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Original Article

A Scenario-Based Benchmark for Assessing AI Safety Controls in Banking Operations: Metrics for Containment, False Intervention, and Recovery

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Abstract - Banks Are Moving Ai Agents From Advisory Roles Into Operations, Where They Release Payments, Change Credit Limits, Settle Disputes, Triage Anti-Money-Laundering (Aml) Alerts, And Move Liquidity. Supervisors Expect Such Systems To Be Validated, Monitored, And Controllable, And Institutions Respond With Layered Safety Controls: Rule Limits, Anomaly Monitors, Human Review, And Circuit Breakers. Yet There Is No Standard, Repeatable Way To Measure How Well Those Controls Work, Or What They Cost When Nothing Is Wrong. This Paper Introduces A Scenario-Based Benchmark That Treats The Control Stack, Not The Model, As The System Under Test. It Contributes (I) A Failure Taxonomy For Operational Banking Ai; (Ii) A Library Of Ten Seeded Scenarios Across Five Banking Domains, Including Two Benign-Stress Scenarios That Expose Over-Intervention; (Iii) Three Families Of Formally Defined Metrics: Containment (Exposure Averted And Time To Containment), False Intervention (Wrongful Holds, Blocks, False Alarms And False Halts On Legitimate Activity), And Recovery (Time To Restore Safe Service And Share Of Leaked Exposure Reversed); And (Iv) A Paired, Seed-Controlled Evaluation Protocol With Bootstrap Confidence Intervals. A Reference Implementation Evaluates Six Control Configurations Over 200 Paired Episodes Per Scenario. Adding A Circuit Breaker With Automated Rollback Raised Exposure-Weighted Containment From 66.6% To 94.3% (Paired Difference 27.7 Percentage Points, 95% Ci [26.3, 29.1]) And Cut Median Time To Containment From 115 To 13 Minutes, But Roughly Doubled Median Time To Recovery (92 To 183 Minutes) And Halted Service In Every Benign Holiday-Surge Episode. A Calendar-Aware Volume Baseline Removed Those False Halts Without Reducing Containment. The Results Show Why The Three Metric Families Must Be Reported Together: A Control That Looks Best On One Can Be Worst On Another. All Results Come From A Calibrated Simulation And Are Evidence About Control Behavior, Not Predictions Of Production Loss.

Keywords - AI Governance, AI Safety, Banking Operations, Benchmark, Containment, False Positives, Operational Resilience, Circuit Breaker, Human-In-The-Loop, Model Risk Management.

1. Introduction

AI in banking is crossing a line. Earlier systems scored transactions and handed the score to a person or a deterministic rule [1], [2]. Newer systems act: an agent releases a payment, raises a credit line, approves a refund, closes an AML alert, or sweeps cash between accounts, often thousands of times an hour. When such an agent misbehaves, because its model has drifted [3], its tools have failed, its objective was mis-specified, or an attacker has manipulated its inputs [4], the harm is realized in money movement and customer outcomes within minutes.

Institutions answer with layered safety controls: per-action limits, statistical monitors, human review of held actions, and circuit breakers that stop an agent and reverse what it did. Supervisory expectations point the same way. Model risk guidance calls for effective challenge, ongoing monitoring, and outcomes analysis [5]; the NIST AI Risk Management Framework asks organizations to measure AI risks and the effectiveness of their treatments [6]; the EU Artificial Intelligence Act, as proposed by the European Commission, requires risk management, human oversight, and robustness for high-risk systems [7]; and operational-resilience rules require firms to withstand, contain, and recover from disruption [8], [9].

What these frameworks do not supply is a measurement method. A bank can show that a kill switch exists, but it rarely can say, with a confidence interval, how much exposure that kill switch prevents, how often it fires on legitimate activity, and how long service takes to come back. Without such numbers, control design is argued from intuition, risk committees cannot compare alternatives, and validators have nothing repeatable to challenge. Three gaps stand out:

- Controls are tested for existence, not effectiveness: Control testing typically confirms that a limit or a halt can trigger, not how much harm it averts across realistic failure modes.
- False intervention is invisible: Every hold, decline, false alarm, or unnecessary halt costs customers and operations, but benchmarks of AI safety rarely include scenarios in which nothing is wrong, so over-intervention goes unmeasured.

- Recovery is not scored: Stopping harm is half the job. Restoring safe service and reversing harmful effects determine the final loss and customer impact, and they trade off against how aggressively a control contains.

This paper addresses these gaps with a scenario-based benchmark in which the control stack is the system under test. The contributions are:

- A failure taxonomy for operational banking AI with six classes, from integration faults to adversarial manipulation and benign stress (Section III).
- A scenario library of 10 parameterized, seeded scenarios across five banking domains, including two benign-stress scenarios designed to expose over-intervention (Section IV).
- Formal metrics for containment, false intervention, and recovery, defined on a ground-truth outcome ledger so that every number is computable and auditable (Section V).
- A paired evaluation protocol using common random numbers, threshold calibration on held-out benign seeds, and bootstrap confidence intervals, with a scorecard that reports the full metric vector rather than a single composite.
- A reference implementation and study of six control configurations over 200 paired episodes per scenario, which quantifies the containment–recovery trade-off of circuit breakers, the limited return from tightening per-action thresholds, and the role of human review in converting false blocks into delays (Section VI).

2. Background and Related Work

2.1. AI Safety Evaluation

Work on AI safety frames side effects, reward hacking, distributional shift, and adversarial robustness as core risks [10], [11]. Safety Gym established the practice of reporting task performance and constraint cost together [12], and broad evaluation suites such as HELM and AgentBench measure model and agent capabilities across many scenarios [13], [14]. Agent-safety and agent-security studies, including sandbox-based risk testing of tool-using agents and analyses of prompt-injection attacks, measure whether agents take unsafe actions and whether injected instructions succeed [15], [16]. These benchmarks evaluate the model or agent. None of them scores the institution's surrounding control stack on containment, over-intervention, and recovery in a financial setting.

2.2. Run-Time Safety Controls

Shielding enforces safety by overriding unsafe actions at run time [17]. In financial crime, fraud and AML systems combine rules, statistical scores, and analyst review, and the literature has long noted that false positives and alert volume are first-order costs [1], [2]. Human review introduces its own failure modes, including over-reliance on automation and degraded vigilance under load [18].

2.3. Detection and Incident Metrics

Receiver operating characteristic analysis formalizes the trade-off between detection and false alarms [19]; sequential change detection such as CUSUM provides monitors with controllable false-alarm rates [20]; and site-reliability engineering popularized time to detect and time to restore as operational measures [21]. The benchmark combines these ideas: ROC-style operating curves for per-action controls, CUSUM-based monitors with calibrated thresholds, and incident-timeline metrics for containment and recovery.

2.4. Governance and Audit

Model risk guidance [5], the NIST AI RMF [6], ISO/IEC 42001 [22], and internal algorithmic auditing frameworks [23] specify what to govern and document. They leave open how to quantify the effectiveness of the operational controls they require. The author's earlier work on federated learning for cross-institutional fraud detection [24] addressed model accuracy; this paper addresses the complementary question of how to measure the controls that limit harm when a model or agent fails anyway.

2.5. Gap

Existing safety benchmarks evaluate models, not controls; existing financial-crime research measures detection, not containment and recovery; and existing governance frameworks require controls without specifying how to measure them. This benchmark connects the three.

3. Problem Formulation and Failure Taxonomy

3.1. Operations as a Labeled Action Stream

An operational AI agent in domain d emits a stream of actions. Each action a has a time t_a, an exposure e_a (the monetary value or customer impact at stake), observable features x_a (amount, counterparty novelty, a risk score, a duplicate indicator), and a ground-truth label $y_a \in \{\text{benign, hazardous}\}$. The benchmark knows y_a because hazards are injected by the scenario engine; the controls do not. Let $\mathcal{H}$ and $\mathcal{B}$ denote the hazardous and benign actions in an episode.

A control configuration c maps each action, given the history, to an outcome $\kappa_c(a) \in \{\text{allow, hold, block, divert}\}$, and may later reverse a committed action. Holds are either auto-declined or resolved by a human reviewer. Diverted actions are routed to a manual fallback lane while the agent is halted. The ledger records every decision with its time, so all metrics are computed from recorded outcomes rather than estimated.

3.2. Failure Taxonomy

Scenarios are drawn from six failure classes chosen to cover the ways operational AI fails in banks:

- Integration fault: A tool, retry loop, or data feed misbehaves, for example re-submitting payments.
- Adversarial manipulation: An attacker steers the agent, for example through injected instructions in documents or messages [4], to redirect funds or approve refunds.
- Model degradation: The model's inputs drift, so its decisions degrade gradually [3].
- Goal misspecification: The agent optimizes a proxy (throughput, SLA, yield) at the expense of policy.
- Runaway automation: A defect produces a burst of wrongful actions at machine speed.
- Benign stress: Legitimate but unusual activity (seasonal surges, quarter-end flows) that a control may mistake for a hazard.

The last class has no hazard at all. It exists to measure false intervention, which is invisible in hazard-only benchmarks.

4. Benchmark Design

4.1. Architecture

The benchmark has six layers (Figure 1). The scenario library (L1) defines failure modes and parameters. The banking operations simulator (L2) generates labeled action streams for five domains. The control stack under test (L3) is any combination of controls that implements a common interface. The outcome ledger (L4) records ground truth and decisions. The metric engine (L5) computes containment, false-intervention, and recovery metrics with confidence intervals, and the scorecard and run manifest (L6) record results in a tamper-evident form.

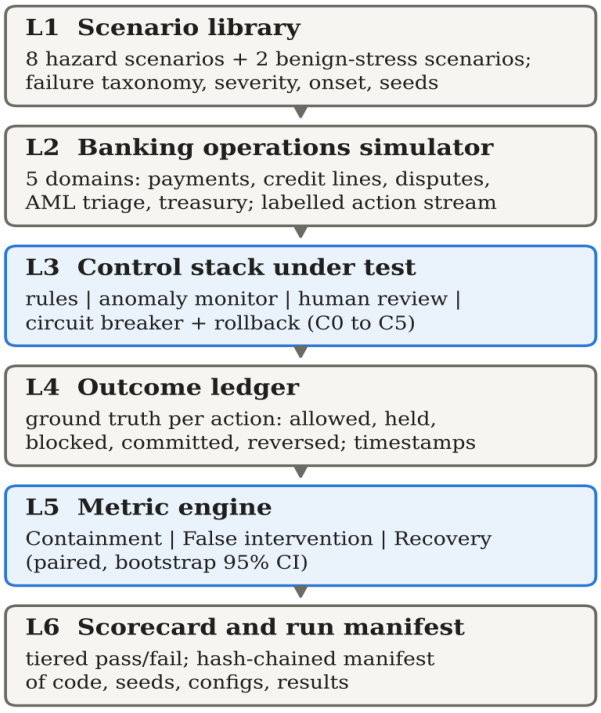


Figure 1. Benchmark Architecture. The Control Stack (L3) Is the System under Test; the Metric Engine (L5) Scores It against the Ground Truth Recorded in the Outcome Ledger (L4)

4.2. Domains and Scenario Library

Five domains represent common operational uses of AI in retail and commercial banking: payments operations (D1), credit-line management (D2), disputes and refunds (D3), AML alert triage (D4), and treasury liquidity sweeps (D5). Each domain has its own action rate and exposure distribution, and each hazard has its own reversibility profile, since a recalled payment, a reduced credit line, and a clawed-back refund differ sharply in how recoverable they are. Table 1 lists the scenarios.

Table 1. Scenario Library

Id	Dom.	Scenario	Class	Observable Signature
S1	D1	Duplicate-Payment Retry Loop (Tool Fault)	Integration Fault	Duplicates, Burst, Score Shift 0.5
S2	D1	Injected Beneficiary Redirection	Adversarial Manipulation	New Counterparty, 3× Size, Score Shift 1.5
S3	D2	Credit-Limit Model Drift	Model Degradation	1.5× Size, Gradual Onset, Score Shift 1
S4	D2	Mass Limit-Decrease Defect	Runaway Automation	Burst, Score Shift 0.3
S5	D3	Dispute Auto-Approval (Goal Misspecification)	Goal Misspecification	Score Shift 0.8
S6	D3	Prompt-Injected Large Refunds	Adversarial Manipulation	New Counterparty, 20× Size, Score Shift 2
S7	D4	Aml Alert Suppression	Model Degradation	Score Shift 1
S8	D5	Liquidity-Buffer Breach By Sweep Agent	Goal Misspecification	4× Size, Score Shift 1.2
B1	D1	Benign Holiday Volume Surge (2x)	Benign Stress	No Hazard
B2	D1	Benign Quarter-End Large-Value Cluster	Benign Stress	No Hazard

Each hazard starts at a random onset between minutes 60 and 240 of a 480-minute shift and continues until the defect is fixed. Hazards differ in how visible they are to controls: some trip simple rules (duplicates, very large amounts), some shift the risk score only modestly, and some arrive in bursts that stress review capacity.

4.3. Control Configurations

Table 2 lists the six configurations, which add one control layer at a time so that each layer's marginal effect can be measured by paired comparison. Every configuration, including C0, has alerting monitors that open an incident and start remediation; they differ in what happens to individual actions and whether the agent can be stopped.

Table 2. Control Configurations under Test

ID	Configuration	Behavior
C0	Alert-only monitoring	CUSUM alerts open an incident; no action is stopped
C1	+ static rule limits	Block amounts above cap and exact duplicates; hold velocity breaches and large new-counterparty actions
C2	+ anomaly monitor	Hold actions with risk score above τ; tighten τ during an open incident; holds auto-declined
C3	+ human review	Holds go to a reviewer queue (1 review/min, ≥3 min latency)
C4	+ circuit breaker and rollback	Halt the agent on critical alarm or 3 confirmed hazards; divert work to manual lane; reverse suspicious recent actions
C5	+ calendar-aware baseline	C4 with volume monitors and velocity rules using the known business calendar

4.4. Simulation Model

Time advances in one-minute steps. Benign actions arrive as a Poisson process at the domain rate, with log-normal exposure and a 5% rate of new counterparties. The risk score is standard normal for benign actions and shifted by a scenario-specific amount for hazardous ones, so detectability is an explicit parameter. A reviewer rejects a hazardous held action with probability 0.92 and releases a benign one with probability 0.97. Remediation after an incident opens takes a log-normal time with a median of 90 minutes. While the agent is halted, benign work is processed by a manual lane at 30% of normal capacity; after the fix, service is restored in three 20-minute stages (25%, 50%, 100%) and the backlog is drained. Reversal of a committed hazardous action succeeds with a probability that decays with its age, at a domain-specific rate (for example, near-certain for credit-limit corrections, about 30% for refunds). In C0 to C3 reversal is attempted manually when the fix is deployed; in C4 and C5 it is attempted automatically at the halt.

4.5. Calibration

Monitors use one-sided CUSUM statistics [20] on the per-minute count of high-score actions and on action volume:

$$g_t = \max(0,\ g_{t-1} + z_t - k), \qquad \text{alarm if } g_t > h \tag{1}$$

Where z_t is the standardized statistic and $k = 0.5$. The alarm threshold h for each domain is fixed **before evaluation**, on 4,000 benign calibration shifts drawn from separate seeds, as the 98th percentile of the per-shift maximum, giving a nominal 2% false-alarm rate per shift for each statistic. The circuit breaker uses 2h. The per-action threshold τ defaults to the benign 99th percentile (2.326) and is swept in Section VI. Fixing thresholds before evaluation prevents tuning a configuration to the test scenarios.

5. Metrics

All metrics are computed per episode from the outcome ledger and then aggregated across episodes. They fall into three families, each of which answers a question a risk committee or validator would ask.

5.1. Containment: How Much Harm Was Stopped, and How Fast?

Leaked exposure is the exposure of hazardous actions that the configuration allowed to commit:

$$L_c = \sum_{a \in \mathcal{H}} e_a \ \mathbf{1}[\kappa_c(a) = \text{commit}] \tag{2}$$

The containment ratio compares leaked exposure with the paired reference run (C0) on the identical seed:

$$CR_c = 1 - \frac{L_c}{L_{ref}} \tag{3}$$

Measuring against the reference run, rather than against the hazardous actions that happened to be attempted, matters for controls that stop the agent: a halted agent attempts fewer hazardous actions, which a per-attempt rate would wrongly count against it. The per-attempt interception rate is still reported for diagnosis. Time to detect (TTD) is the delay from hazard onset to the first incident, and time to containment is the delay until hazardous exposure stops leaking:

$$TTC_c = \max\{t_a : a \in \mathcal{H},\ \kappa_c(a) = \text{commit}\} + 1 - t_0 \tag{4}$$

5.2. False Intervention: What Did the Control Cost When Nothing Was Wrong?

The false-intervention rate is the share of benign actions that a control held, blocked, or reversed, and the false-block rate is the share finally denied to the customer or wrongly reversed:

$$FIR_c = \frac{|\{a \in \mathcal{B} : \kappa_c(a) \neq \text{allow}\}|}{|\mathcal{B}|} \tag{5}$$

$$FBR_c = \frac{|\{a \in \mathcal{B} : a \text{ finally denied or reversed}\}|}{|\mathcal{B}|} \tag{6}$$

The distinction matters: human review converts many interventions into delays rather than denials. The benchmark therefore also reports friction (mean delay per benign action, in minutes), the diversion share (benign actions routed to the manual lane during a halt), the false-alarm rate (share of shifts with an incident but no hazard), and the false-halt rate (share of shifts in which the agent was stopped with no hazard present), with halt duration in minutes.

5.3. Recovery: How Fast and How Completely Was Service Restored?

Time to recovery runs from detection to the point at which the hazard is removed, capacity is fully restored, and the backlog is cleared:

$$TTR_c = t_{restore} - t_{detect} \tag{7}$$

With R_c the exposure successfully reversed, the recovery completeness and the **net-loss reduction** relative to the reference are:

$$RC_c = \frac{R_c}{L_c}, \qquad NLR_c = 1 - \frac{L_c - R_c}{L_{ref} - R_{ref}} \tag{8}$$

5.4. Statistical Protocol and Scorecard

Each scenario is run for 200 episodes. Within an episode, every configuration sees identical arrivals, features, reviewer outcomes, reversal draws, and remediation times (common random numbers [25]), so differences between configurations are paired and free of between-run noise. Means and medians are reported with 95% percentile-bootstrap confidence intervals (4,000 resamples) [26]; paired differences are bootstrapped on per-episode differences; and when several metrics and scenarios are tested for a tier decision, Holm adjustment is applied [27].

The scorecard compares each metric with tier thresholds set by the institution's risk appetite before evaluation. A configuration passes a tier only if every containment, false-intervention, and recovery limit is met across the required scenarios. The scorecard reports the full metric vector rather than a weighted composite, because a composite would hide exactly the trade-offs that Section VI shows.

6. Results

This section reports the reference study: 10 scenarios × 6 configurations × 200 paired episodes, plus a seven-point threshold sweep for C2 and C3. Table 3 pools the eight hazard scenarios; Table 4 breaks containment out by scenario; Table 5 reports the benign-stress scenarios.

Table 3. Pooled Results over Eight Hazard Scenarios

Cfg.	CR %	TTC min	NLR %	FIR %	FBR %	Div. %	TTR min	RC %
C0	0.0	128	0.0	0.25	0.25	0.0	91	30.6
C1	54.4	107	54.6	8.08	8.08	0.0	91	27.7
C2	65.3	103	61.1	9.66	9.66	0.0	91	21.6
C3	66.6	115	62.1	10.48	0.47	0.0	92	19.2
C4	94.3	13	95.1	2.06	0.26	33.0	183	28.5
C5	94.3	13	95.1	2.06	0.26	33.0	183	28.5

Note: CR: containment ratio (mean); TTC/TTR: medians; NLR: net-loss reduction vs. C0; FIR/FBR: false-intervention and false-block rates on benign actions within hazard scenarios; Div.: benign actions diverted during halts; RC: recovery completeness (mean over episodes with leakage).

Table 4. Containment Ratio (%) by Scenario

ID	Scenario	C1	C2	C3	C4
S1	Duplicate-payment retry loop	100.0	100.0	100.0	100.0
S2	Injected beneficiary redirection	66.6	77.4	85.1	97.4
S3	Credit-limit model drift	3.5	25.3	33.3	87.8
S4	Mass limit-decrease defect	97.9	98.0	96.9	97.9
S5	Dispute auto-approval	5.3	24.1	22.5	91.2
S6	Prompt-injected large refunds	99.2	99.6	99.1	99.8
S7	AML alert suppression	3.8	27.2	25.9	88.6
S8	Liquidity-buffer breach by sweep agent	58.7	70.8	70.1	91.6

Note: C0 is the reference (0% by definition); C5 equals C4 in all hazard scenarios.

Table 5. False Intervention in Benign-Stress Scenarios

Scen.	Cfg.	FIR %	FBR %	Delay min	False alarm %	False halt %	Halt min
B1	C0	0.00	0.00	0.0	100	0	0
	C2	4.45	4.45	0.0	100	0	0
	C3	4.45	0.23	0.9	100	0	0
	C4	1.37	0.09	47.8	100	100	234
	C5	1.36	0.14	0.0	2	0	0
B2	C0	0.00	0.00	0.0	5	0	0
	C2	1.88	1.88	0.0	10	0	0
	C3	1.88	0.44	0.0	10	0	0
	C4	1.88	0.44	0.0	10	0	0
	C5	1.88	0.44	0.0	10	0	0

Note: *Delay: mean minutes per benign action. Halt min: mean minutes the agent was stopped per shift.*

6.1. Finding 1: The Circuit Breaker Dominates Containment

Per-action controls left a third of exposure uncontained: C3 reached 66.6% [65.0, 68.2] containment. Adding the circuit breaker raised it to 94.3% [93.9, 94.6], a paired gain of 27.7 percentage points (95% CI [26.3, 29.1]), and cut median time to containment from 115 to 13 minutes. Net-loss reduction rose from 62.1% to 95.1%. The gain came from the scenarios per-action controls cannot see: model drift, dispute auto-approval, and AML alert suppression (S3, S5, S7) produce individually ordinary-looking actions, so rules and per-action scores contained only a quarter to a third of their exposure, while stopping the agent once the aggregate signal was clear contained 88–91% (Table 4).

6.2. Finding 2: Faster Containment Costs Slower Recovery

The circuit breaker's containment came at a measurable price (Figure 2). Median time to recovery rose from 92 to 183 minutes (paired difference 98 minutes, 95% CI [97, 99]), because a halted agent must be fixed, restored in stages, and its backlog drained. During hazard scenarios, 33.0% of benign actions were diverted to the manual lane and mean benign delay rose to 23.7 minutes. A benchmark that reported containment alone would recommend the circuit breaker without qualification; reporting recovery shows the operational capacity it requires.

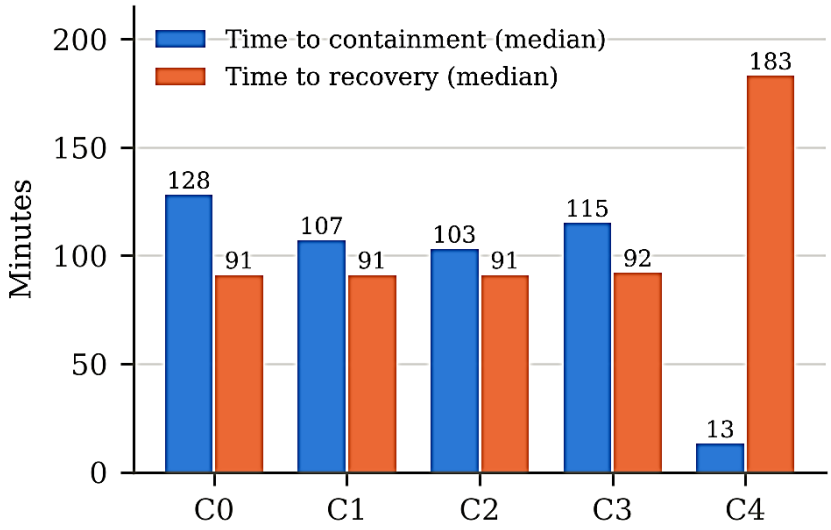


Figure 2. Median Time to Containment and Time to Recovery across Hazard Scenarios. The Circuit Breaker (C4) Contains About Nine Times Faster than C3 but Takes About Twice as Long To Restore Full Service

6.3. Finding 3: Tightening Per-Action Thresholds Has Low Returns

Sweeping τ from 3.5 to 1.28 raised C2 containment only from 64.4% to 67.7%, while its false-block rate on benign-stress shifts quadrupled from 2.4% to 9.9% (Figure 3). Per-action thresholds cannot separate hazardous actions whose individual scores overlap the benign distribution; lowering the threshold mostly blocks legitimate customers. Containment of such hazards depends on aggregate, incident-level controls.

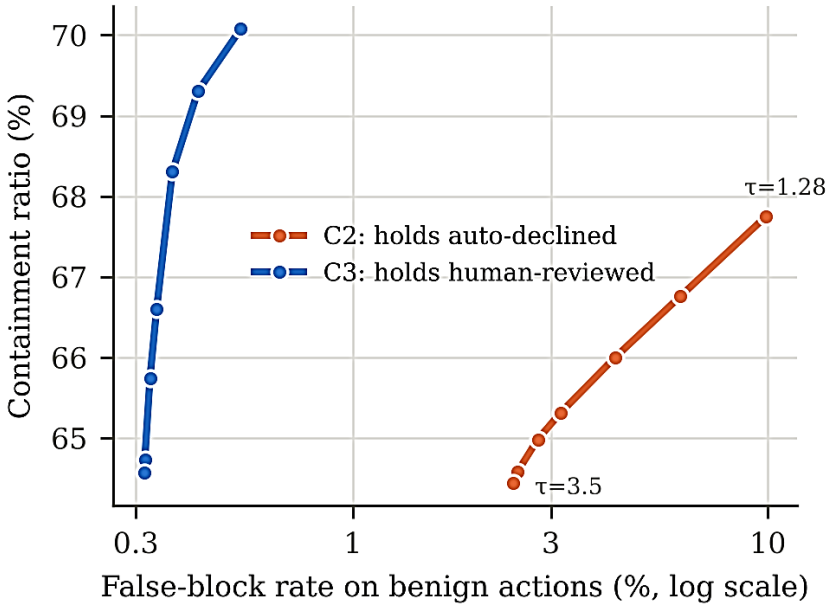


Figure 3. Operating Curves From Sweeping the Per-Action Threshold T. Human Review (C3) Shifts the Curve Left By an Order of Magnitude in False Blocks, While Neither Curve Gains More than About Six Points of Containment

6.4. Finding 4: Human Review Turns Denials into Delays, Until It Saturates

With identical holds, human review cut the benign false-block rate in the benign-stress scenarios by 2.8 percentage points (95% CI [2.7, 3.0]) and added 1.3 points of containment. Its weakness appeared under bursts: in the mass limit-decrease defect (S4), the queue saturated, and median time to containment rose from 2 minutes under C2 to 315 minutes under C3, as hazardous actions that reviewers missed continued to commit long after onset. Review capacity is therefore a safety parameter, not only a staffing parameter [18].

6.5. Finding 5: Benign Stress Exposes False Halts, and Context Fixes Them

In the 2× holiday surge (B1), the volume monitor raised a false alarm in 100% of shifts under C4, and the circuit breaker halted the agent in 100% of shifts for a mean of 234 minutes, diverting 44.4% of legitimate activity. C5, which gives the

volume monitor and velocity rule the known business calendar, reduced false alarms to 2% and false halts to 0% (paired reduction in halt time 234 minutes per shift, 95% CI [229, 239]) while matching C4's containment in every hazard scenario. Without benign-stress scenarios this failure, and its remedy, would not have been visible.

7. Discussion

7.1. Implications for Control Design

Four design lessons follow, each tied to a metric. First, invest in incident-level containment (aggregate monitors plus a circuit breaker), because per-action controls cannot contain hazards that look individually normal. Second, budget for recovery: a circuit breaker is only as good as the fallback capacity, staged restoration, and rollback tooling behind it. Third, size human review for bursts, not averages, and route bursts to automated containment rather than to a queue. Fourth, give monitors business context, such as calendars and known campaigns, before giving them authority to halt.

7.2. Use in Model Risk Management and Supervision

The benchmark is designed to slot into existing governance rather than add a new process. Table 6 maps its outputs to supervisory expectations. It is a design aid, not legal advice; the applicability of each instrument should be confirmed with compliance and counsel.

Table 6. Mapping of Benchmark Outputs to Governance Expectations

Expectation (source)	Benchmark output
Ongoing monitoring and outcomes analysis; effective challenge (SR 11-7) [5]	Paired scenario results, CIs, run manifests
Measure risks and effectiveness of risk treatments (NIST AI RMF, MEASURE/MANAGE) [6]	Containment, false-intervention, recovery metrics
Human oversight, robustness, risk management for high-risk AI (EU AI Act) [7]	Human-review and circuit-breaker scenarios; scorecard
Withstand, contain, recover from disruption (BCBS principles; DORA) [8], [9]	TTC, TTR, diversion share, false-halt rate
AI management system controls and evidence (ISO/IEC 42001) [22]	Tiered scorecard and audit trail

In practice, an institution would replace the simulator's distributions with ones calibrated to its own action logs, encode its own controls behind the common interface, and run the benchmark at each material control change, so that the effect of a new threshold, review staffing level, or halt rule is quantified before deployment rather than inferred after an incident.

7.3. Reproducibility and Audit

Every run writes a manifest that fixes the code version, scenario and control configurations, calibration thresholds, seeds, and a hash of the results, and manifests are appended to a hash-chained log so that results cannot be silently altered after the fact. The reference implementation (Python, standard scientific libraries) is available from the author.

8. Limitations and Threats to Validity

- Simulation, not production: Results describe control behavior in a calibrated simulation. Absolute loss figures depend on the assumed distributions and are not predictions of any institution's losses; the relative effects and the trade-offs between metric families are the intended findings.
- Stylized agents and hazards: Hazards are injected as shifts in observable features. Real failures, especially adaptive adversaries, may evade monitors in ways the scenarios do not capture; adversarial scenario search is future work.
- Simplified human review: Reviewers have fixed accuracy and capacity. Real reviewer accuracy degrades with fatigue and queue pressure [18], which would likely make Finding 4 stronger.
- Ground-truth labels: The metrics rely on labels that the benchmark knows by construction. In production, containment and false intervention must be estimated from investigated samples.
- Thresholds are policy: Tier thresholds and calibration targets encode risk appetite and must be agreed with risk and compliance functions; the benchmark makes their consequences visible but does not choose them.

9. Conclusion and Future Work

As AI agents take on operational authority in banks, the governance question shifts from whether safety controls exist to how well they work and what they cost. This paper has presented a scenario-based benchmark that answers that question with three families of formally defined, auditable metrics (containment, false intervention, and recovery), a failure taxonomy and scenario library spanning five banking domains, and a paired statistical protocol. The reference study shows that the metric families must be read together: the configuration with the best containment also had the slowest recovery and, without business context, halted service on every benign holiday surge.

Future work will calibrate the scenario distributions to production action logs, add adaptive adversaries and adversarial scenario search, model reviewer fatigue, extend the library to LLM-based customer-servicing agents with tool access, and publish the scenario specifications so that institutions and supervisors can compare control stacks on a common basis.

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