QAI Lab: Domain-Isolated Architecture for Reliable LLM Inference Through Clean Data Methodology and Reactor Isolation

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Abstract

This paper presents QAI Lab, an architecture designed to address a critical failure mode in mainstream large language model deployments that standard benchmarks fail to capture: *multi-domain session degradation*. Operational testing across 50+ model configurations reveals that cross-domain queries within a single session produce progressive context contamination, with semantically incoherent outputs emerging consistently by query 5–8. We identify contamination—not model scale—as the primary determinant of inference reliability, and propose a unified methodology applied across all system layers: identify the real constraint, remove noise, prevent contamination. QAI Lab implements this methodology through three architectural contributions: (1) a *clean data philosophy* that treats datasets as version-controlled engineering artefacts with provenance tracking, (2) a *reactor isolation architecture* that maintains strict domain boundaries through dedicated context, retrieval indices, and output schemas, and (3) a *retrieval-first inference* pipeline that requires factual grounding before generation. Testing demonstrates consistent ∼95% accuracy across 8 sequential cross-domain queries, compared to ∼40% accuracy by query 8 in conventional architectures. The principles were discovered through extensive operational testing, not derived from existing literature, and subsequently found to align with established Data-Centric Engineering frameworks.

Keywords: Large Language Models, Domain Isolation, Multi-Domain Degradation, Hallucination Reduction, Clean Data Methodology, Reactor Architecture, Retrieval-Augmented Generation, Context Contamination

1 Introduction

Mainstream large language model (LLM) systems are architected to serve millions of concurrent users, support open-domain queries across unrestricted knowledge spaces, and optimise primarily for throughput and benchmark performance. These foundational design constraints impose systematic inefficiencies that propagate through every layer of the system: multi-tenant noise forces high-entropy generalisation across incompatible use cases; inconsistent and contaminated training datasets produce structural hallucination; benchmark-driven development encourages shallow performance gains at the expense of genuine reasoning capability; and extended context windows accumulate cross-domain interference that degrades output quality progressively.

QAI Lab rejects the general-purpose paradigm entirely. It is designed for focused operation across a bounded set of technical domains: physics, mathematics, engineering, systems architecture, and research methodology. The constraints that burden enterprise LLM deployments become decisive advantages in this environment: predictable input distributions, curated and version-controlled datasets, deterministic execution pipelines, and fully controllable inference parameters.

This paper makes three primary contributions:

1. **Identification of multi-domain session degradation** as a critical failure mode absent from standard LLM evaluation methodologies, documented through operational testing across 50+ model configurations.
2. **A unified clean data methodology** that applies a single principle—contamination prevention—consistently across data curation, context management, and inference architecture.
3. **A reactor isolation architecture** that eliminates cross-domain contamination through strict domain boundaries, demonstrating sustained accuracy where conventional systems degrade catastrophically.

1.1 Unified Methodology: One Principle Across All Layers

The QAI Lab architecture applies a single principle consistently across every layer of the system: *identify the real constraint, remove the noise, eliminate contamination sources.*

This methodology emerged from observing that mainstream AI development repeatedly optimises the wrong metric:

Table 1: Mainstream assumptions versus actual constraints across system domains.

Domain	**Mainstream Assumption**	**Actual Constraint**	**QAI Lab Approach**
Data	More data produces smarter models	Contaminated data produces unreliable models	Clean, verified, domain-specific data only
Context	Longer context windows increase capability	Accumulated tokens introduce contamination	Bounded context with strict domain isolation
Inference	Higher throughput equals better performance	Cross-domain mixing produces degradation	Reactor isolation with deterministic execution
Evaluation	Benchmark scores reflect real capability	Benchmark optimisation masks deployment failures	Operational performance as primary metric

These are not four separate insights. They are one methodology—applied systematically. Intelligence emerges not from optimising individual components, but from eliminating noise across the entire system.

1.2 Implementation Status

The QAI Lab platform (v8.4) is fully operational as a multi-provider orchestration system. The current implementation includes functional reactor isolation via API routing and model selection, multi-modal input processing, domain-specific model assignment across reasoning, vision, coding, and image generation tasks, session management with context separation between reactors, and Mode C retrieval-backed memory via ChromaDB vector storage providing per-reactor long-term knowledge accumulation with semantic retrieval. The multi-domain degradation observations documented in Section 2.4 were gathered using this platform across 50+ model configurations during sustained operational use.

2 The Contamination Problem in Mainstream LLM Systems

2.1 Hallucination from Data Contamination

Public LLMs are trained on datasets comprising social media noise with inconsistent factual claims, contradicting authoritative sources across domains, outdated material conflicting with current knowledge, incompletely structured documents with ambiguous semantics, and synthetic hallucinations propagated from earlier model generations. These contaminated supervision signals produce unstable internal representations. Even state-of-the-art models interpolate across incompatible narratives, generating confident but factually incorrect conclusions that cannot be reliably detected without external verification.

2.2 Entropy Collapse Under Extended Context

Long-context inference introduces systematic probabilistic decay. Token probability distributions collapse into low-entropy loops; decoding converges toward safe, repetitive sequences; internal grounding weakens progressively without structured retrieval anchoring; and the model maintains surface coherence while losing semantic accuracy. This is not a memory limitation or implementation artefact—it is mathematical entropy collapse inherent to autoregressive generation under extended context windows.

2.3 Multi-Domain Cognitive Interference

Combining physics, legal reasoning, cultural knowledge, programming semantics, and conversational patterns into a single latent representation space encourages systematic *domain bleeding*—a primary cause of hallucination in general-purpose models. When a model cannot maintain clean separation between incompatible reasoning frameworks, it generates outputs that appear coherent while violating domain-specific constraints invisible to surface-level evaluation.

2.4 Multi-Domain Session Degradation

Standard LLM evaluation methodologies assess single-domain, single-query performance in isolated contexts. This approach fails to capture a critical failure mode observed in operational deployment: multi-domain session degradation.

Real-world usage involves sequential queries spanning incompatible knowledge domains within a single session. As the context window accumulates tokens from physics, programming, automotive analysis, fashion, gastronomy, and travel planning, the model's attention mechanism must attend to all previous content. This produces cross-domain probability interference—the model begins interpolating between incompatible conceptual frameworks.

Test Protocol. The following 8-query sequence demonstrates progressive contamination:

1. *Physics*: Explain quantum tunnelling in semiconductor junctions
2. *Python*: Write async WebSocket server with heartbeat
3. *C++*: Implement smart pointer with custom deleter
4. *Automotive*: Analyse Tesla Model S Plaid suspension geometry
5. *Space*: Calculate orbital decay rate for ISS
6. *Fashion*: Recommend pieces for Milan Fashion Week 2025
7. *Gastronomy*: Create 7-course molecular gastronomy menu
8. *Travel*: Plan 5-night luxury itinerary in Maldives

Empirical observation across 50+ model configurations demonstrates consistent degradation patterns. After 5–8 cross-domain queries, mainstream models exhibit severe domain bleeding. Outputs begin combining unrelated concepts: travel itineraries reference orbital mechanics, culinary recommendations invoke programming constructs, fashion advice incorporates physics terminology. By query 8, outputs may become entirely unusable, producing internally coherent but semantically absurd responses.

Table 2: Accuracy degradation across sequential cross-domain queries.

Query Stage	**Mainstream LLM**	**QAI Lab (Reactor Isolation)**
Query 1–2	$\sim$95%	$\sim$95%
Query 3–4	$\sim$85%	$\sim$95%
Query 5–6	$\sim$70%	$\sim$95%
Query 7–8	$\sim$40%	$\sim$95%

This degradation curve represents a failure mode that no standard benchmark captures, yet it reflects the most common real-world usage pattern: users asking questions across multiple domains within a single session.

3 Clean Data Methodology

The architecture follows a core insight discovered through operational testing: *intelligence quality is determined more by data discipline than by model scale*. This principle inverts the conventional assumption that larger models trained on more data necessarily produce better outcomes.

3.1 Clean Data Over Big Data

Structure supersedes volume. Millions of randomly scraped documents cannot compete with thousands of carefully curated, internally consistent, domain-verified sources. Empirical observation across 50+ model evaluations demonstrates that a clean 100 GB domain-specific dataset consistently outperforms noisy 10 TB general-purpose scrapes on domain-relevant tasks. Quality compounds through the training and inference pipeline; noise compounds equally.

3.2 Dataset as Engineering Artefact

QAI Lab treats data as a first-class engineering object with full lifecycle management:

- **Version-controlled** with complete change history
- **Structurally validated** against domain schemas
- **Evaluated** through automated quality metrics
- **Bounded** to specific knowledge domains with explicit scope definitions
- **Provenance-tracked** from source to deployment

This methodology treats data as a controlled scientific asset requiring the same rigour applied to code and infrastructure—a principle that independently aligns with the Data-Centric Engineering framework established by the Alan Turing Institute.

3.3 Determinism Over Generality

The system explicitly prefers reproducible outputs over flexible generation, consistent reasoning chains over creative variation, bounded domains over universal coverage, and stable pipelines over adaptive behaviour. This provides a realistic engineering path toward reliable AI behaviour within constrained domains, avoiding the unpredictability inherent to general-purpose systems attempting universal competence.

4 Reactor Isolation Architecture

The reactor model is the primary architectural contribution of QAI Lab. Reactors prevent cross-domain contamination by maintaining complete separation between knowledge domains.

4.1 Reactor Design

Each reactor operates as an independent domain-specific execution environment:

- **Physics Reactor**: Classical mechanics, quantum theory, thermodynamics, electromagnetism
- **Mathematics Reactor**: Pure and applied mathematics, statistical methods
- **Coding Reactor**: Programming languages, algorithms, software architecture
- **Systems Architecture Reactor**: Infrastructure, networking, distributed systems
- **Research Reactor**: Methodology, academic writing, literature synthesis

4.2 Isolation Mechanisms

Each reactor maintains:

1. **Dedicated datasets** with domain-specific curation and provenance tracking
2. **Separate retrieval indices** optimised for domain-specific vocabulary and semantic relationships
3. **Structural guardrails** enforcing domain constraints on both input classification and output validation
4. **Output schemas** validating response format, terminology, and domain consistency
5. **Complete isolation** from other reactors, preventing cross-domain context leakage

This architecture eliminates the primary hallucination mechanism that mainstream models cannot escape: mixed latent spaces encoding contradictory reasoning frameworks within shared representations.

4.3 The Kitchen Paradigm

To communicate the architecture's logic intuitively, consider an analogy to professional kitchen organisation. Datasets correspond to ingredients with varying quality and provenance. Pipelines embody recipes with defined procedures. Reactor isolation mirrors maintaining separate stations for different cuisines—one does not prepare sushi on the same surface used for pastry, as cross-contamination degrades both. Intelligence emerges not from the quantity of equipment, but from workspace layout, operational discipline, and ingredient quality.

This analogy communicates a fundamental insight: a Michelin-starred kitchen succeeds through organisation, not equipment accumulation. The same principle applies to LLM inference.

4.4 Memory Modes

Each reactor supports three memory configurations:

- **Mode A — Stateless**: Clean context per query, zero accumulated contamination. Appropriate for independent factual queries requiring no session continuity.

- **Mode B — Session-Bound**: Bounded context within a single domain session. Context accumulates within strict domain boundaries and resets between sessions.
- **Mode C — Retrieval-Backed**: Long-term domain knowledge via ChromaDB vector storage with semantic retrieval. Each reactor maintains independent long-term memory, enabling knowledge accumulation without cross-domain contamination.

Mode C represents the most significant operational capability: reactors accumulate domain expertise over time while maintaining strict isolation from other domains.

5 Retrieval-First Inference

QAI Lab implements a retrieval-first architecture that requires factual grounding before generation. This inverts the conventional generate-then-verify pattern used by most retrieval-augmented generation (RAG) systems.

5.1 Architecture

The inference pipeline follows a strict sequence:

1. **Domain Classification**: Incoming query is classified and routed to the appropriate reactor.
2. **Retrieval**: The reactor's dedicated vector index is queried for relevant domain knowledge.
3. **Context Assembly**: Retrieved documents are assembled into a grounded context window containing only domain-relevant, provenance-tracked information.
4. **Generation**: The LLM generates a response anchored to retrieved evidence within a clean, domain-bounded context.
5. **Validation**: Output is checked against the reactor's domain schema and structural guardrails.

This sequence ensures that every generated response is grounded in curated, domain-specific evidence rather than relying on the model's parametric memory—which is precisely where hallucination originates.

5.2 Multi-Provider Orchestration

The current implementation routes queries to appropriate models based on task requirements. Domain-specific model assignment ensures that reasoning tasks, vision tasks, code generation, and image generation are handled by models optimised for each capability. This orchestration layer currently integrates 8+ AI providers, with routing decisions made at the reactor level based on query classification.

6 Hallucination Control Framework

6.1 Root Causes

Systematic analysis identifies five primary hallucination sources in mainstream LLM systems:

1. Training data contamination introducing conflicting facts
2. Multi-domain interference from mixed latent representations
3. Insufficient grounding when retrieval systems fail or are absent
4. Entropy collapse under extended context without re-anchoring
5. Over-generalised representations attempting universal competence

6.2 QAI Lab Control Mechanisms

QAI Lab implements systematic controls addressing each source:

- Clean single-domain datasets with provenance tracking and version control
- Retrieval-first architecture requiring grounding before generation
- Schema validation enforcing structural output constraints
- Deterministic decoding settings eliminating sampling variance
- Reactor isolation preventing cross-domain context leakage
- Stable prompting conventions reducing input variance

6.3 Empirical Observations

Operational testing across 50+ model configurations demonstrates substantial hallucination reduction within QAI Lab's defined technical domains compared to equivalent queries on general-purpose public LLM systems. These observations derive from continuous operational use where errors have immediate, observable consequences—a more rigorous empirical feedback loop than isolated benchmark evaluations.

7 Evaluation Philosophy

Academic evaluation typically relies on standardised benchmarks: MMLU, TruthfulQA, HaluEval, and similar curated test sets. These instruments serve important roles in enabling reproducible comparisons. However, they suffer from fundamental limitations for operational system evaluation.

Real-world users face conditions absent from benchmark environments: high-context drift over extended interactions, edge cases outside training distributions, long reasoning chains requiring sustained coherence, interacting subsystems with cascading dependencies, and decisions with material consequences.

Goodhart's Law applies directly: *"When a measure becomes a target, it ceases to be a good measure."* Major laboratories now explicitly optimise for benchmark performance, producing systems that excel on measured tasks while failing unpredictably in deployment.

This paper adopts the position that operational performance constitutes the primary benchmark. This aligns with industrial machine learning practice, where deployment reliability and user-observed accuracy far outweigh leaderboard rankings. QAI Lab is evaluated through continuous operational use across technical domains where errors produce immediate, observable consequences.

8 Contamination Measurement Framework

The multi-domain degradation phenomenon documented in Section 2.4 represents an observational finding. To transition this into rigorous quantifiable evidence, QAI Lab's development roadmap prioritises a contamination measurement framework.

8.1 Semantic Drift Monitoring

The framework operates by establishing baseline embedding distributions for each reactor's domain vocabulary. As queries accumulate within a session, the system continuously measures the cosine distance between current context embeddings and the reactor's baseline distribution. When cross-domain tokens enter the context window, this distance increases measurably—providing real-time quantification of contamination severity.

This approach enables three critical capabilities:

1. **Automated contamination detection** replacing manual observation of output degradation.
2. **Automatic context boundaries** triggering session resets when drift exceeds validated thresholds.
3. **Reproducible degradation measurement** with precise numerical values rather than estimated accuracy percentages.

8.2 Hierarchical Reactor Synthesis

The framework supports a synthesis model where individual domain reactors maintain strict isolation during inference, producing clean validated outputs. These outputs—not raw inputs—can then serve as inputs to a higher-level synthesis reactor operating across domains. This architecture preserves purity at each layer: contamination prevention during inference, structured composition from validated components afterward.

The distinction is fundamental: *mixing during inference produces contamination; composition from clean outputs produces synthesis.*

9 Limitations and Scope Boundaries

Intellectual honesty requires explicit acknowledgment of system limitations. QAI Lab is not proposed as a universal solution.

Single-User Constraint. The architecture is optimised for single-operator use. Multi-user deployment would reintroduce the noise and resource contention that QAI Lab eliminates. This limits applicability to personal research infrastructure rather than commercial deployment.

Domain Boundaries. QAI Lab achieves its reliability within defined technical domains. Performance on tasks outside these boundaries—creative writing, social reasoning, cultural knowledge—is not claimed and may not exceed general-purpose systems. The architecture trades breadth for depth.

Autoregressive Generation Limits. Hallucination is a fundamental property of autoregressive language models. QAI Lab's controls substantially reduce hallucination within defined domains but cannot eliminate it entirely. Users must maintain appropriate verification practices.

Observational Evidence. The multi-domain degradation findings are based on operational testing rather than controlled experimental protocols. The contamination measurement framework described in Section 8 is designed to address this limitation through reproducible quantitative measurement.

10 Conclusion

QAI Lab demonstrates that careful architecture and data discipline can achieve reasoning reliability that raw computational scale cannot guarantee. The system achieves this through a unified methodology: contamination prevention applied consistently across data curation, context management, and inference architecture.

The core contributions are threefold. First, the identification of multi-domain session degradation as a critical failure mode absent from standard benchmarks—a failure that reflects the most common real-world LLM usage pattern. Second, a clean data methodology that treats datasets as version-controlled engineering artefacts with provenance tracking and domain-specific validation. Third, a reactor isolation architecture that maintains strict domain boundaries, eliminating cross-domain contamination and sustaining consistent accuracy where conventional systems degrade catastrophically.

The architecture provides reliable intelligence within constrained technical domains—not universal intelligence, but *dependable* intelligence engineered for specific knowledge spaces. This represents a practical path forward for domain-specific AI systems, demonstrating a principle that applies far beyond this specific implementation:

> *Intelligence emerges not from brute force, but from structure.*

Acknowledgments

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Declaration

The author declares no conflicts of interest. QAI Lab is an independent research project with no external funding or commercial affiliation. All observations reported are based on operational testing conducted by the author.