CANONICAL LIVING OVERVIEW GUIDE

Artificial Intelligence Engineering

A broad AI engineering guide covering model architectures, data and training, inference, quantization, evaluation, multimodal systems, local models, routing, fine-tuning, observability, safety, deployment, and lifecycle governance.

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Publication position
This is a living field guide. It is designed for frequent revision while retaining a stable permanent identity. Candidate status means the content is ready for structured use and review but is not represented as an external certification or authority publication.

LEVEL	CLASS	CADENCE	EVIDENCE
L1-L4	FIELD GUIDE	QUARTERLY	SOURCE-BOUND
Foundational through frontier	Practical and educational	Interim updates as needed	Limitations remain visible

Reader orientation

Dimension	Engineering position
Primary domain	MYTHOS-AI - Artificial Intelligence & Agentic Systems
Secondary domain	MYTHOS-DAT; MYTHOS-SWE; MYTHOS-SEC; MYTHOS-CLD
Audience	AI engineers, ML engineers, software and platform engineers, data teams, model evaluators, architects, security teams, and technical leaders.
Prerequisites	Basic programming, probability, data, and systems knowledge. Mathematical concepts are explained operationally, but deeper model chapters benefit from linear algebra and machine-learning familiarity.
Publisher / owner	Mythos Systems / Aaron Stovall
Public classification	Public technical guidance

Expected outcomes

Understand major AI model classes and how architecture, data, objectives, hardware, and serving choices shape behavior.

Build reproducible data, training, fine-tuning, inference, evaluation, and deployment systems with explicit lineage.

Evaluate capability, quality, safety, robustness, latency, cost, privacy, and operational fit using disclosed methods.

Engineer multimodal, local, routed, and tool-using AI systems with observable boundaries and failure recovery.

Govern AI lifecycle risk through evidence, human authority, source freshness, security, and controlled adoption.

How to use this guide

Read the guide as a progressive system rather than a disconnected encyclopedia. Foundational material establishes the mental model; practitioner sections convert it into repeatable implementation and operations; advanced sections expose architecture, scale, security, and failure behavior; frontier sections describe technologies whose evidence or maturity is still evolving.

Suggested reading path
New practitioners should follow the chapters in order and complete the laboratories. Experienced engineers may begin with the architecture, failure, validation, or frontier sections, then use the related-document map to deepen a specific topic.

Learning and assurance model

Level	Reader outcome
L1 - Foundational	Terminology, first principles, component roles, packet or state flow, and simple working examples.
L2 - Practitioner	Implementation, configuration, automation, testing, troubleshooting, and operational evidence.
L3 - Advanced	Architecture, scale, concurrency, resilience, threat models, performance, and complex migrations.
L4 - Frontier	Emerging systems, research directions, technical uncertainty, readiness gates, and adoption signals.

Contents

CHAPTER 01

AI systems mental model and architecture families

Understand AI as a complete system of data, objectives, models, compute, interfaces, evaluation, operations, and governance.

Chapter operating position

Understand AI as a complete system of data, objectives, models, compute, interfaces, evaluation, operations, and governance.

1.1 Machine learning problem formulation

Machine learning problem formulation is treated here as an engineering capability rather than a vocabulary item. Define task, target, input, output, objective, constraints, evaluation population, and acceptable failure before selecting a model. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for machine learning problem formulation.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating machine learning problem formulation as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for machine learning problem formulation.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

1.2 Transformers, attention, and language models

Transformers, attention, and language models is treated here as an engineering capability rather than a vocabulary item. Understand tokenization, embeddings, attention, position, layers, decoding, context, and the difference between next-token training and system capability. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for transformers, attention, and language models.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating transformers, attention, and language models as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
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Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for transformers, attention, and language models.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

1.3 Mixture of experts, state-space, and hybrid models

Mixture of experts, state-space, and hybrid models is treated here as an engineering capability rather than a vocabulary item. Compare sparse experts, recurrent or state-space approaches, retrieval, tools, symbolic components, and multimodal encoders. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for mixture of experts, state-space, and hybrid models.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating mixture of experts, state-space, and hybrid models as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for mixture of experts, state-space, and hybrid models.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

1.4 System architecture beyond the model

System architecture beyond the model is treated here as an engineering capability rather than a vocabulary item. Include prompts, retrieval, memory, tools, routing, safety, telemetry, user interface, policy, and human review in the evaluated system. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for system architecture beyond the model.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.

Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

Treating system architecture beyond the model as a product feature rather than an end-to-end engineering behavior.

Automating an undocumented process and scaling its ambiguity.

Relying on a happy-path demonstration without degraded-state or rollback testing.

Using aggregate dashboards without retaining trace-level evidence.

Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for system architecture beyond the model.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 01 laboratory and review

Practical laboratory

Diagram a complete AI application from data and model through retrieval, tools, policy, interface, telemetry, and human authority. Identify which failures belong to the model and which belong to the surrounding system.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Track neuro-symbolic models, state-space architectures, world models, embodied systems, sparse computation, and architectures designed for long context or continual adaptation.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 02

Data, labeling, synthetic data, and governance

Build data systems with known origin, rights, quality, representation, contamination, privacy, and lifecycle.

Chapter operating position

Build data systems with known origin, rights, quality, representation, contamination, privacy, and lifecycle.

2.1 Dataset definition and lineage

Dataset definition and lineage is treated here as an engineering capability rather than a vocabulary item. Record source, license, consent, collection, transformations, versions, splits, ownership, and intended use. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for dataset definition and lineage.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating dataset definition and lineage as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for dataset definition and lineage.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

2.2 Quality, representation, and bias

Quality, representation, and bias is treated here as an engineering capability rather than a vocabulary item. Measure coverage, duplication, errors, imbalance, harmful content, proxy variables, and population-specific limitations. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for quality, representation, and bias.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating quality, representation, and bias as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for quality, representation, and bias.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

2.3 Labeling and human feedback

Labeling and human feedback is treated here as an engineering capability rather than a vocabulary item. Define guidance, adjudication, quality checks, worker conditions, disagreement, and provenance for labels and preference data. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for labeling and human feedback.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating labeling and human feedback as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for labeling and human feedback.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

2.4 Synthetic data and contamination control

Synthetic data and contamination control is treated here as an engineering capability rather than a vocabulary item. Use generated data with disclosed generator, filtering, validation, diversity, leakage, recursion, and separation from evaluation sets. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for synthetic data and contamination control.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating synthetic data and contamination control as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for synthetic data and contamination control.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 02 laboratory and review

Practical laboratory

Create a data card for a small training or evaluation dataset. Include lineage, license, quality checks, representation, privacy, contamination controls, limitations, and approved uses.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore privacy-preserving data collaboration, federated learning, machine unlearning, verifiable data lineage, synthetic environments, and self-generated curricula with external validation.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 03

Training, fine-tuning, alignment, and continual learning

Engineer optimization and adaptation with reproducible configuration, measurement, safety, and rollback.

Chapter operating position
Engineer optimization and adaptation with reproducible configuration, measurement, safety, and rollback.

3.1 Pretraining and optimization systems

Pretraining and optimization systems is treated here as an engineering capability rather than a vocabulary item. Connect objective, batching, sequence length, optimizer, schedule, precision, distributed strategy, checkpointing, and hardware utilization. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for pretraining and optimization systems.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating pretraining and optimization systems as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for pretraining and optimization systems.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

3.2 Supervised fine-tuning and parameter-efficient methods

Supervised fine-tuning and parameter-efficient methods is treated here as an engineering capability rather than a vocabulary item. Use representative data, frozen baselines, adapters, validation, overfit checks, and deployment compatibility. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for supervised fine-tuning and parameter-efficient methods.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating supervised fine-tuning and parameter-efficient methods as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for supervised fine-tuning and parameter-efficient methods.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

3.3 Preference optimization and reinforcement learning

Preference optimization and reinforcement learning is treated here as an engineering capability rather than a vocabulary item. Define reward evidence, annotator behavior, policy constraints, evaluation, gaming risk, and regression monitoring. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for preference optimization and reinforcement learning.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating preference optimization and reinforcement learning as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for preference optimization and reinforcement learning.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

3.4 Continual learning and catastrophic forgetting

Continual learning and catastrophic forgetting is treated here as an engineering capability rather than a vocabulary item. Balance adaptation with retained capability, replay, modularity, evaluation history, rollback, and change governance. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

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Engineering practices

- Define the authoritative source and ownership boundary for continual learning and catastrophic forgetting.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.

Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

Treating continual learning and catastrophic forgetting as a product feature rather than an end-to-end engineering behavior.

Automating an undocumented process and scaling its ambiguity.

Relying on a happy-path demonstration without degraded-state or rollback testing.

Using aggregate dashboards without retaining trace-level evidence.

Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for continual learning and catastrophic forgetting.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 03 laboratory and review

Practical laboratory

Fine-tune or simulate adaptation of a small model using a documented dataset, configuration, baseline, held-out tests, safety cases, resource metrics, checkpoint lineage, and rollback decision.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore online adaptation, evidence feedback, modular experts, memory-augmented learning, federated updates, and continual systems with cryptographically tracked lineage.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 04

Inference, quantization, serving, and local models

Deliver models with bounded latency, memory, throughput, quality, cost, privacy, and failure behavior across hardware and environments.

Chapter operating position

Deliver models with bounded latency, memory, throughput, quality, cost, privacy, and failure behavior across hardware and environments.

4.1 Inference graphs, batching, and scheduling

Inference graphs, batching, and scheduling is treated here as an engineering capability rather than a vocabulary item. Understand prefill, decode, batching, queueing, parallelism, compilation, kernels, and service-level tradeoffs. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for inference graphs, batching, and scheduling.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating inference graphs, batching, and scheduling as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for inference graphs, batching, and scheduling.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

4.2 Quantization and compression

Quantization and compression is treated here as an engineering capability rather than a vocabulary item. Evaluate numeric formats, calibration, weight and activation quantization, sparsity, distillation, and quality regression by workload. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for quantization and compression.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating quantization and compression as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for quantization and compression.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

4.3 KV cache, context, and memory pressure

KV cache, context, and memory pressure is treated here as an engineering capability rather than a vocabulary item. Manage cache size, eviction, prefix reuse, long-context cost, concurrency, and hardware limits. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for kv cache, context, and memory pressure.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating kv cache, context, and memory pressure as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for kv cache, context, and memory pressure.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

4.4 Local, edge, browser, and sovereign inference

Local, edge, browser, and sovereign inference is treated here as an engineering capability rather than a vocabulary item. Select runtimes, formats, hardware, privacy boundaries, update paths, observability, and fallback for constrained deployment. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency,

orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for local, edge, browser, and sovereign inference.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating local, edge, browser, and sovereign inference as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for local, edge, browser, and sovereign inference.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 04 laboratory and review

Practical laboratory

Benchmark one model across at least two serving or quantization configurations. Disclose hardware, software, model, workload, context, concurrency, latency distribution, throughput, memory, quality, and energy assumptions.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore speculative decoding, disaggregated serving, photonic accelerators, NPUs, browser-local inference, confidential model execution, and edge model swarms.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 05

Evaluation, benchmarks, and model selection

Measure systems against real workloads, representative populations, failure cases, evidence confidence, and operational constraints.

Chapter operating position
Measure systems against real workloads, representative populations, failure cases, evidence confidence, and operational constraints.

5.1 Evaluation design and task validity

Evaluation design and task validity is treated here as an engineering capability rather than a vocabulary item. Define the decision, population, dataset, contamination risk, scoring, uncertainty, failure cost, and what the evaluation does not prove. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for evaluation design and task validity.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating evaluation design and task validity as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for evaluation design and task validity.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

5.2 Capability, quality, safety, and robustness

Capability, quality, safety, and robustness is treated here as an engineering capability rather than a vocabulary item. Combine task performance with calibration, consistency, adversarial behavior, refusal quality, bias, privacy, and tool or retrieval behavior. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for capability, quality, safety, and robustness.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating capability, quality, safety, and robustness as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for capability, quality, safety, and robustness.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

5.3 System benchmarks and operational metrics

System benchmarks and operational metrics is treated here as an engineering capability rather than a vocabulary item. Measure latency, throughput, memory, energy, availability, cost, context, tool success, retrieval quality, and human effort. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for system benchmarks and operational metrics.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating system benchmarks and operational metrics as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for system benchmarks and operational metrics.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

5.4 Evidence confidence and revalidation

Evidence confidence and revalidation is treated here as an engineering capability rather than a vocabulary item. Grade source and experiment quality, retain versions and methods, and schedule reevaluation when models or systems change. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

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Engineering practices

- Define the authoritative source and ownership boundary for evidence confidence and revalidation.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating evidence confidence and revalidation as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for evidence confidence and revalidation.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 05 laboratory and review

Practical laboratory

Build an evaluation suite for a model-supported workflow with representative cases, adversarial cases, retrieval and tool checks, human rubric, latency and cost metrics, and reproducible result records.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore continuously generated evaluations, causal testing, adaptive adversaries, agent benchmarks, long-horizon task evaluation, and public benchmark contamination defenses.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 06

Multimodal, retrieval, tools, and AI applications

Compose models with external information and action systems while preserving grounding, permissions, latency, and recovery.

Chapter operating position
Compose models with external information and action systems while preserving grounding, permissions, latency, and recovery.

6.1 Retrieval-augmented generation and grounding

Retrieval-augmented generation and grounding is treated here as an engineering capability rather than a vocabulary item. Control source authority, chunking, indexing, retrieval, reranking, context assembly, citation, freshness, privacy, and deletion. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for retrieval-augmented generation and grounding.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating retrieval-augmented generation and grounding as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for retrieval-augmented generation and grounding.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

6.2 Vision, audio, voice, and multimodal fusion

Vision, audio, voice, and multimodal fusion is treated here as an engineering capability rather than a vocabulary item. Engineer preprocessing, alignment, temporal behavior, latency, accessibility, privacy, and modality-specific evaluation. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for vision, audio, voice, and multimodal fusion.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating vision, audio, voice, and multimodal fusion as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for vision, audio, voice, and multimodal fusion.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

6.3 Tool use, APIs, and action boundaries

Tool use, APIs, and action boundaries is treated here as an engineering capability rather than a vocabulary item. Define schemas, permissions, validation, side effects, timeouts, retries, approval, idempotency, and evidence for model-selected actions. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

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Engineering practices

- Define the authoritative source and ownership boundary for tool use, apis, and action boundaries.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating tool use, apis, and action boundaries as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for tool use, apis, and action boundaries.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

6.4 Memory, personalization, and user control

Memory, personalization, and user control is treated here as an engineering capability rather than a vocabulary item. Separate session state, durable memory, profile, preference, source knowledge, deletion, consent, correction, and sensitive data. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for memory, personalization, and user control.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

Treating memory, personalization, and user control as a product feature rather than an end-to-end engineering behavior.

Automating an undocumented process and scaling its ambiguity.

Relying on a happy-path demonstration without degraded-state or rollback testing.

Using aggregate dashboards without retaining trace-level evidence.

Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for memory, personalization, and user control.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 06 laboratory and review

Practical laboratory

Build a multimodal or retrieval-enabled application with source citations, typed tools, scoped permissions, latency measurements, privacy controls, evaluation cases, and one recoverable tool failure.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore embodied multimodal systems, real-time voice agents, persistent presence, semantic world models, privacy-preserving personalization, and interoperable tool protocols.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 07

Safety, security, privacy, and red teaming

Engineer defenses for model, data, prompt, tool, supply-chain, privacy, misuse, and operational risks.

Chapter operating position
Engineer defenses for model, data, prompt, tool, supply-chain, privacy, misuse, and operational risks.

7.1 Threat modeling AI systems

Threat modeling AI systems is treated here as an engineering capability rather than a vocabulary item. Model prompt injection, data poisoning, model theft, sensitive disclosure, tool abuse, supply-chain compromise, excessive agency, and denial of service. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for threat modeling ai systems.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating threat modeling ai systems as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for threat modeling ai systems.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

7.2 Alignment, misuse, and harmful behavior evaluation

Alignment, misuse, and harmful behavior evaluation is treated here as an engineering capability rather than a vocabulary item. Test target risks with representative and adversarial cases while documenting policy, tradeoffs, false refusal, and residual gaps. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for alignment, misuse, and harmful behavior evaluation.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating alignment, misuse, and harmful behavior evaluation as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for alignment, misuse, and harmful behavior evaluation.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

7.3 Privacy and sensitive data

Privacy and sensitive data is treated here as an engineering capability rather than a vocabulary item. Control training and inference data, logs, embeddings, memory, prompts, outputs, access, retention, deletion, and provider boundaries. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for privacy and sensitive data.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating privacy and sensitive data as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for privacy and sensitive data.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

7.4 AI supply chain and artifact provenance

AI supply chain and artifact provenance is treated here as an engineering capability rather than a vocabulary item. Track base models, adapters, datasets, code, containers, runtimes, prompts, policies, evaluators, signers, and deployments. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for ai supply chain and artifact provenance.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating ai supply chain and artifact provenance as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for ai supply chain and artifact provenance.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 07 laboratory and review

Practical laboratory

Threat-model an AI application and run a controlled red-team exercise across prompt, retrieval, memory, tool, identity, privacy, and availability boundaries. Produce remediation and retest evidence.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore model watermarking and provenance, confidential inference, privacy-preserving training, mechanistic interpretability, formal tool policies, and autonomous red-team systems.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

CHAPTER 08

Deployment, observability, governance, and lifecycle

Operate AI systems through controlled release, monitoring, incident response, model change, deprecation, and accountable decision-making.

Chapter operating position

Operate AI systems through controlled release, monitoring, incident response, model change, deprecation, and accountable decision-making.

8.1 AI platform and deployment architecture

AI platform and deployment architecture is treated here as an engineering capability rather than a vocabulary item. Manage model registry, artifacts, environments, endpoints, routing, secrets, scaling, isolation, canary, rollback, and capacity. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for ai platform and deployment architecture.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating ai platform and deployment architecture as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for ai platform and deployment architecture.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

8.2 AI observability and semantic telemetry

AI observability and semantic telemetry is treated here as an engineering capability rather than a vocabulary item. Trace requests, model and prompt versions, context, retrieval, tools, latency, cost, tokens, quality signals, errors, and feedback. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for ai observability and semantic telemetry.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating ai observability and semantic telemetry as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for ai observability and semantic telemetry.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

8.3 Governance, documentation, and accountability

Governance, documentation, and accountability is treated here as an engineering capability rather than a vocabulary item. Maintain model and system cards, owners, risk decisions, approvals, limitations, change records, user disclosures, and escalation. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency, orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for governance, documentation, and accountability.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating governance, documentation, and accountability as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for governance, documentation, and accountability.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

8.4 Monitoring, incidents, and retirement

Monitoring, incidents, and retirement is treated here as an engineering capability rather than a vocabulary item. Detect drift, quality regression, abuse, privacy incidents, provider changes, cost anomalies, and unsupported versions and retire safely. The design objective is to make the behavior understandable before it is automated, measurable before it is optimized, and recoverable before it is scaled.

Within MYTHOS-AI - Artificial Intelligence & Agentic Systems, this capability should be represented through explicit boundaries, typed or otherwise enforceable contracts, observable state transitions, and named owners. A production design separates intent from mechanism, control-plane decisions from data-plane execution, and nominal behavior from degraded or adversarial behavior. The resulting system is easier to test, review, migrate, and operate because its assumptions are visible rather than embedded in tribal knowledge.

Implementation begins with a small, inspectable baseline. Establish the authoritative inputs, expected outputs, invariants, timeout and retry behavior, identity context, telemetry, and rollback path. Only then add abstraction, concurrency,

orchestration, optimization, or autonomous behavior. This sequence prevents sophistication from hiding incomplete fundamentals and makes later evidence comparable across revisions.

Engineering practices

- Define the authoritative source and ownership boundary for monitoring, incidents, and retirement.
- Make preconditions, invariants, error states, and recovery actions explicit.
- Instrument the critical path with stable identifiers, timestamps, and outcome codes.
- Validate in a representative environment before widening blast radius.
- Capture repeatable evidence so another engineer can reproduce the conclusion.

Failure patterns

- Treating monitoring, incidents, and retirement as a product feature rather than an end-to-end engineering behavior.
- Automating an undocumented process and scaling its ambiguity.
- Relying on a happy-path demonstration without degraded-state or rollback testing.
- Using aggregate dashboards without retaining trace-level evidence.
- Allowing ownership, version, or authority to become implicit.

Validation and evidence

Method	Expected evidence
Examine	Architecture, configuration, contracts, runbooks, and source authority for monitoring, incidents, and retirement.
Interview	Engineers and operators responsible for design, implementation, review, and incident ownership.
Test	Nominal, boundary, failure, timeout, recovery, and rollback scenarios with retained evidence.
Measure	Correctness, latency, reliability, resource use, security outcomes, and operator effort.

Chapter 08 laboratory and review

Practical laboratory

Create a production readiness package for an AI service including architecture, model and data lineage, evaluations, risk register, telemetry, canary, rollback, incident plan, user disclosure, and retirement criteria.

Laboratory evidence package

- Architecture or topology showing boundaries, identities, dependencies, and authoritative inputs.
- Versioned configuration or code with explanatory comments and reproducible setup instructions.
- Nominal-path validation plus at least two injected failure or boundary conditions.
- Structured logs, traces, metrics, packet captures, test output, or other appropriate evidence.
- A concise decision record covering findings, limitations, residual risks, and next actions.

Frontier extension

Explore continuously governed AI, dynamic model routing, local-cloud federations, self-improving systems under fixed policy, AI assurance cases, and regulation-aware deployment.

Review gate

Advance only when another engineer can reproduce the result, explain the architecture, identify the failure boundary, and distinguish measured evidence from assumptions or projections.

Integrated learning roadmap

The guide is intended to be revisited. First establish fluency, then build a small implementation, operate it under failure, automate repeatable work, and finally evaluate emerging techniques against a stable baseline. Progress is demonstrated through evidence rather than reading completion alone.

Stage	Demonstrated capability
Foundation	Explain the system from first principles and trace its critical path without relying on product terminology.
Build	Implement the smallest representative system with explicit contracts, identities, telemetry, and tests.
Operate	Diagnose injected failures, recover safely, and preserve evidence of the causal chain.
Automate	Convert a proven manual workflow into bounded, idempotent, observable automation.
Architect	Design for scale, resilience, security, interoperability, and lifecycle change.
Explore	Evaluate frontier techniques using stated hypotheses, limitations, and adoption gates.

Source authority register

Source policy
Official standards, specifications, and project documentation remain with their issuing organizations. Mythos Systems provides original engineering interpretation, synthesis, implementation guidance, and relationship mapping. Source verification dates do not guarantee that an authority has not changed since review.

01. NIST - Artificial Intelligence Risk Management Framework 1.0
Role: AI risk, governance, measurement, and management framework.
Verified: 2026-07-26
Official source: https://www.nist.gov/itl/ai-risk-management-framework

02. NIST - AI 600-1 - Generative Artificial Intelligence Profile
Role: Generative-AI risk profile and action guidance.
Verified: 2026-07-26
Official source: https://doi.org/10.6028/NIST.AI.600-1

03. OWASP - Top 10 for Large Language Model Applications 2025
Role: LLM and generative-AI application security risks.
Verified: 2026-07-26
Official source: https://genai.owasp.org/llm-top-10/

04. MLCommons - MLPerf Training and Inference Benchmarks
Role: Reproducible model performance and system benchmarking reference.
Verified: 2026-07-26
Official source: https://mlcommons.org/benchmarks/

05. OpenTelemetry - Semantic Conventions
Role: Telemetry semantic conventions for distributed systems and generative AI.
Verified: 2026-07-26
Official source: https://opentelemetry.io/docs/specs/semconv/

06. Model Context Protocol - Model Context Protocol Specification
Role: Tool and context interoperability protocol reference.
Verified: 2026-07-26
Official source: https://modelcontextprotocol.io/specification/2025-11-25

07. NIST - SP 800-218 - Secure Software Development Framework
Role: Secure software development practices.
Verified: 2026-07-26
Official source: https://csrc.nist.gov/pubs/sp/800/218/final

08. NIST - Cybersecurity Framework 2.0
Role: Cybersecurity risk and governance framework.
Verified: 2026-07-26
Official source: https://www.nist.gov/cyberframework

Authority application and refresh triggers

Authority class	Required library action
Protocols and specifications	Recheck interoperability, security considerations, defaults, and migration guidance when a referenced specification changes.
Security and assurance frameworks	Update control mappings, evidence expectations, risk language, and assessment procedures after material framework revision.
Languages, runtimes, and projects	Re-run examples, tests, deprecation checks, and operational recommendations against supported releases.
Benchmarks and evaluations	Re-execute claims when workloads, methods, models, compilers, drivers, hardware, or scoring rules change.
Operational evidence	Incorporate validated incidents, failure tests, reader corrections, and measured implementation outcomes into the next revision.

Limitations, freshness, and revision control

Boundary	Statement
Publication limitation	This guide synthesizes broad engineering practice. It does not replace product documentation, legal advice, safety certification, or environment-specific design review.
Evidence limitation	Not every pattern is benchmarked in every environment. Examples illustrate engineering methods and must be validated against actual versions, workloads, hardware, policy, and failure conditions.
Freshness limitation	Vendor behavior, software libraries, AI models, security threats, and emerging standards can change quickly. Volatile claims require source revalidation before operational adoption.
Adoption limitation	Frontier content is not an implicit adoption recommendation. Adoption requires defined value, qualification gates, controlled proof, rollback, ownership, and residual-risk acceptance.
Status boundary	Candidate Living Guide describes the publication, not certification of a product, implementation, engineer, or organization.

Revision record

Version	Revision statement
1.0.0-candidate	Initial candidate living-guide edition. Published 2026-07-26; scheduled review 2026-10-26.

Search and relationship metadata

Dimension	Engineering position
Primary domain	MYTHOS-AI - Artificial Intelligence & Agentic Systems
Secondary domain	MYTHOS-DAT; MYTHOS-SWE; MYTHOS-SEC; MYTHOS-CLD
Publication class	Field Guide / Canonical Living Overview Guide
Skill levels	L1 Foundational; L2 Practitioner; L3 Advanced; L4 Frontier
Tags	AI engineering, machine learning, model architecture, training, fine-tuning, inference, quantization, local models, evaluation, multimodal, AI safety, observability
Canonical route	/library/field-guides/mythos-guide-ai-0001/

Living publication

Corrections, expanded laboratories, improved diagrams, authority changes, and new engineering evidence should revise this permanent publication rather than create disconnected replacements.