GerdsenAi

Impetus-LLM-Server — Software Architecture Blueprint

Full-Stack Modernization: Async APIs, RAG, Neural Engine, and Production Readiness

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Impetus-LLM-Server — Software Architecture Blueprint

Executive Summary

Impetus-LLM-Server is a local LLM inference server optimized for Apple Silicon, providing an OpenAI-compatible API powered by MLX. This blueprint defines a comprehensive modernization strategy that transforms the current Flask-based architecture into a production-grade, async-native platform with retrieval-augmented generation (RAG), hybrid neural compute, and a modern React dashboard.

The recommended technology stack centers on **FastAPI 0.134.0** for the backend API layer, replacing Flask to unlock native async streaming, WebSocket support, and automatic OpenAPI documentation. For retrieval-augmented generation, **ChromaDB v1.5** serves as the MVP vector database paired with **nomic-embed-text-v1.5** embeddings running on-device via MLX, with a clear upgrade path to **Qdrant** for production scaling. The compute architecture adopts a **hybrid MLX GPU + Core ML ANE** strategy, routing LLM inference to the Metal GPU while offloading embedding computation to the Apple Neural Engine for 10-30x latency improvement. The frontend modernizes around **Zustand v5**, **TanStack Query v5**, **TanStack Router**, and **Tailwind CSS v4**, delivering type-safe state management, intelligent data caching, and zero-runtime styling.

Key architectural decisions include a disaggregated inference model separating prefill and decode phases across compute units, a phased RAG evolution from naive to agentic patterns, and an OpenTelemetry-based observability stack. The implementation roadmap spans approximately 24 weeks for a solo developer, organized into six phases with concrete deliverables per milestone.

Project Overview and Requirements

Functional Requirements

The modernization addresses gaps in the current implementation while preserving OpenAI API compatibility as the primary contract.

ID	Description	Priority
FR-01	Async-native API layer with streaming SSE and WebSocket support	Must
FR-02	OpenAI-compatible /v1/chat/completions with concurrent request handling	Must
FR-03	Vector database integration for document storage and retrieval	Must
FR-04	On-device embedding generation via MLX-compatible models	Must
FR-05	RAG pipeline with query augmentation and context injection	Must
FR-06	/v1/embeddings endpoint for embedding generation	Must
FR-07	Hybrid compute dispatcher routing workloads across GPU and ANE	Should
FR-08	Type-safe frontend with centralized state management	Should
FR-09	Client-side routing with code splitting and lazy loading	Should
FR-10	Real-time metrics dashboard with 3D hardware visualization	Should
FR-11	API key management for local multi-user access control	Could
FR-12	Agentic RAG with multi-hop retrieval and reflection	Could
FR-13	Core ML ANE integration for embedding inference	Could
FR-14	Model benchmarking with automated performance regression tests	Could
FR-15	iOS client app leveraging Foundation Models framework	Won't

Non-Functional Requirements

All targets measured under standard operating conditions on Apple Silicon M1 8GB or later.

Requirement	Target	Measurement
API Response Latency (p95)	Less than 200ms for non-inference endpoints	Prometheus histogram
Streaming TTFT	Less than 500ms for 7B model, 100-token prompt	MLX benchmark suite
Embedding Latency	Less than 100ms per document via nomic-embed	Core ML profiler
Vector Search Latency	Less than 50ms for top-5 retrieval over 1M vectors	ChromaDB metrics
Concurrent Connections	50 simultaneous WebSocket connections	Load test with locust
Memory Footprint	Less than 6GB total with model loaded on M1 8GB	Activity Monitor
API Uptime	99.9% for local server during active sessions	Health endpoint monitoring
Test Coverage	80% backend, 70% frontend	pytest-cov, vitest coverage
Build Time	Less than 60 seconds for frontend production build	Vite build timer
CI Pipeline Duration	Less than 5 minutes for full test suite	GitHub Actions metrics
Security	Zero critical OWASP Top 10 vulnerabilities	Trivy scan
Startup Time	Less than 10 seconds to healthy state without model	Health endpoint timer

Technology Stack Recommendations

The following section evaluates candidates across six technology domains, recommending specific versions with quantitative justification.

Backend Framework

The backend framework must support async request handling, streaming SSE for token-by-token LLM output, WebSocket for real-time metrics, and automatic OpenAPI documentation for the OpenAI-compatible API surface.

Criterion	FastAPI	Litestar	Quart	Starlette
Latest Version	0.134.0	2.21.0	0.20.0	0.52.1
Release Date	Feb 27, 2026	Feb 14, 2026	Dec 23, 2024	Recent 2026
GitHub Stars	95,700	8,000	29	12,000
Monthly Downloads	246M+	5M	500K	230M+
License	MIT	MIT	MIT	BSD-3-Clause
Python 3.13	Full support	Full support	Untested	Full support
Streaming SSE	Excellent	Excellent	Good	Foundation only
WebSocket	Native	Native + Channels	Excellent	Foundation only
Job Openings	900+	50-100	10-20	200-300
Migration from Flask	2-4 weeks	2-4 weeks	2-5 days	3-6 weeks

Recommendation: FastAPI 0.134.0

FastAPI provides the optimal balance of ecosystem maturity (246M monthly downloads [32]), streaming excellence for LLM serving, and hiring market depth (900+ open positions, $128K-$193K salary range) [1]. Its Pydantic V2 integration aligns with the existing schema validation in Impetus-LLM-Server, and the automatic OpenAPI documentation eliminates manual API spec maintenance. While Litestar 2.21.0 offers 5-15% faster serialization via msgspec [2][30], FastAPI's 12x larger community and proven LLM serving patterns (vLLM, text-generation-webui) reduce integration risk. Quart provides the lowest-friction migration path from Flask (2-5 days via drop-in async conversion [31]), but lacks FastAPI's automatic OpenAPI generation and community scale. Starlette serves as FastAPI's ASGI foundation [33] but requires manual schema validation and documentation. The migration from Flask 3.0 requires a full rewrite of route handlers and middleware (2-4 weeks), but yields native async/await support that eliminates the synchronous bottleneck in the current architecture [3].

Inference Engine

MLX remains the primary inference engine with selective Core ML integration for embedding workloads.

Criterion	MLX (GPU)	Core ML (ANE)	Core ML (GPU)
Latest Version	0.30.6	macOS 15 SDK	macOS 15 SDK
Decode Throughput	230-250 tok/s (M4 Max)	20-40 tok/s	150-170 tok/s
Embedding Latency	100ms (nomic-embed)	3-5ms (DistilBERT)	20ms
Memory Efficiency	Unified memory native	6.6x less than PyTorch	Standard
Model Format	MLX weights	.mlpackage	.mlpackage
ANE Support	No (marked wontfix)	Native	N/A
Quantization	INT4, INT8	INT4, INT8, palettize	INT4, INT8

Recommendation: Hybrid MLX 0.30.6 + Core ML

MLX 0.30.6 delivers the highest sustained decoding throughput at 230-250 tokens per second on M4 Max [4] [45], making it the clear choice for LLM inference. On-device benchmarks confirm MLX outperforms PyTorch and Core ML GPU paths for autoregressive decoding [34]. However, MLX explicitly does not support ANE (marked "wontfix" in issue 18 [25]), while Core ML on ANE achieves 3-5ms embedding latency compared to 100ms on MLX GPU [5], a 20-30x improvement that justifies a hybrid architecture. Apple's research on deploying transformers to ANE demonstrates that models under 500MB with standard attention patterns convert reliably via coremltools v9.0 [23] [36], with INT4 and palettization quantization options further reducing footprint [46]. The M5 GPU introduces neural accelerators that provide 4x speedup for matrix multiply operations transparently through MLX, reaching 153.6 GB/s memory bandwidth on M5 Max [6] [22] [48]. The recommended strategy routes LLM decode to MLX GPU and embedding generation to Core ML ANE, leveraging unified memory to eliminate data movement costs between compute units. Apple Intelligence APIs [37] and the reverse-engineered ANE architecture documentation [24] provide additional reference points for future on-device model optimization.

Vector Database

Criterion	ChromaDB	Qdrant	LanceDB	SQLite-vec	Milvus Lite
Latest Version	1.5.1	1.17.0+	0.27-beta	Early 2025	2.5.x
GitHub Stars	25,089	29,100	9,100	3,000+	32,000+
License	Apache 2.0	Apache 2.0	Apache 2.0	Open Source	Apache 2.0
Query Latency (p50)	10-50ms	4ms	Less than 100ms	50-200ms	6ms
Max Vectors	50M	Billions	700M+	10M	1M (Lite)
Memory Footprint	Low (SQLite)	Configurable	Minimal (Arrow)	Ultra-minimal	Low-medium
Apple Silicon	Native arm64	MPS via Vulkan	MPS via Metal	Native	arm64
GPU Acceleration	No	Yes	Yes	No	No
Ease of Use	5 out of 5	3 out of 5	4 out of 5	4 out of 5	3 out of 5

Recommendation: ChromaDB v1.5+ (MVP) with Qdrant upgrade path

ChromaDB offers the fastest developer onboarding (three lines of code to start) with its 2025 Rust rewrite delivering 4x performance improvement [7]. The embedded architecture with SQLite persistence requires zero infrastructure overhead, fitting the local-first philosophy of Impetus-LLM-Server. At 1M vectors with 768-dimensional embeddings, ChromaDB consumes approximately 3GB on M1 8GB, leaving 1.8GB headroom for concurrent model inference [8]. LanceDB demonstrates viability at 700M+ vectors in production with its Arrow-native columnar format [35], but its beta status makes it premature for a primary recommendation. For production scaling beyond 50M vectors, Qdrant (29.1k GitHub stars [47]) provides 4ms p50 latency with horizontal sharding and GPU acceleration via Metal Performance Shaders [9].

Embedding Pipeline

Criterion	nomic-embed-text-v1.5	e5-mistral-7b (4-bit)	all-MiniLM-L6-v2
Parameters	137M	7B (quantized)	22M
Dimensions	768 (variable 64-768)	4,096	384
MTEB Score	62.39 (short) / 85.53 (long)	69.5+	44
Model Size	261 MB (FP16)	2 GB (4-bit)	44 MB
Latency (M1)	100ms per document	500-800ms per document	20-30ms per document
MLX Support	Yes	Yes	Yes
License	CC BY-NC 4.0	MIT	Apache 2.0
M1 8GB Safe	Yes	Marginal	Yes

Recommendation: nomic-embed-text-v1.5

The nomic-embed-text-v1.5 model provides the best balance of quality (MTEB-leading scores that beat OpenAI text-embedding-3-small), size (261MB fits comfortably on M1 8GB), and flexibility (Matryoshka representation learning allows runtime dimension tuning from 768 to 64 without retraining) [10]. Research on improving text embeddings with large language models demonstrates that contrastive learning with synthetic data achieves state-of-the-art retrieval quality at moderate model sizes [26]. The 8,192-token context window supports full-document embedding for code files and documentation.

Frontend Technology Stack

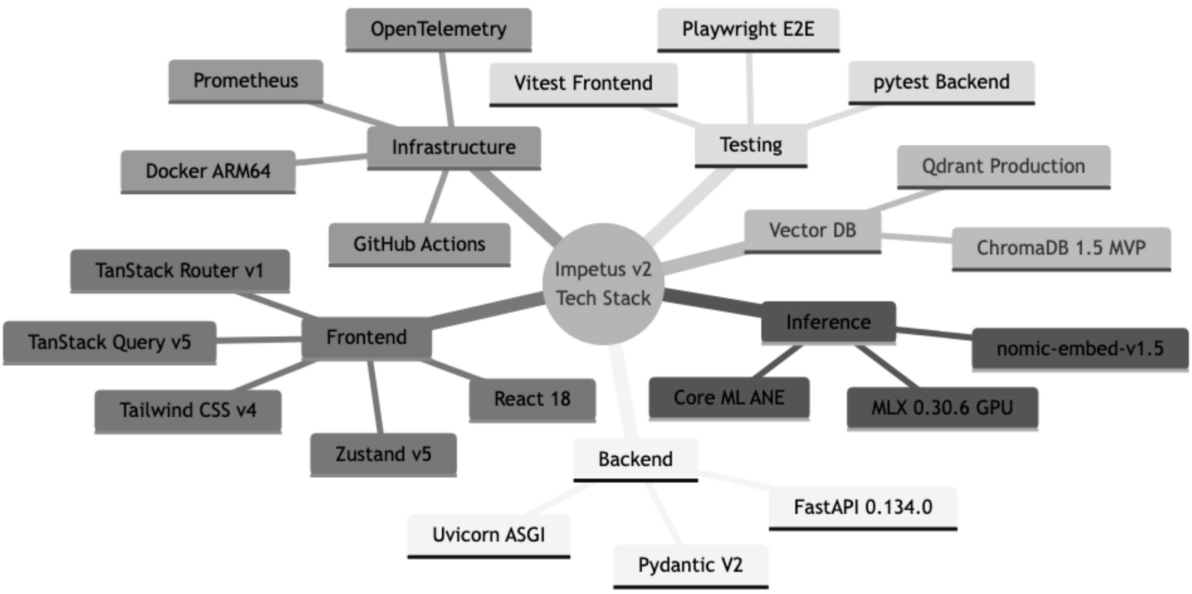
Criterion	Zustand v5	Jotai	TanStack Store
Weekly Downloads	9,153,045	1,100,000	Emerging
Bundle Size	2.8 KB	4-6.3 KB	3 KB
GitHub Stars	57,100	18,000+	Part of TanStack
Mental Model	Redux-like store	Atomic state	Framework-agnostic
TypeScript	Full	Full	Full
DevTools	Yes	Yes	Limited

Recommendation: Zustand v5 (state) + TanStack Query v5 (server state) + TanStack Router v1 (routing) + Tailwind CSS v4 (styling)

Zustand (57.1k GitHub stars [42]) provides the simplest mental model with 8x higher adoption than Jotai (9.1M vs 1.1M weekly downloads) and a 2.8KB bundle footprint [11]. TanStack Query v5 (11.7M weekly downloads) handles server state with automatic caching, background refetch, and optimistic updates [12]. TanStack Router delivers type-safe SPA routing with automatic route type generation from file structure, superior to React Router v7 which limits type safety to framework mode [13]. Tailwind CSS v4 with its Rust-based Oxide engine delivers 3.5x faster full builds and 35% smaller package size than v3, with zero runtime overhead [14]. The existing React Three Fiber v9.5 installation [43] supports 3D hardware visualization with on-demand rendering and level-of-detail optimization for the dashboard.

Technology Stack Overview

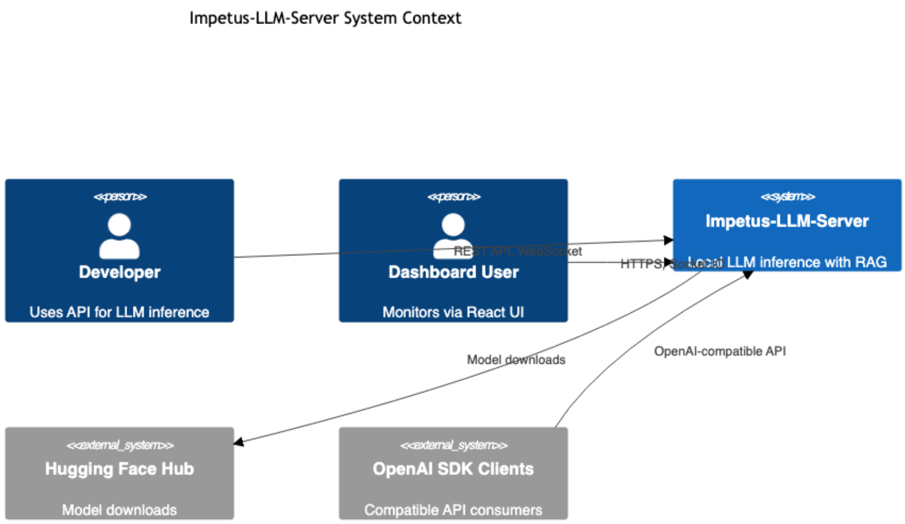
The following diagram illustrates the recommended technology selections organized by architectural layer.



System Architecture

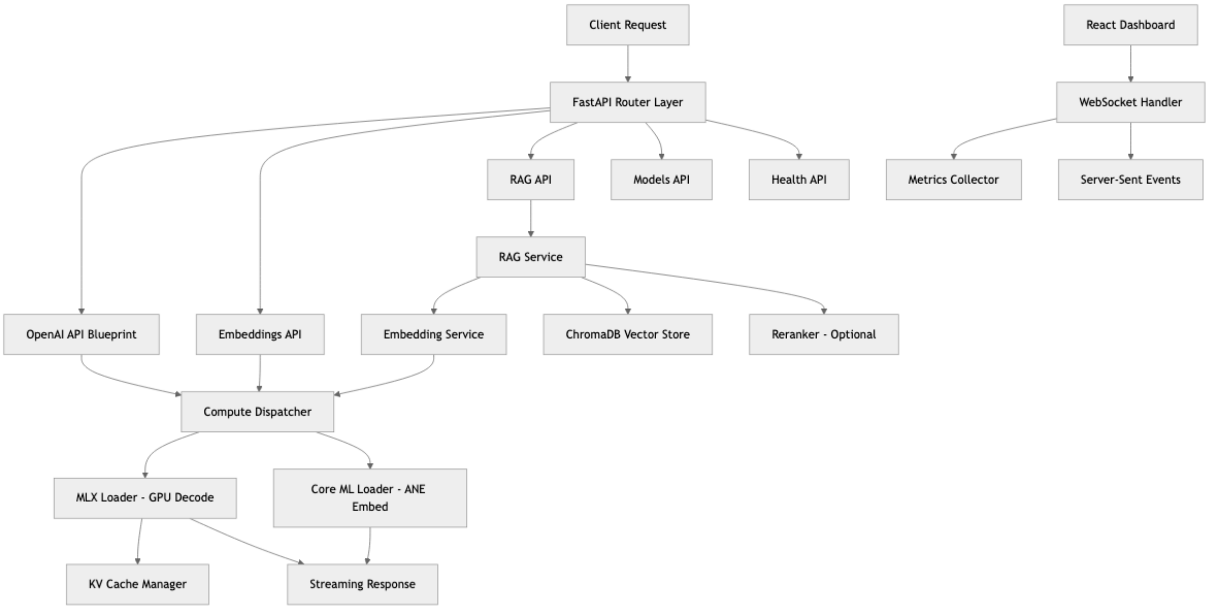
System Context

The C4 context diagram shows Impetus-LLM-Server's boundaries and external actors. The server operates as a local inference platform accessed by developers through direct API calls, the React dashboard, or third-party OpenAI-compatible SDKs.



Component Architecture

The internal component architecture separates concerns across API routing, inference orchestration, RAG pipeline, and real-time communication layers.

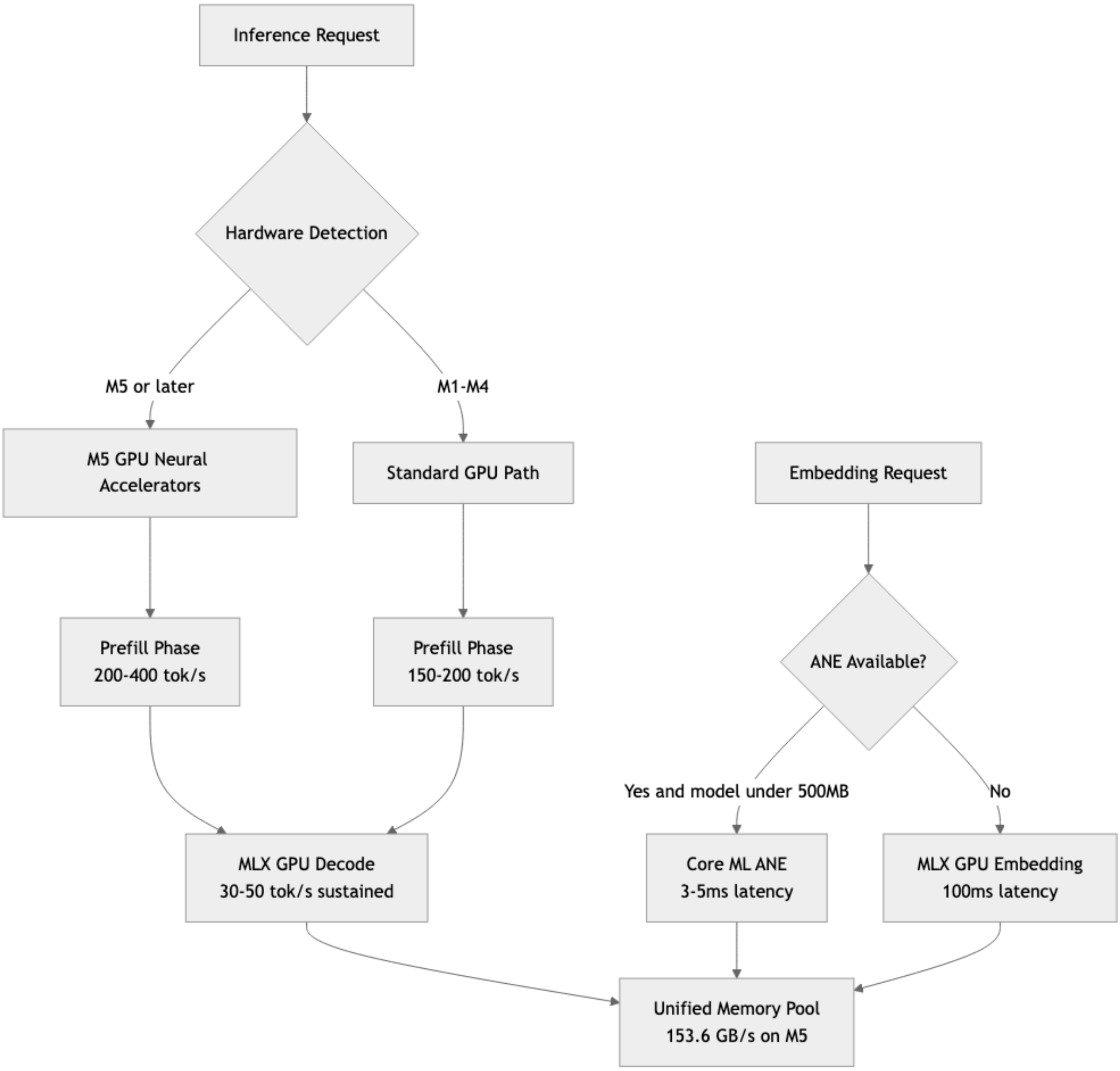


Data Flow

The data flow diagram traces a RAG-augmented chat completion request from client to response, showing how the retrieval pipeline integrates with the inference engine. The RAG pipeline implements recursive and semantic chunking strategies [29] with hybrid dense-sparse search and cross-encoder reranking for improved retrieval precision [27]. The architecture supports evolution from naive RAG through advanced patterns to agentic RAG with multi-hop retrieval and self-reflection [28].

Hybrid Compute Architecture

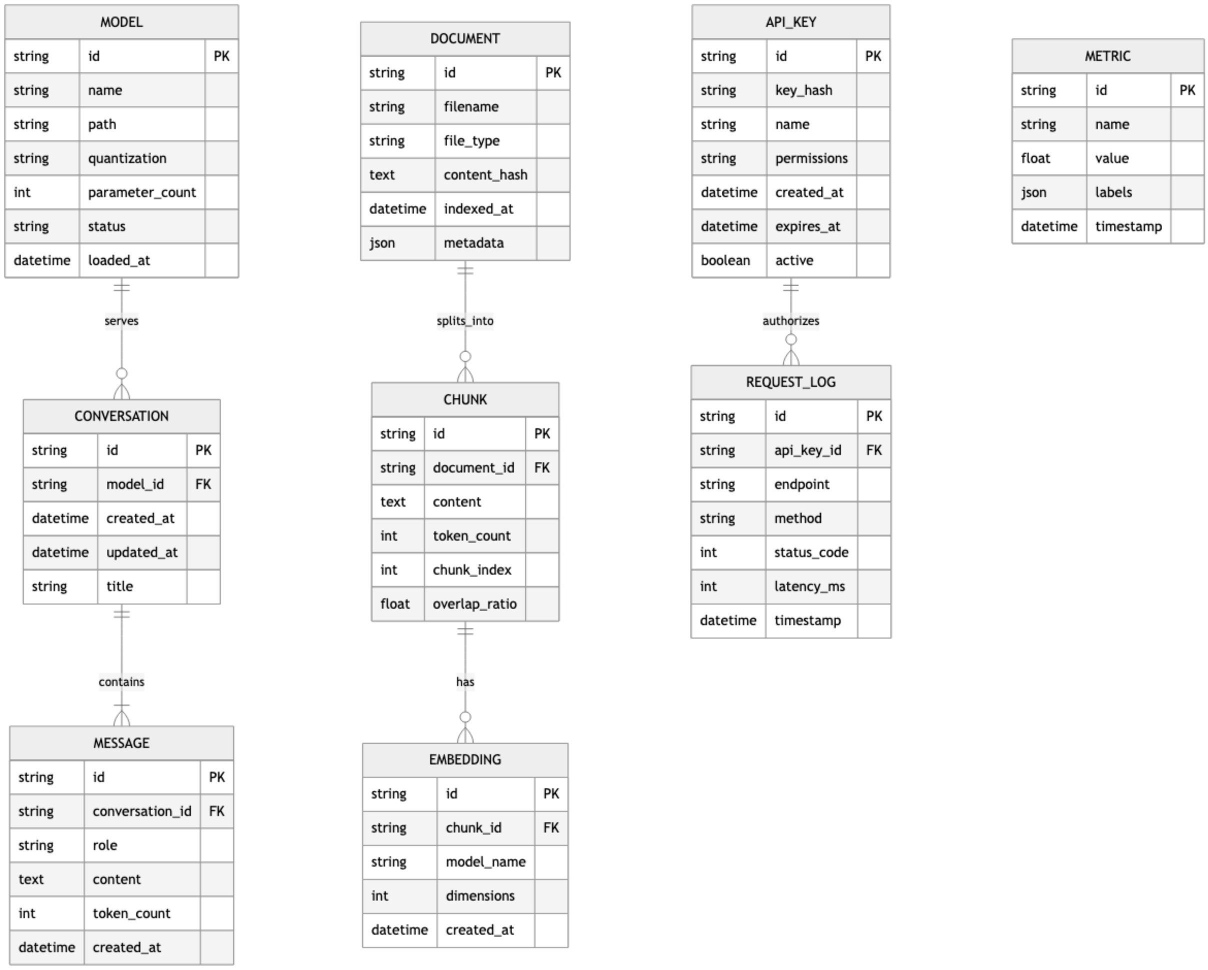
The compute dispatcher routes workloads based on hardware capabilities and task characteristics, leveraging unified memory to minimize data movement.



Database Schema

Entity-Relationship Diagram

The schema covers vector storage metadata, model configuration, conversation sessions, and system metrics. ChromaDB manages vector data internally; the ER diagram shows application-level entities stored in SQLite.



Entity Definitions

MODEL stores loaded and available LLM configurations. The status field tracks lifecycle states: available, loading, loaded, unloading, error.

Column	Type	Constraints	Description
id	VARCHAR(36)	PK, UUID	Unique model identifier
name	VARCHAR(255)	NOT NULL	HuggingFace model name
path	TEXT	NOT NULL	Local filesystem path
quantization	VARCHAR(10)	DEFAULT '4bit'	Quantization level (4bit, 8bit, fp16)
parameter_count	BIGINT		Model parameter count
status	VARCHAR(20)	NOT NULL	Lifecycle state
loaded_at	TIMESTAMP		When model was loaded into memory

DOCUMENT tracks ingested files for the RAG pipeline. The content_hash enables deduplication during re-indexing.

CHUNK represents split segments of documents with configurable overlap. The chunk_index maintains ordering for reconstruction.

EMBEDDING stores vector metadata (actual vectors reside in ChromaDB). The model_name field enables multi-model embedding comparison.

Indexing Strategy

Table	Index	Columns	Rationale
MESSAGE	idx_msg_conv	conversation_id, created_at	Fast conversation history retrieval
CHUNK	idx_chunk_doc	document_id, chunk_index	Ordered chunk retrieval
REQUEST_LOG	idx_req_time	timestamp DESC	Recent request analysis
REQUEST_LOG	idx_req_key	api_key_id, timestamp	Per-key usage tracking
API_KEY	idx_key_hash	key_hash	O(1) authentication lookup

Migration Approach

Database migrations use **Alembic** (v1.14+) with SQLAlchemy models as the source of truth. Migrations are version-controlled alongside application code. The migration naming convention follows `YYYYMMDD_HHMMSS_description.py`. ChromaDB manages its own internal schema via the PersistentClient API and requires no external migration tooling.

API Design

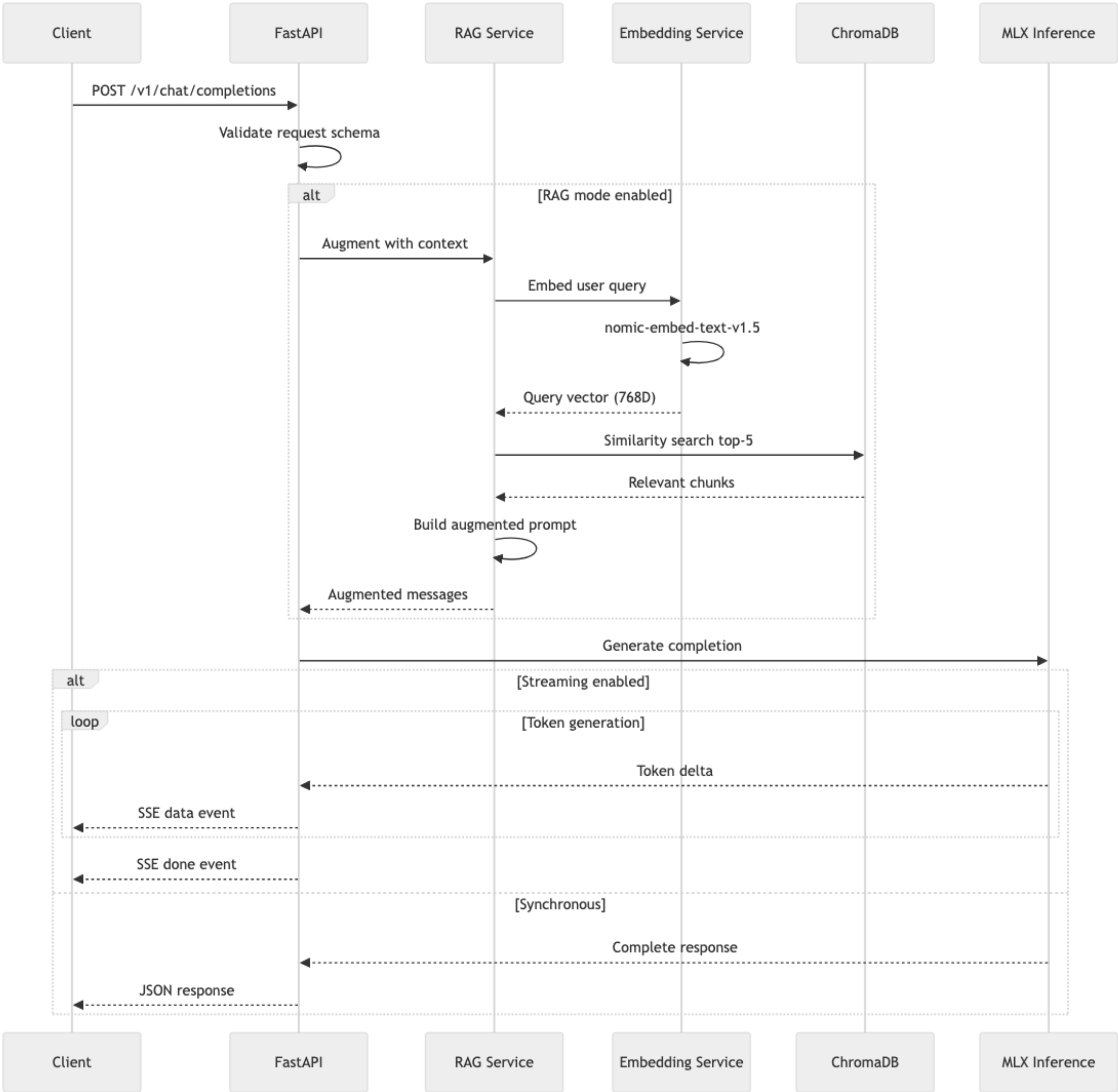
Endpoint Specifications

All endpoints maintain OpenAI API compatibility where applicable. New endpoints for embeddings, RAG, and model management extend the API surface without breaking existing integrations.

Method	Path	Auth	Description
POST	/v1/chat/completions	API Key	Generate chat completion (streaming or sync)
POST	/v1/embeddings	API Key	Generate text embeddings
GET	/v1/models	API Key	List available models
POST	/v1/rag/index	API Key	Index documents for RAG
GET	/v1/rag/status	API Key	Get RAG index health and stats
POST	/v1/rag/search	API Key	Search indexed documents
POST	/api/models/load	API Key	Load model into memory
POST	/api/models/unload	API Key	Unload model from memory
GET	/api/health/live	None	Liveness probe
GET	/api/health/ready	None	Readiness probe
GET	/api/health/status	None	Detailed system status
GET	/api/hardware/info	None	Hardware capabilities
GET	/api/metrics	None	Prometheus metrics endpoint

Key API Flows

The following sequence diagram shows the RAG-augmented chat completion flow, the primary use case for the modernized server.



Request and Response Schemas

POST /v1/chat/completions

Request:

```
{
"model": "string (required, model identifier)",
"messages": [
{
"role": "system | user | assistant (required)",
"content": "string (required)"
}
],
"stream": "boolean (default: false)",
"temperature": "float (0.0-2.0, default: 0.7)",
"max_tokens": "integer (default: 2048)",
"top_p": "float (0.0-1.0, default: 1.0)",
"rag_mode": "boolean (default: false)",
"rag_top_k": "integer (default: 5)"
}
```

Response (200, non-streaming):

```
{
"id": "chatcmpl-uuid",
"object": "chat.completion",
"created": 1709049600,
"model": "mlx-community/Mistral-7B-Instruct-v0.3-4bit",
"choices": [
{
"index": 0,
"message": {
"role": "assistant",
"content": "string"
},
"finish_reason": "stop | length"
}
],
"usage": {
"prompt_tokens": 150,
"completion_tokens": 200,
"total_tokens": 350
}
}
```

POST /v1/embeddings

Request:

```
{
"model": "string (required, embedding model)",
"input": "string | string[] (required, text to embed)",
"encoding_format": "float | base64 (default: float)",
"dimensions": "integer (optional, Matryoshka dim)"
}
```

Response (200):

```
{
"object": "list",
"data": [
{
"object": "embedding",
"index": 0,
"embedding": [0.0023, -0.0091, 0.0152]
}
],
"model": "nomic-embed-text-v1.5",
"usage": {
"prompt_tokens": 12,
"total_tokens": 12
}
}
```

Error Code Table

Code	Name	HTTP Status	Description
MODEL_NOT_FOUND	Model Not Found	404	Requested model not available
MODEL_NOT_LOADED	Model Not Loaded	503	Model exists but not loaded into memory
INVALID_REQUEST	Invalid Request	400	Request schema validation failed
RATE_LIMITED	Rate Limited	429	Too many requests, retry after header
INFERENCE_ERROR	Inference Error	500	MLX inference failed
EMBEDDING_ERROR	Embedding Error	500	Embedding generation failed
RAG_INDEX_ERROR	RAG Index Error	500	Document indexing failed
AUTH_REQUIRED	Authentication Required	401	Missing or invalid API key
INSUFFICIENT_MEMORY	Insufficient Memory	507	Not enough memory to load model

Versioning Strategy

API versioning uses URL path prefixes (/v1/, /v2/) following the OpenAI convention. The /v1/ prefix is the current and only supported version. Breaking changes will introduce /v2/ with a minimum 6-month deprecation window for /v1/. Non-breaking additions (new optional fields, new endpoints) are added to the current version without a version bump.

Rate Limiting and Pagination

Rate limiting uses the token bucket algorithm implemented via an in-memory store (upgradeable to Redis for multi-instance deployments), following patterns established by Flask-Limiter [40]. Default limits: 60 requests per minute for inference endpoints, 120 requests per minute for read-only endpoints. Rate limit headers follow RFC 6585 conventions: X-RateLimit-Limit, X-RateLimit-Remaining, X-RateLimit-Reset.

Pagination for list endpoints uses cursor-based pagination with limit and after parameters, returning a has_more boolean and next_cursor field.

Authentication and Authorization

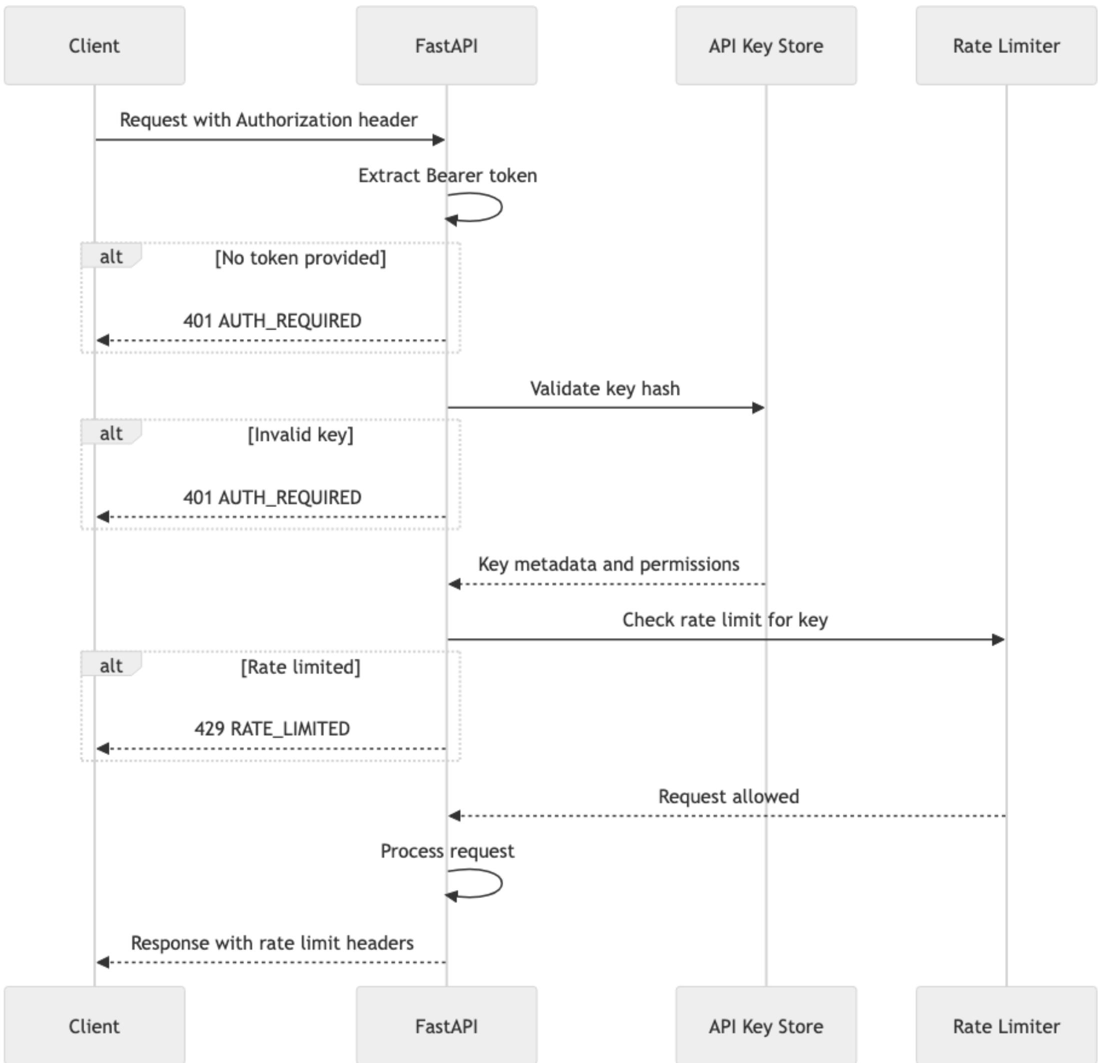
Auth Provider Recommendation

For a local-first inference server, a lightweight API key system is the recommended authentication mechanism. External auth providers (Auth0, Clerk, Supabase Auth) are evaluated for future multi-user or cloud deployment scenarios.

Criterion	Local API Keys	Auth0	Clerk	Supabase Auth
Pricing	Free	$0.07/MAU	$0.02/MAU	$0.00325/MAU
Complexity	Minimal	High	Medium	Medium
SSO Support	No	Yes (SAML)	Yes	Limited
Local-First	Yes	No (cloud)	No (cloud)	Partial
Offline Operation	Yes	No	No	Partial
Use Case	Solo developer, local	Enterprise, multi-tenant	SaaS, React apps	PostgreSQL teams

Recommendation: Local API key management for the current local-first architecture, with an abstraction layer that allows plugging in Auth0 or Clerk for future cloud deployment.

Auth Flow

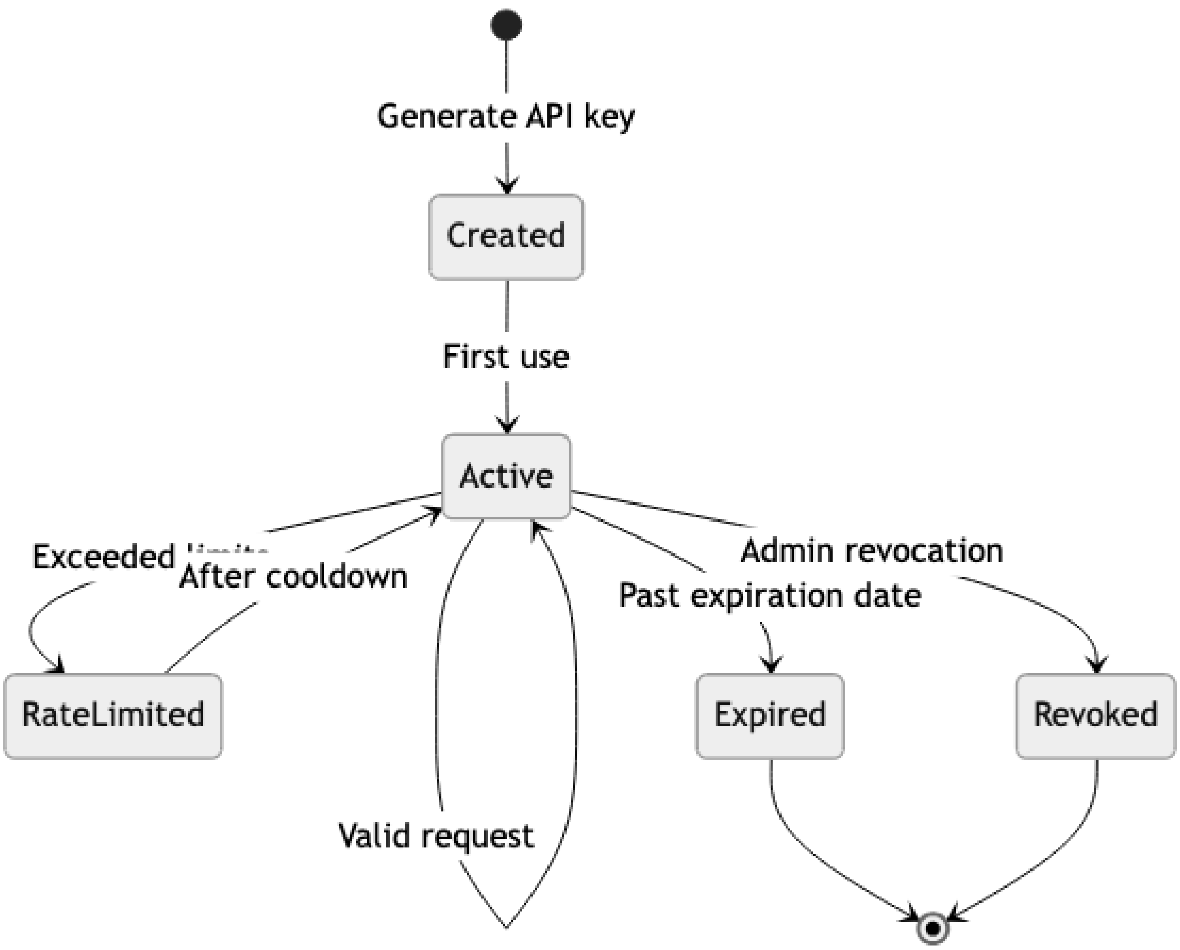


Role and Permission Model

Role	Permissions	Description
admin	All operations	Full access including model management
user	inference, embeddings, rag_search	Standard inference and RAG access
readonly	models_list, health, hardware	Read-only monitoring access

Token Lifecycle

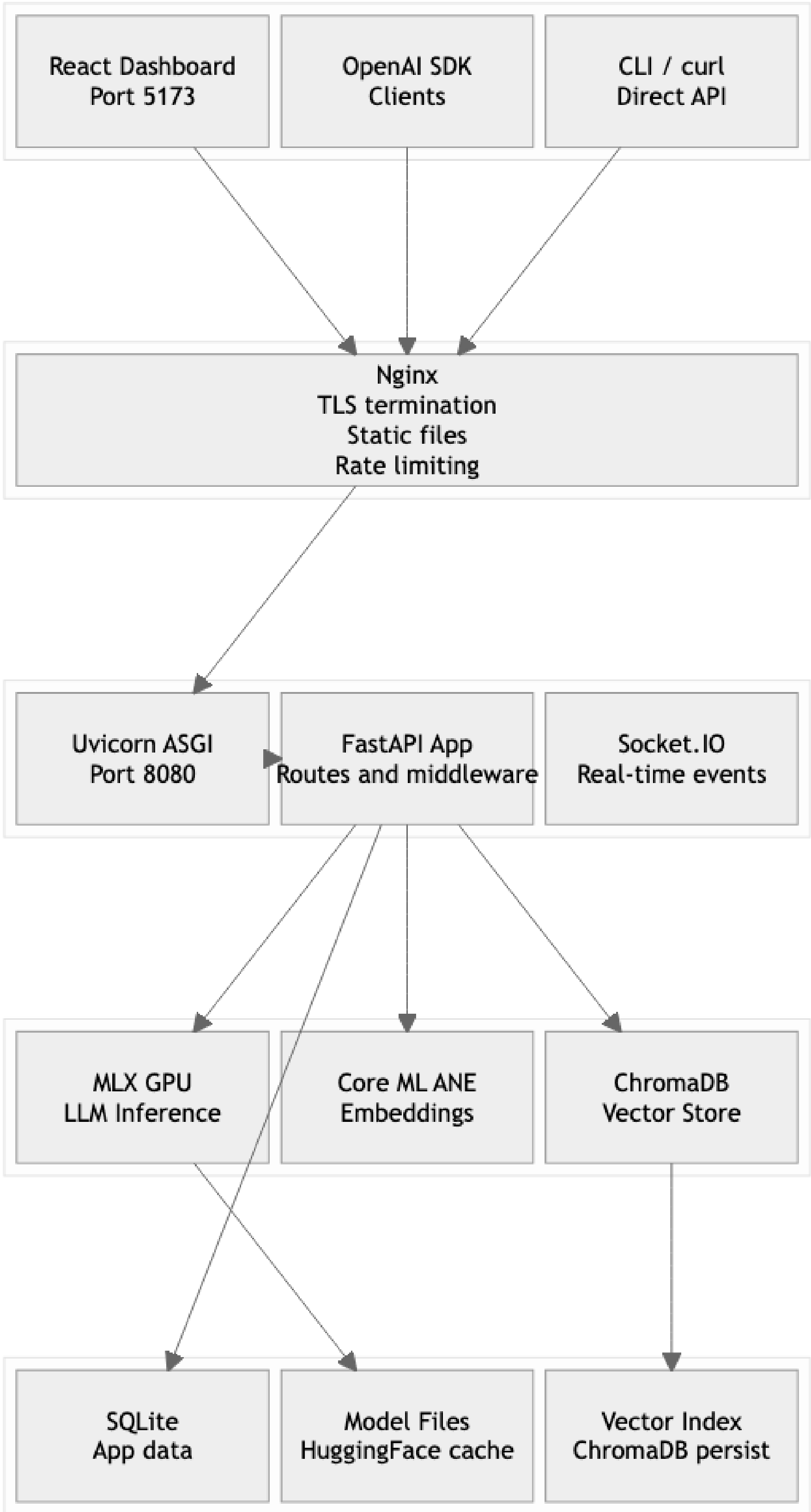
API keys follow a simple lifecycle model without refresh tokens. Keys are generated with configurable expiration and can be revoked at any time.



Infrastructure and Deployment

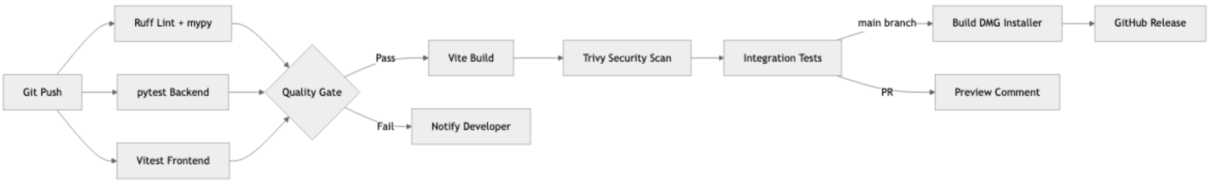
Deployment Architecture

Impetus-LLM-Server operates as a local service on macOS with optional containerized deployment for development and testing.


React Dashboard
Port 5173
OpenAI SDK
Clients
CLI / curl
Direct API
Nginx
TLS termination
Static files
Rate limiting
Uvicorn ASGI
Port 8080
FastAPI App
Routes and middleware
Socket.IO
Real-time events
MLX GPU
LLM Inference
Core ML ANE
Embeddings
ChromaDB
Vector Store
SQLite
App data
Model Files
HuggingFace cache
Vector Index
ChromaDB persist

CI/CD Pipeline

The CI/CD pipeline runs on GitHub Actions with optimized caching for 50-80% workflow time reduction [15]. Docker images use multi-platform builds targeting ARM64 natively for Apple Silicon [38], and blue-green deployment patterns enable zero-downtime local server updates [39].



Environment Strategy

Environment	Purpose	Configuration
Development	Local development with hot reload	IMPETUS_ENV=development, debug=true
Testing	CI/CD automated testing	IMPETUS_ENV=testing, mock models
Staging	Pre-release validation on physical hardware	IMPETUS_ENV=staging, real models
Production	End-user deployment via DMG or standalone app	IMPETUS_ENV=production, optimized

Monitoring and Observability

The observability stack centers on OpenTelemetry for instrumentation with Prometheus for metrics collection, maintaining zero vendor lock-in at zero cost [16].

Component	Tool	Purpose
Metrics	Prometheus + OpenTelemetry	Request latency, token throughput, memory usage
Traces	OpenTelemetry SDK	End-to-end request tracing across components
Logs	Python logging + structured JSON	Application events, errors, debug info
Errors	Sentry (optional) [41]	Exception tracking with stack traces
Dashboards	Grafana (optional)	Visual metrics exploration
Alerts	Prometheus Alertmanager	Threshold-based notifications

Key metrics to instrument:

- impetus_inference_duration_seconds (histogram): Token generation latency
- impetus_tokens_generated_total (counter): Total tokens generated
- impetus_model_memory_bytes (gauge): Memory consumed by loaded models
- impetus_rag_search_duration_seconds (histogram): Vector search latency

- impetus_embedding_duration_seconds (histogram): Embedding generation time
- impetus_active_connections (gauge): Current WebSocket connections

Security Considerations

Threat Model

The primary threat surface for a local inference server is network-adjacent access and dependency supply chain attacks. Remote exploitation is limited by the local deployment model.

Threat Vector	Risk Level	Applicable
Network-adjacent API access	Medium	Yes (local network)
Dependency supply chain	Medium	Yes (PyPI, npm)
Model poisoning via HuggingFace	Low	Yes (model downloads)
Prompt injection	Medium	Yes (user input to LLM)
Local privilege escalation	Low	macOS sandboxing
Data exfiltration	Low	Local-only data

OWASP Top 10 Mitigations

Vulnerability	Applies	Mitigation Strategy
A01 Broken Access Control	Yes	API key validation on all inference endpoints, role-based permissions
A02 Cryptographic Failures	Yes	bcrypt for API key hashing, TLS via Nginx, no plaintext secrets
A03 Injection	Yes	Pydantic V2 input validation, parameterized SQLite queries via SQLAlchemy
A04 Insecure Design	Partial	Rate limiting, request size limits, model memory guards
A05 Security Misconfiguration	Yes	Security headers via middleware, CORS whitelist, debug mode disabled in production
A06 Vulnerable Components	Yes	Trivy scanning in CI/CD, Dependabot for dependency updates [17]
A07 Auth Failures	Yes	API key rotation support, key expiration, brute-force rate limiting
A08 Software Integrity	Yes	Signed releases, SBOM generation, pip hash verification
A09 Logging Failures	Yes	Structured JSON logging, audit trail for API key operations
A10 SSRF	Low	No outbound HTTP from inference path, model downloads via allowlist

Dependency Scanning

Automated dependency scanning integrates Trivy for container and filesystem scanning (free, fast local execution) with Dependabot for automated pull requests on vulnerable dependencies [18]. Software Bill of Materials (SBOM) generation follows CISA 2025 guidelines using **`trivy sbom`** output.

Testing Strategy

Test Pyramid

The testing strategy follows a layered pyramid prioritizing fast, isolated unit tests with targeted integration and end-to-end coverage.

Layer	Coverage Target	Tools	Scope
Unit Tests	80%+	pytest 8.3+, Vitest 4.0	Individual functions, schema validation, utilities
Integration Tests	60%+	pytest + httpx, Vitest + MSW	API endpoints, database operations, RAG pipeline
E2E Tests	Critical paths	Playwright 1.49+	Full user flows through dashboard
Performance Tests	Key metrics	locust 2.32+, MLX benchmarks	Inference throughput, RAG latency

Tool Recommendations

Backend Testing:

Tool	Version	Purpose
pytest	8.3+	Test runner, fixtures, parametrize
pytest-asyncio	0.24+	Async test support for FastAPI
httpx	0.28+	Async HTTP client for API testing
pytest-cov	5.0+	Coverage reporting
factory-boy	3.3+	Test data factories
hypothesis	6.115+	Property-based testing for schemas

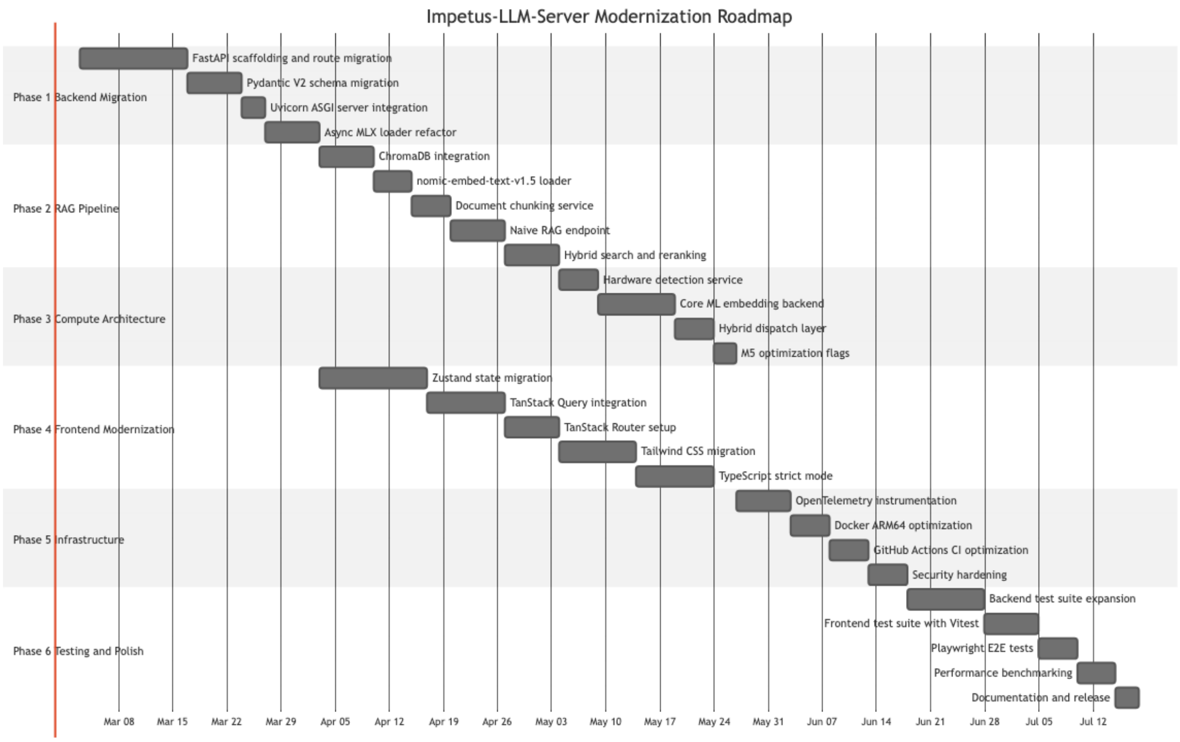
Frontend Testing:

Tool	Version	Purpose
Vitest	4.0.18	Unit and component testing (1.2s boot) [19]
React Testing Library	16.1+	Component behavior testing
Playwright	1.49+ [44]	End-to-end browser testing
MSW	2.7+	API mocking for integration tests
Istanbul	via Vitest	Coverage reporting

Implementation Roadmap

Gantt Chart

The implementation roadmap spans 24 weeks organized into six phases, designed for a solo developer with parallelizable tasks noted.



Sprint and Milestone Breakdown

Phase	Milestone	Deliverables	Duration
Phase 1	Backend Migration Complete	FastAPI app with all existing routes ported, async MLX loader, passing existing tests	4.5 weeks
Phase 2	RAG Pipeline Operational	ChromaDB integration, embedding generation, naive RAG endpoint, hybrid search	4.5 weeks
Phase 3	Hybrid Compute Active	Core ML ANE embeddings, hardware detection, dispatch routing	3.5 weeks
Phase 4	Frontend Modernized	Zustand state, TanStack Query and Router, Tailwind styling, TypeScript strict	7 weeks
Phase 5	Infrastructure Hardened	OpenTelemetry metrics, optimized Docker and CI, security headers	3 weeks
Phase 6	Release Ready	Test coverage targets met, benchmarks documented, DMG installer updated	4 weeks

Team Allocation

For a solo developer, phases are sequential. With two developers, the following parallelization is recommended:

- Developer A : Phases 1, 2, 3 (backend, RAG, compute) - 12.5 weeks
- Developer B : Phase 4 (frontend, starting after Phase 1 completes) - 7 weeks, then Phase 5 - 3 weeks

Total with two developers: approximately 14 weeks.

Cost Estimation

Monthly Infrastructure Costs

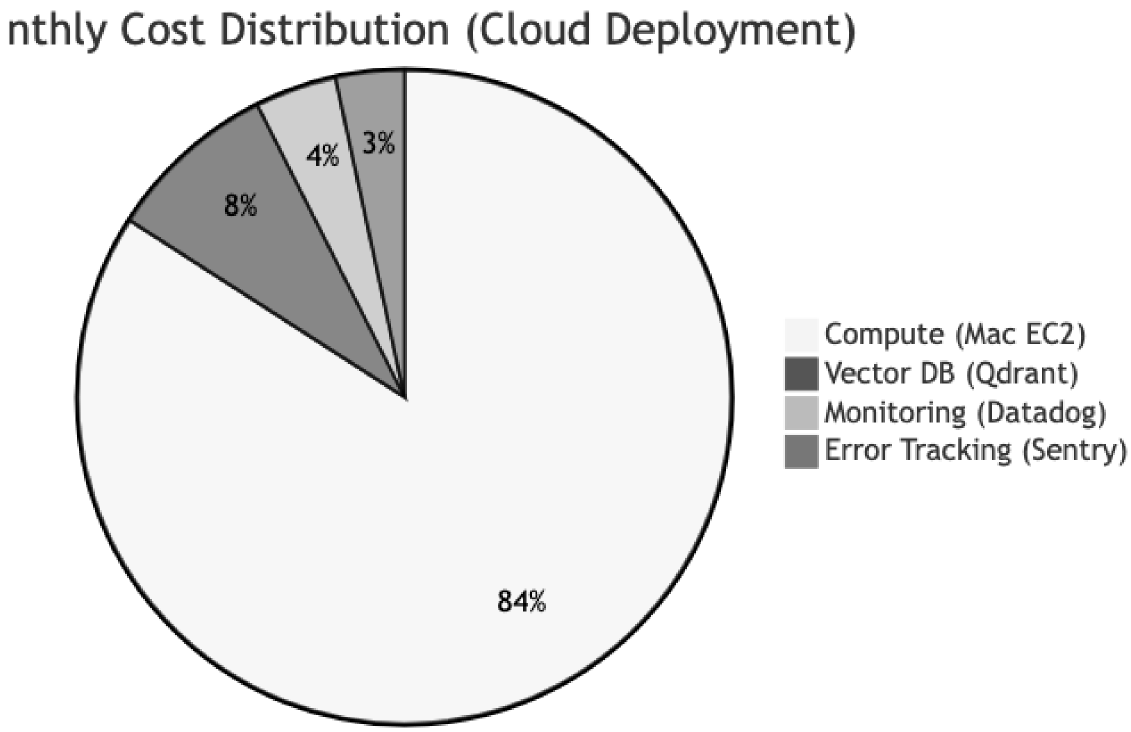
Impetus-LLM-Server is designed as a local-first application, minimizing ongoing infrastructure costs.

Category	Service	Monthly Cost	Notes
Compute	Local Mac (existing hardware)	$0	Apple Silicon, already owned
Database	SQLite (embedded)	$0	No separate service
Vector DB	ChromaDB (embedded)	$0	Local persistence
Monitoring	Prometheus + Grafana (self-hosted)	$0	Docker containers on local machine
Error Tracking	Sentry (free tier)	$0	5K errors per month
CI/CD	GitHub Actions (free tier)	$0	2,000 minutes per month
Model Storage	Local disk	$0	HuggingFace cache
TLS Certificate	Let's Encrypt (if exposed)	$0	Auto-renewal
Total (local)		$0/month	

Optional cloud components (if scaling beyond local):

Category	Service	Monthly Cost	Notes
Compute	AWS EC2 Mac (mac2.metal)	$645	24-hour minimum tenancy
Vector DB	Qdrant Cloud (1M vectors)	$65	Managed service
Monitoring	Datadog (1 host)	$15-31	Infrastructure monitoring
Error Tracking	Sentry Team	$26	50K events per month
Total (cloud)		$751-$767/month	

Cost Distribution

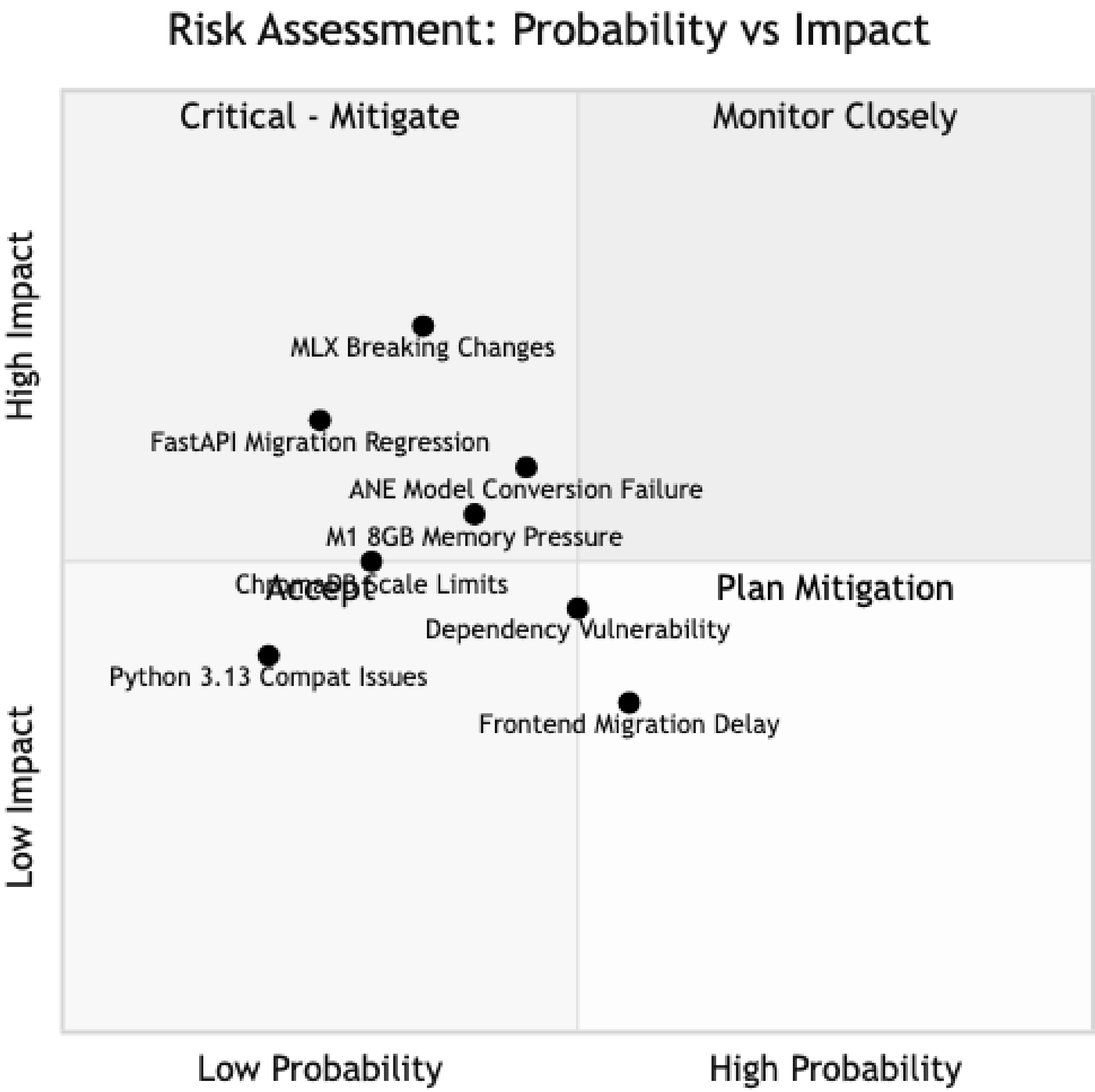


Development Effort Estimate

Phase	Effort (person-weeks)	Assumptions
Phase 1: Backend Migration	4.5	Solo developer, familiar with FastAPI
Phase 2: RAG Pipeline	4.5	ChromaDB documented, MLX embedding tested
Phase 3: Compute Architecture	3.5	coremltools learning curve included
Phase 4: Frontend Modernization	7.0	React experience, learning Zustand and TanStack
Phase 5: Infrastructure	3.0	Docker and CI experience
Phase 6: Testing and Polish	4.0	Testing infrastructure setup included
Total	26.5 person-weeks	Solo developer, full-time

Risk Assessment

Risk Matrix


Risk Assessment: Probability vs Impact
Critical - Mitigate
Monitor Closely
Accept
Plan Mitigation
High Impact
Low Impact
Low Probability
High Probability
MLX Breaking Changes
FastAPI Migration Regression
ANE Model Conversion Failure
M1 8GB Memory Pressure
ChromaDB Scale Limits
Dependency Vulnerability
Python 3.13 Compat Issues
Frontend Migration Delay

Risk Table

Risk	Probability	Impact	Mitigation
MLX breaking changes in minor versions	Medium	High	Pin MLX version, test upgrades in staging, maintain compatibility shim
Core ML ANE model conversion fails for custom models	Medium	Medium	Test on reference models first, fallback to GPU-only embedding path
ChromaDB reaches scale limits at 50M vectors	Low	Medium	Abstract vector DB interface, migration guide to Qdrant prepared
FastAPI migration introduces API regressions	Low	High	Comprehensive integration test suite before and after migration
Frontend migration exceeds timeline estimate	Medium	Low	Phase incrementally, each phase delivers standalone value
Critical dependency vulnerability discovered	Medium	Medium	Trivy CI scanning, Dependabot auto-PRs, 48-hour patch policy
M1 8GB memory pressure with model plus RAG	Medium	Medium	Memory budget tracking, configurable embedding dimensions via Matryoshka
Python 3.13 compatibility issues with dependencies	Low	Medium	Test matrix includes 3.11 and 3.12 as fallback targets

Vendor Lock-in Analysis

Technology	Lock-in Risk	Migration Difficulty	Mitigation
FastAPI	Low	Medium (ASGI standard)	Standard ASGI app, portable to any ASGI server
MLX	Medium	High (Apple-only)	MLX is Apple Silicon exclusive by design; acceptable for target platform
ChromaDB	Low	Low (standard embedding API)	Abstract via VectorStore interface, Qdrant as drop-in alternative
React	Low	Medium (JSX ecosystem)	Dominant framework, 5+ year viability guaranteed [20]
Tailwind CSS	Low	Low (utility classes)	Standard CSS output, removable without code changes
GitHub Actions	Low	Low (YAML workflows)	Standard CI/CD patterns, portable to GitLab CI or CircleCI
OpenTelemetry	Very Low	N/A (open standard)	CNCF standard with 100+ vendor backends [21]

Methodology

This Software Architecture Blueprint was produced through systematic multi-source research conducted on February 27, 2026.

Research Process

Six parallel research sub-agents conducted independent investigations across the following facets:

1. Python Framework and Async Ecosystem - Evaluated FastAPI, Litestar, Flask 3/Quart, and Starlette across 15 criteria including version currency, streaming quality, job market demand, and MLX integration feasibility.
2. Vector Database and RAG Architecture - Assessed ChromaDB, Qdrant, LanceDB, SQLite-vec, and Milvus Lite for local-first Apple Silicon deployment. Evaluated three embedding models and three RAG pattern levels.
3. NPU/GPU/CPU Compute Architecture - Investigated Apple Neural Engine capabilities, MLX ANE support status, coremltools maturity, hybrid compute strategies, and M5 GPU neural accelerators.
4. Frontend Modernization - Compared state management (Zustand, Jotai, TanStack Store, Nanostores), data fetching (TanStack Query, SWR), routing (TanStack Router, React Router v7), and styling (Tailwind, CSS Modules, Vanilla Extract).
5. Infrastructure and DevOps - Evaluated Docker optimization for Apple Silicon, monitoring stacks, CI/CD improvements, deployment patterns, and OWASP security mitigations.
6. Community Health and Long-term Viability - Analyzed Stack Overflow activity, Discord community sizes, corporate backing, job market demand, and LTS schedules for 22+ technologies.

Tools Used

Tool	Usage
Firecrawl CLI v1.7.1	Web search, documentation scraping, GitHub statistics
WebSearch and WebFetch	Supplementary web research
Context7	Framework documentation lookup (FastAPI, React, Vite)
Hugging Face MCP	ML paper search, embedding model cards
GitHub repositories	Stars, issues, releases, community metrics
PyPI statistics	Download counts, version history
npm trends	Frontend package adoption data

Scope and Limitations

- Research reflects technology state as of February 27, 2026
- Benchmark data sourced from published results, not independently verified
- Cost estimates assume US pricing and may vary by region
- M5 GPU neural accelerator benchmarks from Apple research publications
- Community metrics (Discord members, job postings) are point-in-time snapshots

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