DelaySense: Project Delay/Success Prediction

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The Challenge of Project Delays

The Problem:

- Development projects often run months or years behind schedule
- Delays disrupt planning, staffing, budgeting, and mission timelines
- Teams rely on reactive monitoring — risks are identified only after delays occur
- Stakeholders need **predictive insight**, not post-mortems

Traditional Approach Limitations:

- Manual assessments are subjective and inconsistent
- Simple "delayed / on time" labels are not actionable
- Hard to detect patterns across **1.5M+ historical projects**
- No ability to forecast **exact completion dates**

Our Solution

- Machine learning models that predict **actual completion dates**, not just risk labels
- Early-warning signals for potential delays
- Ability to experiment with scenarios and understand what improves timelines

Success Criteria

- Accurate predictions
- Clear risk assessment
- Interactive scenario testing
- Fast

Datasets

Two independent ML models: AidData & IEG

AidData Dataset

- ~630,000 development projects
- Operational and financial attributes
- Donor, sector, region, project cost, start/end dates
- Suitable for predicting **exact completion dates**

IEG Dataset

- Evaluated World Bank projects
- Institutional and performance attributes
- Supervision quality, M&E ratings, lending instrument, approval FY
- Suitable for predicting **completion year**

Why Two Models?

- Each dataset requires **its own features, its own modeling pipeline, and its own predictor**
- A single model would not generalize across both datasets
- Therefore, we trained **two independent ML models**

Dataset 1- AidData

Goal: Predict *exact* project completion **date** and flag potential delays

Key features:

- Donor, recipient country, region
- Sector / purpose classification
- Commitment amount & total project cost
- Start date, proposed end date, commitment date
- Implementing & financing agencies

Outputs:

- Predicted completion **date**
- Schedule residual (proposed − model prediction)
- Delay-risk categories: **early_closure, on_schedule, delayed_closure, significantly_delayed**

Link for the dataset:

https://www.aiddata.org/data/aiddata-core-research-release-level-1-3-1

Dataset 2- IEG World Bank Project Data

Goal: Predict *exact* project completion **year** and flag potential delays

Key features:

- World Bank region
- Practice group and global practice
- Agreement type
- Lending instrument type
- Country lending group
- Implementing agency
- Project name and approval fiscal year
- Quality ratings: quality at entry, quality of supervision, bank performance, M&E quality

Outputs:

- Predicted completion **year**
- Deviation from expected timeline (delay signal)
- Model supports simplified delay interpretation due to year-only granularity
- Delay-risk categories: **early_closure, on_schedule, delayed_closure, significantly_delayed**

Link for the Dataset:

https://financesone.worldbank.org/ieg-world-bank-project-performance-ratings/DS00053

Model Training Pipeline

Data Preparation

We preprocess each dataset separately — cleaning fields, engineering duration targets, encoding categorical variables, and standardizing date information.

Model Training

Each dataset (AidData and IEG) is trained on **four models**:

- Linear Regression
- Random Forest
- XGBoost
- Neural Network

Model Selection

For each dataset, we evaluate all four models and **choose the one with the lowest MAE**.
This best-performing model becomes the final predictor.

Result

Two optimized models — one for AidData, one for IEG — each selected objectively based on error performance.

Risk Assessment with Statistical Methods

Once we identify the best-performing model and generate predicted completion dates (or years), we compute the schedule residuals and use them to assess delay risk.

These residuals feed into three complementary statistical methods.

Method 1: Z-Score Analysis

- z = (residual - mean) / std
- Early: $z < -1$ | On Schedule: $|z| \leqslant 1$ | Delayed: $1 < z \leqslant 2$ | Sig. Delayed: $z > 2$

Method 2: Percentile-Based

- Uses 20th, 80th, 95th percentiles from training data
- Distribution-free approach, captures actual patterns

Method 3: IQR (Interquartile Range)

- IQR = Q3 - Q1, uses 1.5×IQR fences
- Robust to outliers, emphasizes extreme deviations.

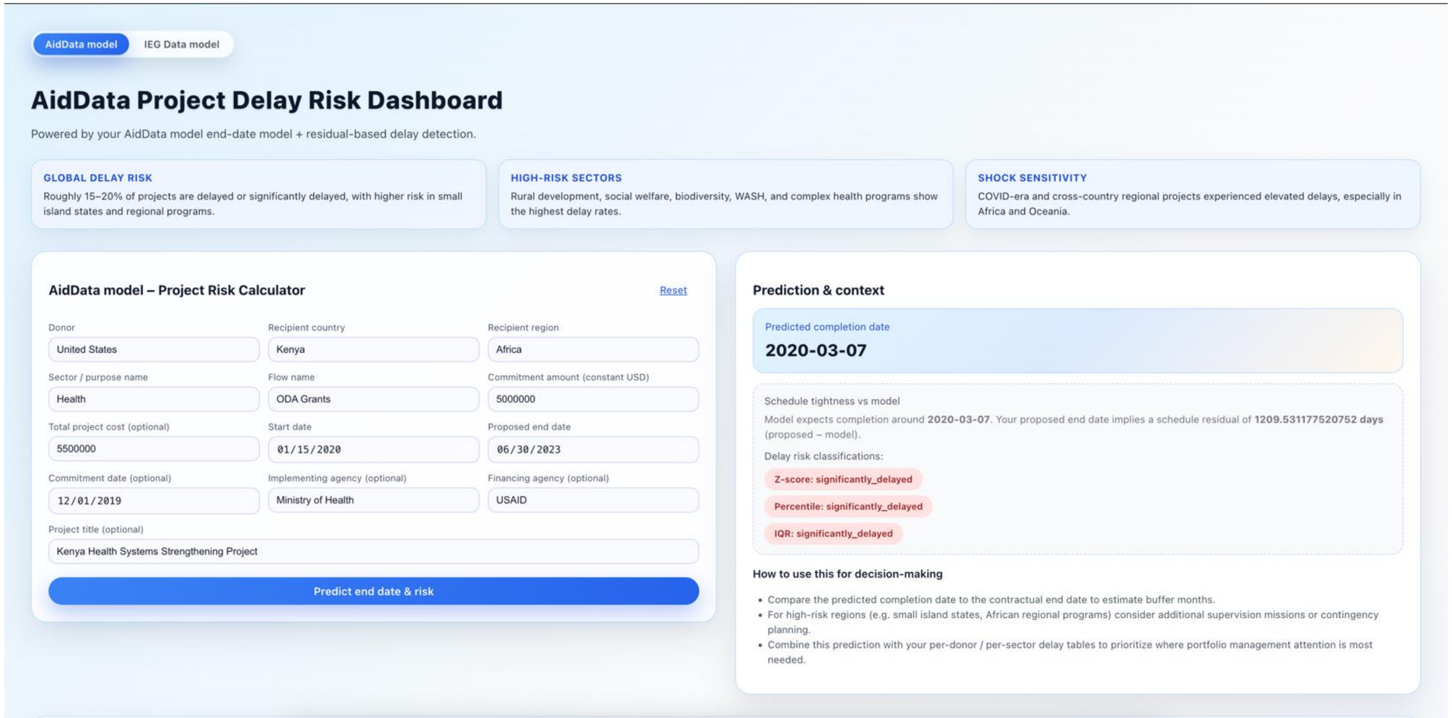
Delay-risk categories: **early_closure, on_schedule, delayed_closure, significantly_delayed**

Introducing the Dashboard

We wanted users to have the freedom to adjust project parameters and immediately see how those changes affect the predicted completion timeline and delay risk.

So, we built an **interactive dashboard** where users can tweak inputs, compare scenarios, and understand what factors help a project stay on schedule.

Dashboard Link - https://delay-sense-ui.vercel.app/



Model Performance Overview

IEG Model (Completion Year Prediction)

We evaluated four models: Linear Regression, Random Forest, XGBoost, and a Deep Neural Network.

Best model: Random Forest
MAE: **1.24 years**
RMSE: **1.70 years**
R^2: **0.61**

Error pattern: Mean residual ≈ **−0.02 years** (almost unbiased)

Interpretation
The model predicts completion timing within **~1.2 years** for a dataset where project durations vary widely.

Aid Data Model (Completion Year Prediction)

We trained the same four models, but here the target is exact **end-date** (in days).

Best model: XGBoost
MAE: **141 days** (≈ 4.6 months)
RMSE: **307 days**
R^2: **0.87**

Error pattern: Mean lateness ≈ **−0.5 days** (extremely well calibrated)

Interpretation:
Because the dataset is much larger and more consistent (~630k projects), the model predicts with **high precision** — average error of only **4–5 months** on multi-year projects.

Real World Applications

- **Pre-Commitment Risk Assessment**
  - Evaluate characteristics before approval, adjust design to mitigate delays
- **Portfolio Monitoring**
  - Prioritize supervision for high-risk projects, early warning system
- **Evidence-Based Planning**
  - Set realistic timelines based on similar projects
- **Stakeholder Communication**
  - Objective, quantitative risk assessments with transparent methodology

Future Enhancements

Some of the future enhancements that we have are

- Advanced Models: LightGBM, neural networks for text
- Explainability: SHAP values, counterfactual analysis
- Real-Time Monitoring: Update predictions as projects progress
- Recommendation System: Suggest risk mitigation strategies