EXECUTIVE SUMMARY

Executive Summary – AI Usage and Engineering Delivery Risk

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Modern engineering teams increasingly use AI tools to accelerate development. However, leadership lacks visibility into how AI usage affects delivery risk, system stability, and operational performance.

This project analyzes engineering task data to understand how AI usage and task complexity influence delivery outcomes such as cycle time, MTTR (rework time), and failure rate.

Key Findings

- AI usage is higher in medium and high complexity tasks
- Tasks marked as high risk show longer cycle time and higher failure rates
- AI is more frequently used in high-risk work, but delivery risk is primarily driven by task complexity rather than AI alone

Business Impact

Organizations should not restrict AI usage blindly. Instead, they should adopt risk-aware monitoring systems that allow safe AI adoption while protecting delivery reliability.

PROBLEM STATEMENT & MOTIVATION

Problem Statement

As AI tools become part of daily engineering workflows, organizations face new challenges:

- Lack of visibility into where AI is used
- No structured way to assess delivery risk linked to AI
- Difficulty balancing productivity with system stability

Without monitoring mechanisms, AI adoption can introduce **hidden operational risks**.

Motivation

Engineering delivery performance is typically measured using:

- **Cycle Time** – Time taken to complete work
- **Rework Time (MTTR)** – Time spent fixing issues
- **Failure Rate** – Frequency of delivery failures

Understanding how AI usage interacts with these metrics is essential for building **safe and scalable AI-assisted development practices**.

DATASET OVERVIEW

Dataset Description

The analysis is based on engineering task and delivery data containing:

- Task completion records
- AI usage indicators (AI used vs not used)
- Task complexity classification (Easy, Medium, Hard)
- Delivery performance metrics

Features Used in Analysis

- Cycle Time
- Rework Time (MTTR)
- Failure Rate
- AI Usage Flag
- Task Complexity Level

This dataset enables both **performance comparison** and **risk pattern identification**.

◇ BASELINE DELIVERY METRICS

Average cycle_time_total
13.870786
Average rework_time_hours
0.2613085
Average change_failure
0.05885

To establish a performance baseline, overall system averages were calculated.

These averages represent **normal delivery behavior** and are later used to identify tasks that deviate into higher risk patterns.

Key metrics observed:

- Average cycle time
- Average rework duration
- Average failure rate

These baselines help differentiate between **routine variation** and **risk signals.**

◇ AI VS NON-AI PERFORMANCE COMPARISON

AI vs Non-AI Comparison			
AI used	**Avg. cycle_time_total**	**avg. rework_time_hours**	**avg. change_failure**
FALSE	9.326734538	0.17804654	0.027556644
TRUE	16.07465771	0.301690674	0.074027324
Grand Total	**13.870786**	**0.2613085**	**0.05885**

A direct comparison was performed between tasks completed **with AI assistance** and those completed **without AI**.

Observations

- AI-assisted tasks show **slightly higher cycle time**
- AI-assisted tasks show **marginally higher failure rates**

However, this comparison **does not account for task complexity**, which may influence these results. AI is often used for more difficult tasks, which naturally carry higher risk.

This indicates the need for **deeper contextual analysis**.

AI USAGE BY TASK COMPLEXITY

AI usage by Task Complexity

Count of pr_id	AI used		
task_complexity	FALSE	TRUE	Grand Total
0.8	651	964	1615
0.9	441	1158	1599
1	692	1054	1746
1.1	942	2401	3343
1.2	627	1062	1689
1.3	424	1240	1664
1.4	608	1068	1676
1.5	1159	2133	3292
1.6	404	1295	1699
1.7	583	1093	1676
Grand Total	**6531**	**13468**	**19999**

AI usage distribution across task complexity levels shows:

- Lower usage in easy tasks
- Increased usage in medium tasks
- Highest usage in hard tasks

Insight

AI tools are primarily used when tasks are more challenging. This suggests AI adoption is driven by **problem difficulty**, not random usage.

CYCLE TIME BY TASK COMPLEXITY

Cycle Time by Task Complexity	
Row Labels	avg. of cycle_time_total
0.8	8.333298267
0.9	9.218105066
1	10.34760023
1.1	11.88306013
1.2	12.24029011
1.3	14.54795072
1.4	15.61381862
1.5	16.41740887
1.6	19.20334314
1.7	20.10405131
Grand Total	**13.870786**

Cycle time increases significantly as task complexity rises.

Insight

Hard tasks take longer regardless of AI usage. This reinforces that **complexity is a major driver of delivery performance.**

AI appears in high-cycle-time tasks because those tasks are inherently complex.

RISK PATTERN INSIGHTS

Risk Flag Pivot

Risk Level	Average of change_failure	Average of cycle_time_total
High Risk	0.059539919	14.52127537
Normal	0.058300395	13.35259163
Grand Total	**0.05885**	**13.870786**

High Risk	(~ 5.95%)
Normal	(~5.83%)

AI Usage by Risk Level Pivot

Count of pr_id	AI Used		
Risk Level	FALSE	TRUE	Grand Total
High Risk	2808	6059	8867
Normal	3723	7409	11132
Grand Total	**6531**	**13468**	**19999**

High Risk % of AI Tasks:	6059 / 13468 ≈ 45%
High Risk % of All Tasks:	8867 / 19999 ≈ 44.3%

Tasks were grouped into **Risk Levels** based on performance deviation.

Findings

- High-risk tasks show **longer cycle time**
- High-risk tasks show **higher failure rates**
- AI usage is more common in high-risk tasks

Key Conclusion

AI does not necessarily cause higher risk. Instead, AI is often used in tasks that are already complex and risky.

This highlights the importance of **risk-aware monitoring rather than AI restriction**.

FROM ANALYSIS TO ACTION

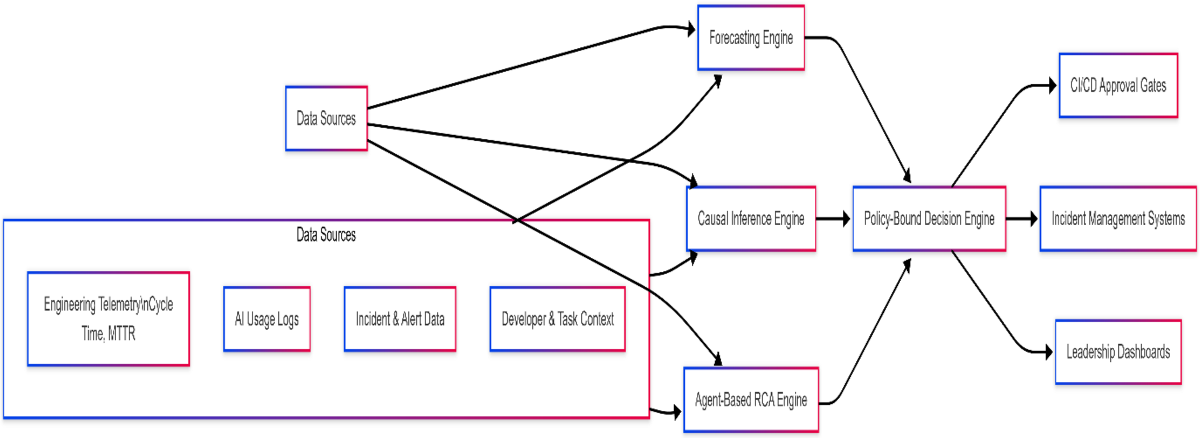
From Insights to System Design

The data analysis shows that AI usage intersects with task complexity and delivery risk. To operationalize these insights, organizations need a system that:

- Continuously monitors delivery signals
- Identifies risk patterns early
- Applies governance policies automatically

The following diagrams illustrate a proposed **AI-Driven Engineering Risk Monitoring System**.

🔷 System Architecture for AI-Assisted Engineering Risk Platform



This architecture shows how engineering delivery data flows through AI-driven components to generate real-time risk insights and operational decisions.

The system collects signals such as **task complexity, AI usage, cycle time, rework (MTTR), and failure rates** from multiple engineering data sources. These inputs are processed by specialized AI engines that perform forecasting, causal analysis, and risk pattern detection.

The outputs from these engines are combined inside a **policy-bound decision layer**, which applies predefined risk rules to classify work into **Low, Medium, or High Risk** categories.

Based on the calculated risk level, the system can:

- Trigger **automatic approvals** for low-risk work
- Route medium-risk tasks for **peer review**
- Escalate high-risk tasks for **senior approval and monitoring**

The final insights are delivered to **dashboards, incident management systems, and CI/CD pipelines**, enabling organizations to adopt AI safely while maintaining delivery reliability.

◇ CAUSAL RELATIONSHIP MODEL

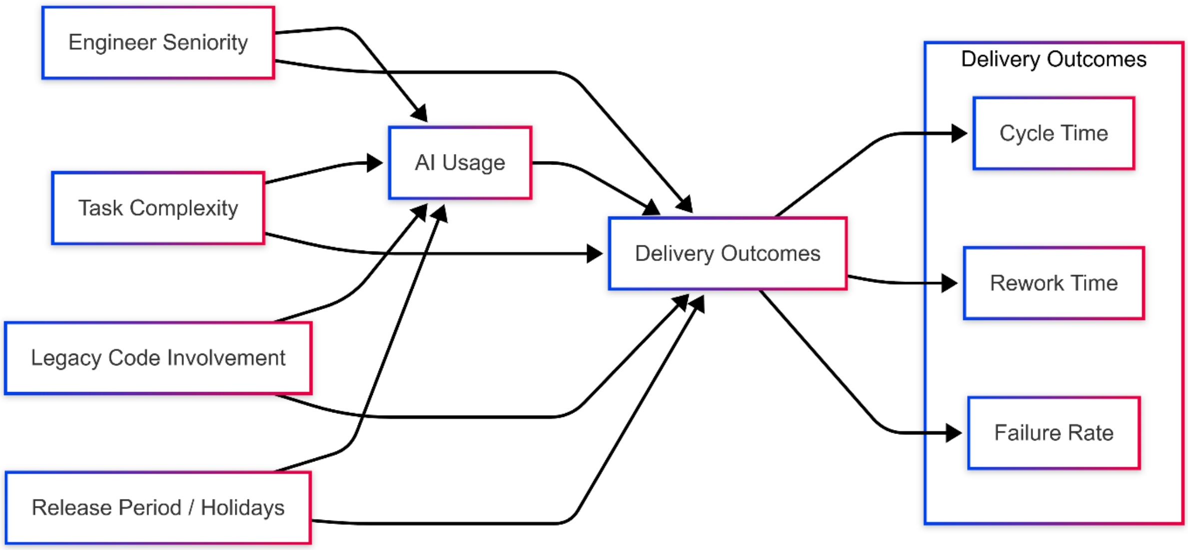


Fig. Causal Relationship Between AI Usage, Task Complexity, and Delivery Outcomes

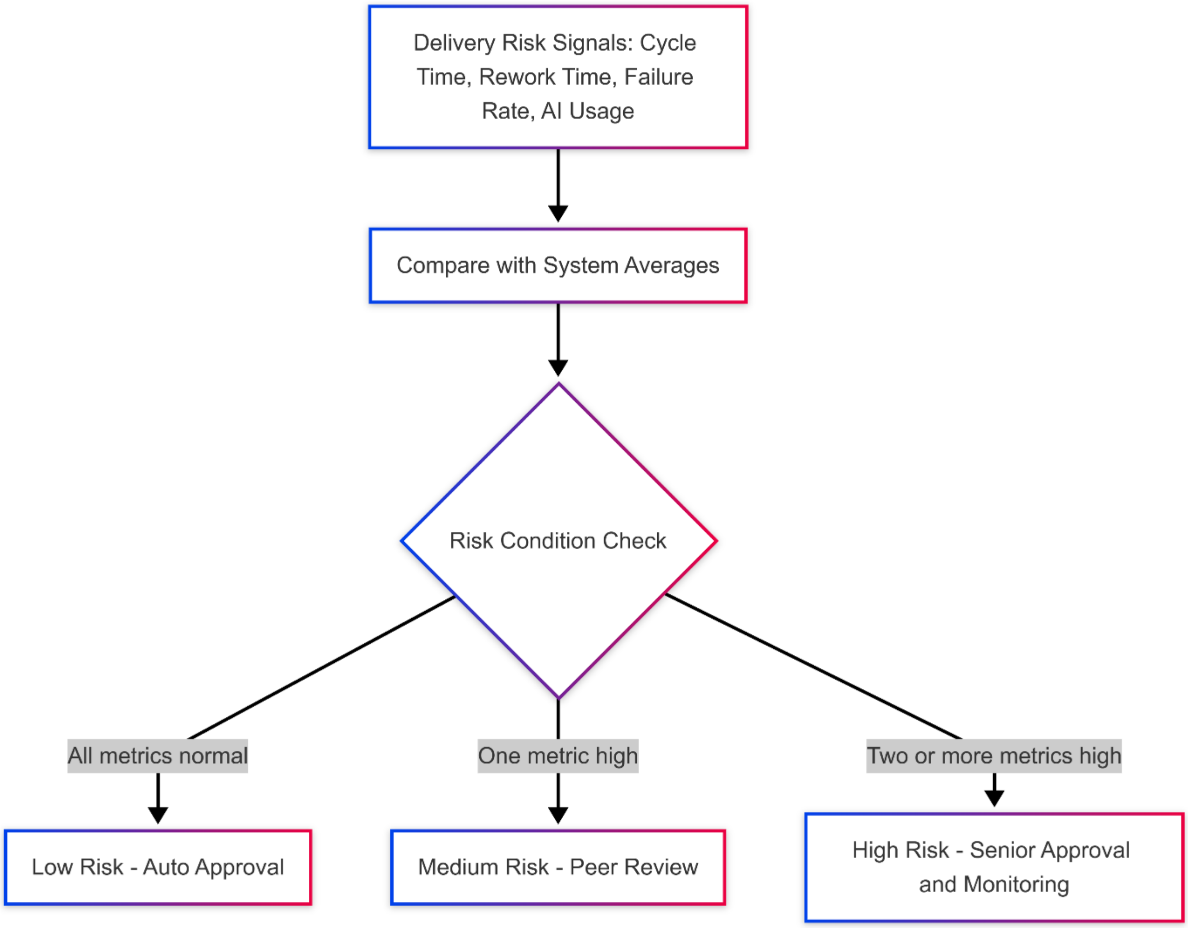
This model explains how:

- Task complexity
- Engineer seniority
- Legacy code involvement
- AI usage

collectively influence delivery outcomes.

It highlights that AI is **one of several interacting factors**, not the sole cause of delivery risk.

POLICY-BASED RISK DECISION FLOW

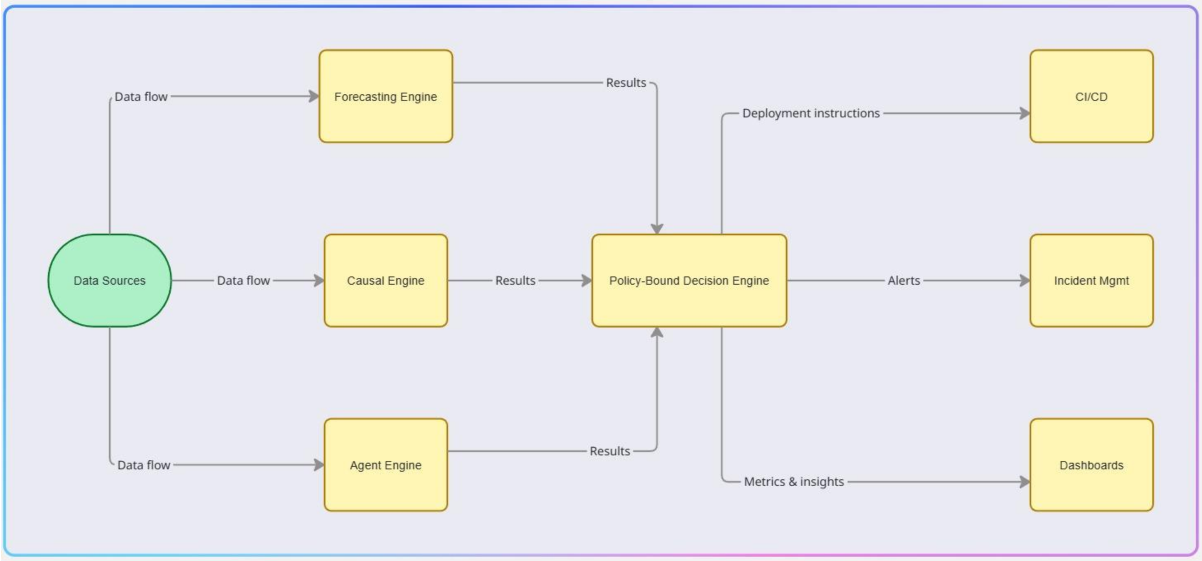


Based on calculated risk levels, the system enforces decision rules:

- **Low Risk → Auto Approval**
- **Medium Risk → Peer Review**
- **High Risk → Senior Approval + Monitoring**

This ensures high-risk work receives appropriate oversight.

AI- Driven Risk Monitoring Platform- Operational View



This architecture shows the end-to-end platform:

Data Sources → AI/Causal/Agent Engines → Policy Decision Engine → Dashboards & Incident Systems

It demonstrates how analytics, governance, and operational workflows integrate into one system.

BUSINESS IMPACT & CONCLUSION

Key Takeaways

- AI usage is more common in medium and high complexity tasks
- Task complexity is a primary driver of delivery risk
- AI usage should be monitored with contextual risk signals rather than restricted blindly

Business Value

- Improved release safety
- Better risk visibility for leadership
- Scalable and responsible AI adoption

This approach enables organizations to benefit from **AI productivity while maintaining delivery reliability and system stability.**

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Skills Demonstrated:
Data Analysis • Risk Modeling • AI Impact Analysis • System Design Thinking

Tools & Methods Used:
Excel (Pivot Analysis) • Data Visualization • Causal Thinking • Risk Segmentation

THANKYOU ALL