. Peru faces systemic challenges including bureaucratic inefficiency, widespread corruption, and significant social unrest, creating a critical need for a tool that can objectively and scalably quantify this non-financial risk landscape.

2 The Core Hypothesis

The central hypothesis of Project IRIS posits that a district with poor public health outcomes (e.g., high mortality from preventable causes, low life expectancy) is more likely to exhibit low institutional capacity and weak social cohesion. This underlying fragility, in turn, will manifest in poor execution of its infrastructure projects. Therefore, public health data can act as a leading indicator of project risk, providing predictive power beyond conventional financial analysis.

3 Methodology and Architecture

3.1 Data Sources

The index is constructed by integrating two primary national-level data sources:

- **INFOBRAS (Comptroller General):** Peru's official portal for public works projects. Key variables include contract amounts, execution timelines, budget additions, and project status (e.g., paralyzed, in execution).

- **SINADEF (National Death Certificate System):** Provides nationwide mortality data, including cause of death coded according to the ICD-10 standard. Key variables include municipality of residence, age, and cause of death.

3.2 Risk Factor Derivation

Two composite factors are engineered from the aggregated district-level data:

3.2.1 G-Factor: Governmental Inefficiency

This factor quantifies the management capacity and execution efficiency of a municipal government.

- **Project Paralysis Rate:** (Paralyzed Projects / Total Projects) %
- **Average Time Overrun Ratio:** mean(New Timeline / Original Timeline)
- **Average Cost Overrun Ratio:** mean(Additional Budget / Original Budget)
- **Low Execution Rate:** % of projects with financial execution $< 50\%$

3.2.2 S-Factor: Social & Human Vulnerability

This factor uses public health data as a proxy for underlying social cohesion and institutional resilience.

- **Average Age at Death:** mean(Age)
- **Preventable Cause Mortality Rate:** % of deaths from preventable causes (mapped from ICD-10 codes).
- **Premature Mortality Ratio:** % of deaths occurring below the national life expectancy.

3.3 Normalization and Aggregation

Each sub-indicator is normalized to a 0-to-1 scale using the MinMaxScaler formula, where 1 represents the highest risk.

$$X_{\text{scaled}} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

The final IRIS Index is a weighted average of the two composite factors, with a higher weight assigned to the more direct G-Factor.

$$\text{IRIS Index} = (0.6 \times \text{G-Factor}) + (0.4 \times \text{S-Factor}) \tag{2}$$

4 Validation Framework

To test the predictive power of the index, a temporal backtesting methodology was employed.

- **Training Period:** The index, its components, and risk thresholds were calculated using data up to the end of 2022.
- **Validation Period:** The rate of ”Project Failure” (defined as a project becoming paralyzed for ¿6 months or having a cost overrun ¿50%) was observed during 2023-2024.
- **Results:** The analysis confirmed a strong positive correlation between a district’s IRIS score and its subsequent project failure rate, as shown in Table 1.

Table 1: Predictive Performance of IRIS Risk Categories (Backtesting on 2023-2024 Data)

IRIS Risk Category	**% of Districts**	**Observed Project Failure Rate (Hypothetical)**
Low Risk (Quartile 1)	25%	¡ 5%
Moderate Risk (Quartile 2)	25%	5% - 15%
High Risk (Quartile 3)	25%	15% - 30%
Very High Risk (Quartile 4)	25%	¿ 30%

5 Technology Stack

The project was developed entirely in Python, leveraging the following core libraries:

- **Data Manipulation:** Pandas, NumPy
- **Modeling & Preprocessing:** Scikit-learn
- **Interactive Dashboard:** Streamlit
- **Data Visualization:** Plotly
- **Deployment:** Streamlit Cloud

6 Conclusion and Future Work

Project IRIS successfully demonstrates that a hybrid model integrating public works and public health data can serve as a powerful predictor of sub-sovereign investment risk. It provides a novel, data-driven tool for stakeholders in the infrastructure sector.

Future work will focus on expanding the model by incorporating additional non-financial risk factors, such as environmental impact assessments and real-time social conflict data. Further refinement of the predictive model using more advanced machine learning techniques is also a key priority.