Quantum-Accelerated Command Injection:
When Fewer Mistakes Mean Total Compromise
A Post-Patch Red-Team Analysis of Modern SIEM Failure

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Case Study: CVE-2025-64155 (FortiSIEM)
Companion Notebooks: Classical vs Quantum Search Simulation

1.1 Abstract

Modern defensive systems frequently detect exploitation not by observing success, but by observing *mistakes*: repeated failed attempts, anomalous inputs, and log-heavy trial-and-error that precede compromise. This document presents an academic, post-patch analysis of a command-injection vulnerability class using a *black-box success oracle* to model exploit viability without providing payloads or operational attack code. We formalize exploitation as a search/inference problem over a candidate space of inputs and show how quantum amplitude amplification reduces expected queries from $\Theta(N)$ to $\Theta(\sqrt{N})$ in an idealized setting. The key security consequence is not "faster hacking" but **certainty compression**: fewer failed attempts are required before a valid input is found, reducing observable signals that detection pipelines rely on for early warning. We provide a practical simulation that runs the same oracle-driven experiment classically and with a quantum-assisted model, reporting query counts, time proxies, and detection-threshold crossing rates. The results clarify why the failure is *pre-cryptographic*: security collapses at the decision layer before encryption, protocols, or downstream algorithmic checks ever engage.

1.2 Threat Model and Scope

Scope

This analysis is educational and defensive in intent. We do not provide exploit payloads, endpoint targeting instructions, or operational weaponization. Instead, we model exploitation as a black-box decision problem:

- A target system exposes an input interface with constraints (format, encoding, length).
- A small subset of inputs pass validation and trigger a dangerous behavior (modeled abstractly).
- The attacker learns by querying the interface and observing a success/failure signal.

1.3 Attacker and Defender Capabilities

Attacker: Can submit candidate inputs and observe a binary outcome. The attacker aims

to minimize the number of *failed* attempts prior to success.
Defender: Observes logs, anomaly scores, and rate/threshold events correlated with failed attempts. Detection is modeled as a function of query count and failure rate.

1.4 What "Better" Means (Red-Team Definition)

From a red-team perspective, **better** means:
Fewer attempts to achieve success.
Fewer failures (less log volume, lower anomaly score, weaker correlation evidence).
Shorter exposure window (less time for defenders to observe learning-in-progress).

1.5 Case Study Overview (Post-Patch Residual Surface)

Command injection vulnerabilities are often "patched" by tightening validation and filtering. In practice, patches frequently *shrink* the feasible input region without eliminating it. This leaves a residual attack surface consisting of inputs that remain valid under the system's own rules.

We define:
N: the size of the attacker's candidate space (possible input variants under consideration).
M: the number of successful candidates (valid inputs that produce compromise behavior in the model).
$\alpha = M/N$: the success fraction.

Post-patch, α is typically small: $\alpha \ll 1$.

1.6 Exploit Decision Structure as a Black-Box Oracle

We represent exploit success with an oracle function:

$$f(x) = \begin{cases} 1, & \text{if candidate } x \text{ triggers the modeled compromise condition} \\ 0, & \text{otherwise} \end{cases}$$

The defender does not see $f(x)$ directly; the defender sees *side effects* of queries and failures (logs, anomalies, thresholds). The core question becomes: **How many oracle queries are needed before $f(x) = 1$ is found?**

1.7 Observability Model (Detection from Mistakes)

Let q be the number of queries. Let $\ell(q)$ be log volume and $a(q)$ be an anomaly score proxy, with both typically increasing in q and in the fraction of failures. A simple detection model is:

$$Detect(q) = a(q) \geq T$$

where T is a detection threshold. In practice, $a(q)$ is driven by repeated failures and correlated behavior.

1.8 4 Classical Baseline

If the attacker searches uniformly at random among candidates, the probability of success per query is α and the expected number of queries until success is:

$$\mathbb{E}[Q_{\text{class}}] = \frac{1}{\alpha} = \frac{N}{M}$$

For the common case $M = 1$ (single viable variant in a large space), this becomes:

$$\mathbb{E}[Q_{\text{class}}] = N$$

and the expected number of failures prior to success is $\mathbb{E}[Q_{\text{class}}] - 1$.

1.9 4.1 Practical Interpretation

Classical exploitation is noisy because it requires many wrong guesses:

- Each wrong guess produces logs/anomalies.
- Defenders correlate repeated failures.
- The attacker's learning is observable as *mistake accumulation*.

1.10 <u>Quantum Enhancement Model: Certainty Compression</u>

Quantum amplitude amplification (Grover-style search) finds a marked element with expected query complexity:

$$\mathbb{E}[Q_{\text{quant}}] \approx \frac{\pi}{4}\sqrt{\frac{N}{M}}$$

For $M = 1$:

$$\mathbb{E}[Q_{\text{quant}}] \approx \frac{\pi}{4}\sqrt{N}$$

This is not "faster payload execution." It is fewer queries (and therefore fewer failures) before success.

1.11 Why This Undermines Detection

Defensive detection pipelines often rely on multiple failed attempts to establish confidence. If the attacker needs $\sqrt{N}$ queries instead of N, then the defender sees dramatically fewer mistakes. The early warning channel collapses.

1.12 Detection Collapse Analysis

We model detection as triggered by cumulative anomaly:

$$a(q) = \sum_{i=1}^{q} w_i \cdot f(x_i) = 0$$

where w_i is a weight capturing severity of each failure (e.g., format violation vs near-miss). A simple approximation sets $w_i = 1$ for failures:

$$a(q) \approx \text{Failures up to } q$$

Then detection triggers when $a(q) \geq T$.

1.13 Key Consequence

If quantum reduces expected failures by a factor of approximately:

$$\frac{\mathbb{E}[Q_{\text{class}}]}{\mathbb{E}[Q_{\text{quant}}]} \sim \sqrt{\frac{N}{M}},$$

then for fixed detection threshold T, many classical attack attempts would be detected before success, while quantum-assisted attempts remain below threshold.

1.14 Why This Is Pre-Cryptographic

Cryptography and protocol logic generally engage *after* an input is accepted and processed. This class of failure occurs earlier:

- The decision layer accepts a candidate as valid (structure $\neq$ intent).
- Downstream encryption/protocol mechanisms do not prevent the decision error.
- The compromise condition can be reached without breaking cryptography.
- Therefore, the threat is pre-cryptographic: security fails before encryption, protocols, or algorithms ever engage.

1.15 Reproducible Experiments (Notebook Summary)

The companion notebook runs the *same* black-box oracle experiment in two modes:

1.16 Experiment A: Classical Search

- Candidate space size N, success count M
- Repeated random queries until success
- Record: queries to success, failures, detection trigger rate

1.17 Experiment B: Quantum-Assisted Model

We simulate amplitude amplification behavior by sampling from the expected query distribution for Grover-style search:

$$Q_{\text{quant}} \approx \left\lceil \frac{\pi}{4}\sqrt{\frac{N}{M}} \right\rceil$$

We then compare:

- query counts
- failure counts
- probability of crossing detection threshold before success

1.18 What "Clear Advantage" Looks Like

For representative N (e.g., 10^4 to 10^6) and small M:

- Classical median queries $\sim N/M$
- Quantum median queries $\sim \sqrt{N/M}$ Detection triggers classically at high rates for moderate thresholds T
- Detection triggers rarely in the quantum-assisted model for the same T

1.19 <u>Defensive Implications</u>

1.20 What Must Change

If detection depends on failures, then reducing failures removes observability. Defenders need:

- signals based on *certainty* and intent, not only error volume
- semantic validation and provenance checks at the decision boundary
- anomaly models that detect *rare correctness* in suspicious contexts

1.21 9.2 Practical Controls

- Tight input provenance, canonicalization, and strict allow-listing at the boundary
- Rate limits and randomized friction on suspicious high-entropy probing patterns
- Canary tokens / invariant checks that trigger on *dangerous correctness*

1.22 Conclusion

This analysis shows that quantum advantage in exploitation is best understood as **certainty compression**: fewer wrong attempts before being right. Because modern detection depends on observing mistakes, reducing mistakes collapses the defender's early warning channel. The failure is pre-cryptographic and occurs at the decision boundary, before encryption, protocols, or algorithmic guarantees engage. The companion notebook provides a reproducible demonstration: identical black-box success conditions, classical versus quantum-assisted query complexity, and the resulting shift in detection-threshold crossing probability.