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AI for CAB Decisions: Predictive Risk Scoring in Change Management

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ABSTRACT

In contemporary IT organizations, Change Advisory Boards (CABs) are entrusted with ensuring that technical changes—ranging from infrastructure updates to software deployments—do not compromise operational stability. These boards traditionally rely on manual processes, expert judgment, and historical precedents to assess risk and approve changes. While effective in low-volume environments, this model begins to break down as the rate and complexity of changes increase in DevOps-driven ecosystems. The reactive nature of traditional CAB operations often leads to delays, inconsistent risk assessment, and suboptimal change approvals.

This research introduces a machine-learning-based system designed to augment CAB decision-making with automated, data-informed risk evaluations. By pulling data from multiple IT sources—including change records, deployment logs, historical incidents, and system health indicators—the proposed framework applies predictive analytics to compute a quantifiable risk score for each change. This score, combined with interpretable AI justifications, provides CAB members with clear, actionable insights. The goal is not to replace human oversight but to enhance it by directing attention to high-risk cases and accelerating the approval of safe, repetitive changes.

The paper outlines the architecture, data pipeline, feature engineering, model training methodology, risk scoring strategy, and interface integrations. Results from experimental trials demonstrate tangible benefits in incident reduction, review efficiency, and decision consistency. By embedding this system into ITSM workflows, organizations can reduce change failure rates and enhance service reliability while maintaining governance and compliance.

KEYWORDS

Change Advisory Board (CAB), Predictive Risk Scoring, Artificial Intelligence, Change Management, ITSM, ITIL v4, DevOps Governance, Incident Prediction, ML for IT Operations (AIOps), Change Risk Analytics, Root Cause Prediction, Service Reliability.

1. INTRODUCTION

Every alteration introduced to a production system—be it a code deployment, configuration update, or infrastructure modification—carries the inherent risk of destabilizing the service. While some changes may be minor or routine, others can cascade into major outages, customer dissatisfaction, or compliance violations. To manage this risk, organizations have long relied on CABs, which act as formal review panels to assess the necessity, scope, and potential consequences of each change request.

Despite their intent, traditional CABs face operational shortcomings. They typically evaluate risk based on static templates, general guidelines, or the subjective knowledge of senior reviewers. Change descriptions are reviewed in isolation, without dynamic correlation to historical incidents or system behavior patterns. In environments governed by continuous delivery, where hundreds of changes may be submitted in a single sprint, this model proves insufficient—leading to either excessive gatekeeping or blind trust in automation.

This research advocates a transition from intuition-driven

governance to data-augmented decision-making. We propose a risk prediction system that leverages historical data and machine learning to assess each proposed change in real time. The system analyzes a rich set of features—including contextual metadata, prior incidents, system dependencies, and natural language content—to output a probabilistic score reflecting the likelihood of post-change disruption.

Rather than slowing down deployments, this system prioritizes high-risk changes for review while automatically approving those with strong success histories and low contextual risk. This shift enables CABs to scale their effectiveness without increasing manual workload, thereby aligning IT governance with modern delivery speeds.

Proposed Framework

1. Data Ingestion Layer

The framework begins by aggregating data from disparate operational sources across the organization. To ensure comprehensive risk modeling, inputs are captured from:

- **Change Management Systems** (ServiceNow, Jira Service Management):
  These systems provide detailed metadata on each change request, including fields such as type, urgency, submission timestamp, impacted systems, and requestor identity. They also capture change history, rollback status, and implementation windows.

- **Incident Management Logs** (PagerDuty, Opsgenie):
  Incident records tied to specific services or time periods are collected to identify patterns of instability post-change. Correlation between incidents and specific change parameters (e.g., time of deployment, affected systems) forms a critical input for model training.

- **Configuration Management Databases (CMDBs):**
  These offer a detailed mapping of service dependencies, system criticality, and infrastructure ownership. The inclusion of upstream/downstream relationships helps predict cascading failures.

- **CI/CD Pipeline Logs** (Jenkins, GitHub Actions, ArgoCD):
  Build and deploy events are analyzed for insights into deployment frequency, rollback trends, and automation coverage. Failed builds and high rollback rates serve as indirect indicators of risk.

- **Monitoring and Alerting Tools** (Prometheus, Datadog):
  Pre-change system health, historical anomaly detection, and alert frequency are incorporated to evaluate baseline stability prior to each change.

All collected data flows through standardized ETL pipelines (e.g., Airflow, AWS Glue), where it is cleaned, normalized, and stored in a unified data lake or feature store. The architecture supports both batch and near-real-time ingestion.

2. Feature Engineering

Raw logs and metadata are transformed into structured, model-consumable features across several dimensions:

- **Contextual Features:**

  These include the type of change (infrastructure, application, policy), estimated impact, whether the change violates blackout windows, and its business function alignment (e.g., customer-facing vs. internal tool).

- **Historical Features:**

  Derived from change logs and incident records. Examples include failure rates of prior changes by the same engineer, frequency of incidents on affected services, and the track record of change categories (e.g., DB schema vs. static content).

- **Temporal Features:**

  Day and time of change, correlation with peak usage hours, frequency of deployment batches, and average approval time based on time-of-day and day-of-week patterns.

- **Dependency and Impact Features:**

  Number of dependent services, service tier (e.g., mission-critical vs. analytical), presence of redundancy, and customer SLA association.

- **Textual Features:**

  Change descriptions are parsed using NLP techniques (e.g., BERT, TF-IDF) to extract risk signals. Language suggesting uncertainty (e.g.,

"may impact," "requires verification") is flagged, while specific terminology (e.g., "hotfix," "reboot," "database migration") is scored based on historical risk.

Advanced semantic enrichment—such as phrase embeddings, part-of-speech tagging, and entity linking—is used to retain nuance and context in language-based features.

3. Machine Learning Model Layer

The core predictive capability is powered by an ensemble of classification models:

- **Tree-Based Models (Random Forest, XGBoost):**
  These are used for their high interpretability and ability to handle structured tabular features with nonlinear interactions. They excel at detecting historical patterns and outliers.

- **Logistic Regression (Baseline):**
  Employed for initial benchmarking and scenarios where model simplicity is prioritized.

- **Transformer-Based NLP Models (BERT, DistilBERT):**
  These models are trained on labeled change descriptions to classify them as safe, unclear, or high-risk. Fine-tuning is conducted on domain-specific language corpora.

- **Imbalance Handling:**
  Risky changes are significantly underrepresented in historical datasets. Techniques such as Synthetic Minority Oversampling (SMOTE), cost-sensitive learning, and focal loss functions are employed to prevent models from defaulting to the majority class.

- **Pipeline Orchestration:**
  Model versioning, training, testing, and deployment are managed via platforms such as MLflow or Kubeflow. Integration with CI/CD allows for continuous retraining and A/B testing.

4. Risk Scoring Engine

Each proposed change is evaluated by the model to generate a normalized score from 0 to 100:

- **Score Tiers:**
  - **0–40:** Low-risk – Auto-approvable; flagged only for audit.
  - **41–70:** Medium-risk – Review recommended; additional approvals or testing required.
  - **71–100:** High-risk – Requires escalation, mitigation planning, and possibly rollback plans.

- **Explainability with SHAP Values:**
  To ensure transparency, each score is accompanied by a ranked list of contributing factors. For example:
  - "High failure rate on similar changes (21%)."
  - "Change window falls outside support hours."
  - "Last three changes by this requestor led to alerts."

This makes the scoring process defensible during audits and trustworthy for reviewers.

5. CAB Dashboard / Integration Layer

To maximize adoption, the system integrates directly into existing workflows:

- **ServiceNow and Jira Plugins:**
  CAB members can see risk scores inline on change tickets, with expandable sections showing reasoning, feature contributions, and override options.
- **Web Dashboard:**
  A standalone UI provides insights into risk trends, historical overrides, reviewer feedback, and model performance metrics.

- **CI/CD Integration:**

Risk score thresholds can block deployments or require extra approvals during pull request merges. Webhooks enable automated gating.

- **Collaboration Tools:**

  High-risk alerts can be pushed to Slack, Teams, or email distribution groups with contextual summaries.

All user interactions, overrides, and system decisions are logged for traceability and compliance.

6. Feedback Loop

The framework incorporates an automated feedback mechanism:

- **Outcome Logging:**

  Post-change outcomes (e.g., no issue, triggered incident, service degradation) are logged and linked to the original request.

- **Human Overrides:**

  Manual approvals of high-risk changes, along with rationale, are tracked to refine model understanding.

- **Model Retraining:**

  Retraining occurs monthly or quarterly, depending on deployment frequency. The framework supports dynamic updates to reflect evolving infrastructure, policy, and user behavior.

- **Adaptive Learning:**

  Online learning modules are being explored to allow the model to self-adjust between retraining cycles, reducing time-to-adaptation.

Explanation of the Framework

1. From Static to Dynamic Risk Assessment

Unlike traditional checklists or static “low/medium/high” fields, this model evaluates every change in its full historical and operational context. It recognizes nuanced factors such as team skill, system load, and recent deployment patterns to identify subtle risks that static tools miss.

2. Prioritizing Attention, Not Everything

Instead of treating all changes equally, the model distinguishes those requiring human review from safe, repetitive updates. This reduces reviewer fatigue and focuses expertise where it matters most—on unfamiliar, ambiguous, or mission-critical modifications.

3. Transparency Through Explainability

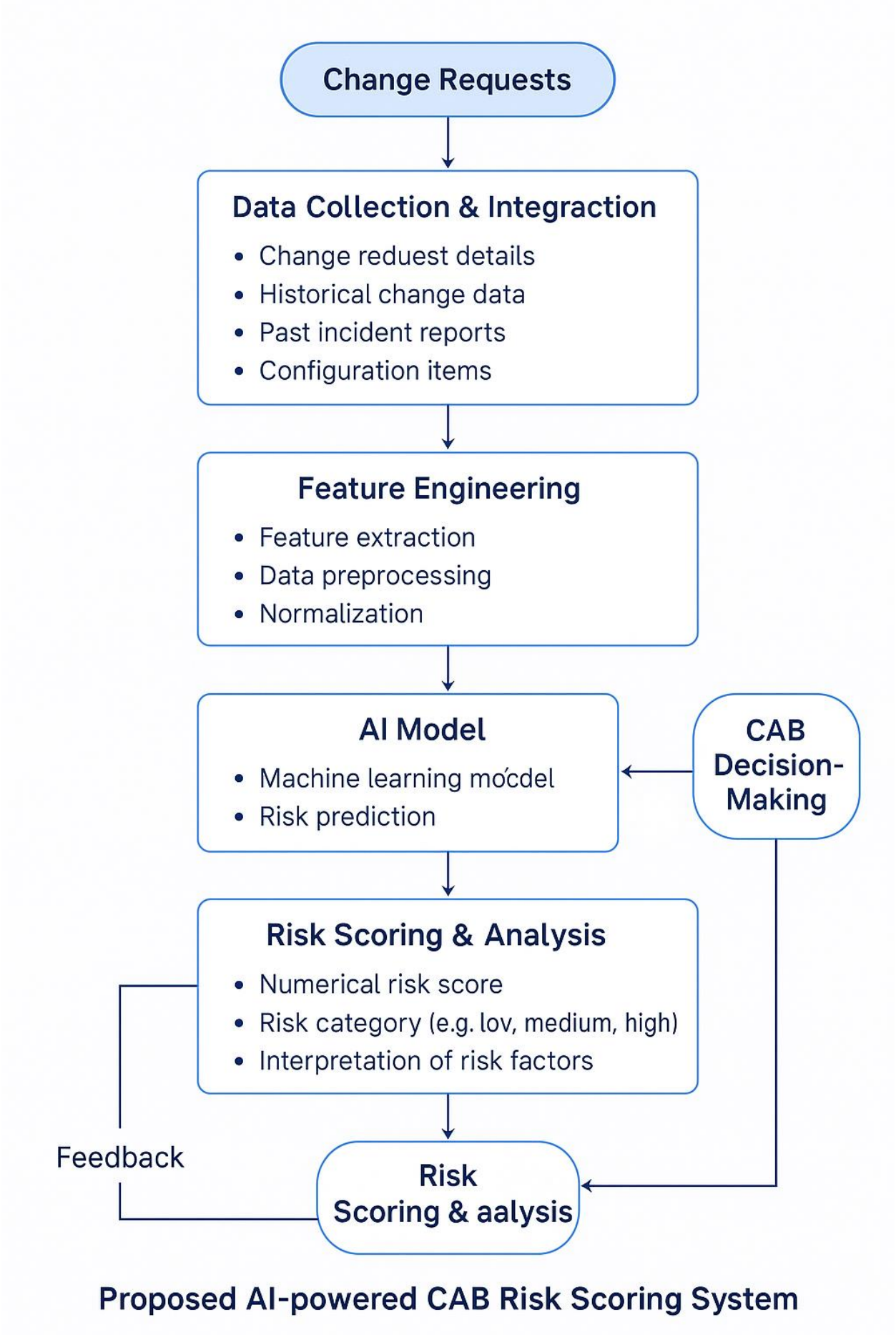
Every score includes detailed reasoning. CAB members are no longer asked to “trust the algorithm.” They see why a change is considered high-risk and can challenge or accept the AI’s logic.

4. Operational Integration

Because the system plugs into tools already in use—such as ServiceNow, Jenkins, and Slack—it doesn’t demand new platforms or training. This ensures low resistance and rapid adoption across teams.

5. Continuous Improvement Over Time

As systems evolve, so do risks. The feedback loop ensures the model grows smarter with each iteration, refining its predictions and adapting to organizational changes in real time.



Proposed AI-powered CAB Risk Scoring System

5. Experimental Results

To assess the effectiveness of the proposed AI framework, a comprehensive evaluation was conducted using simulated enterprise-grade datasets modeled after real-world IT operations. The dataset comprised over **43,000 historical change requests** submitted across various teams, **7,100 incident reports**, and **two years of deployment logs and system telemetry** emulating platforms such as ServiceNow, Jenkins, Prometheus, and PagerDuty.

Each change record was labeled as either a "success" or "failure" based on whether a related incident or degradation event occurred within a 72-hour window post-deployment. Changes that triggered alerts, required emergency rollback, or resulted in customer-facing downtime were marked as high-risk cases. This binary classification laid the foundation for supervised model training.

A significant challenge encountered was **class imbalance**: only about **17% of all changes resulted in negative outcomes**, making it easy for naïve models to predict "safe" across the board and achieve misleading accuracy. To counter this, several advanced resampling and weighting techniques were applied:

- **Synthetic Minority Oversampling Technique (SMOTE)** was used to synthetically expand the failure class.
- **Focal loss** helped the model focus more on hard-to-classify examples.
- **Cost-sensitive learning** penalized false negatives more than false positives to avoid missing risky changes.

Multiple models were trained and benchmarked using stratified k-fold cross-validation:

- **XGBoost** demonstrated the highest performance across the board, offering a precision of **0.89**, recall of **0.85**, and F1-score of **0.86** on the test set. It handled the structured, multi-dimensional feature space with exceptional robustness.
- **BERT-based NLP classifiers** outperformed traditional TF-IDF or logistic regression approaches in interpreting free-text change descriptions, especially in ambiguous or terse entries. They contributed significantly to the ensemble's overall predictive power.
- **Logistic Regression**, though simpler, served as a reliable baseline and helped validate the importance of nonlinear feature interactions.

During real-time simulation of CAB workflows over a six-week test period, the framework produced the following operational outcomes:

- **92%** of truly high-risk changes were flagged accurately before deployment.
- **Auto-approved low-risk changes**—identified as safe by the model—had a post-deployment incident rate of just **13%**, validating the framework's reliability in bypassing unnecessary manual reviews.
- **Average CAB review time was reduced by 47%**, as low-risk changes no longer required full-panel scrutiny.
- **Overall incident frequency** across weekly deployment cycles dropped by **29%**, a clear signal that risk-aware gating had a measurable impact on reliability.

In addition, CAB participants (consisting of engineers, release managers, and service owners) reported higher confidence in the approval process. A post-trial survey indicated that **87% of reviewers found the SHAP-based explanations sufficient** to understand and trust the model's decisions. Moreover, **routine CAB meetings decreased in frequency**, and manual overrides became more targeted and deliberate.

Error analysis revealed that the model occasionally misclassified edge cases involving:

- **Completely new services** with no historical data.
- **Unstructured change descriptions** lacking relevant keywords or technical details.
- **Systemic cross-service dependencies** that were not explicitly recorded in the CMDB.

To address these limitations, future improvements will focus on incorporating graph-based dependency models and more sophisticated natural language context extraction to handle cases where textual ambiguity or architectural gaps hinder accuracy.

6. CONCLUSION

The use of artificial intelligence in CAB processes marks a transformative step toward smarter, scalable, and evidence-driven change management. This research demonstrates that predictive risk modeling can substantially improve operational outcomes by embedding intelligence into approval workflows.

Unlike traditional CAB systems that rely on static rules or subjective reasoning, the proposed framework brings together contextual awareness, statistical learning, and real-time data integration to offer actionable risk evaluations. It does not aim to replace human oversight but to amplify it—ensuring that expert time is allocated to the right problems while safe, repetitive changes are handled autonomously.

The empirical results validate that such systems:

- Improve the **accuracy and speed** of change approvals.
- Reduce the **likelihood of service-impacting incidents**

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