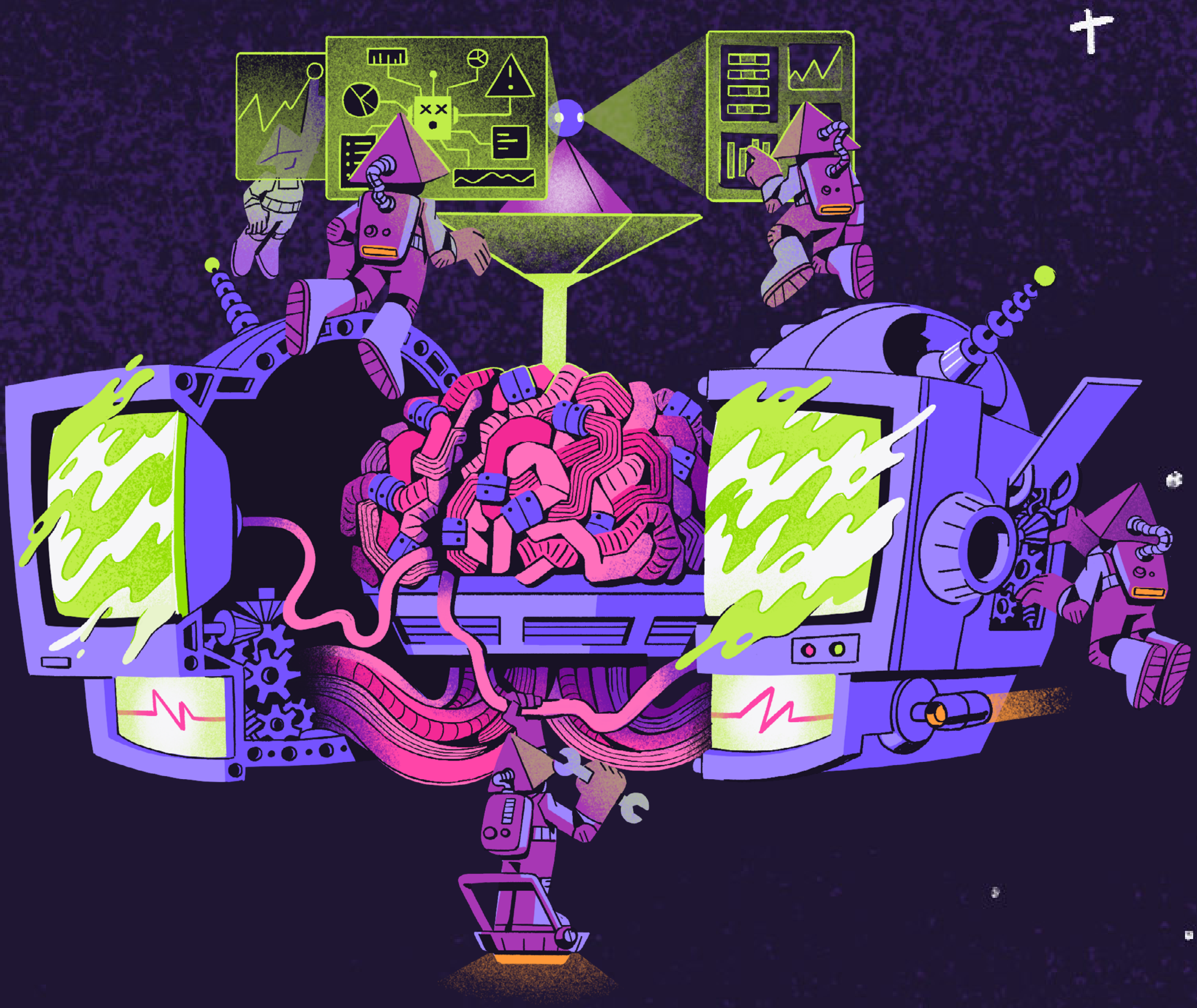


SENTRY

The Core KPIs of LLM Performance and How to Track Them

Sergiy Dybskiy

Introduction

A few months ago, I built an MCP server for Toronto's Open Data portal so an agent could fetch datasets relevant to a user's question. I threw the first version together, skimmed the code, and everything looked fine. Then I asked Claude: "What are all the traffic-related data sources for the city of Toronto?"

The tool call fired. I got relevant results. And then I hit an error: "Conversation is too long, please start a new conversation." I had only asked one question.

The culprit was a huge JSON payload from the API that stuffed the context window on the first call. Easy fix once I saw it. But there are plenty of other ways an AI app without monitoring can go sideways: silent tool timeouts, runaway loops that spike token usage, slow retrieval, model downgrades that break JSON formatting, or plain old 500 errors.

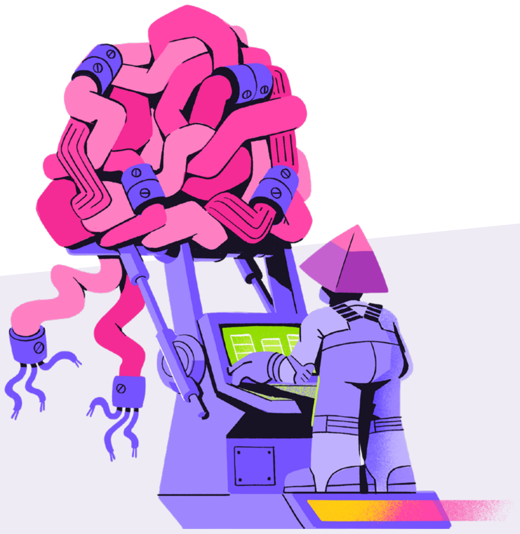
Moments like these are why I've compiled a few key metrics I monitor to surface what matters quickly.

What makes a "good" LLM KPI?

As Rahul put it, "Prompt in and response out is not observability. It is vibes." A good KPI is not a raw counter. It is a directional signal tied to product outcomes, especially for AI agent performance metrics.

Think in three lenses:

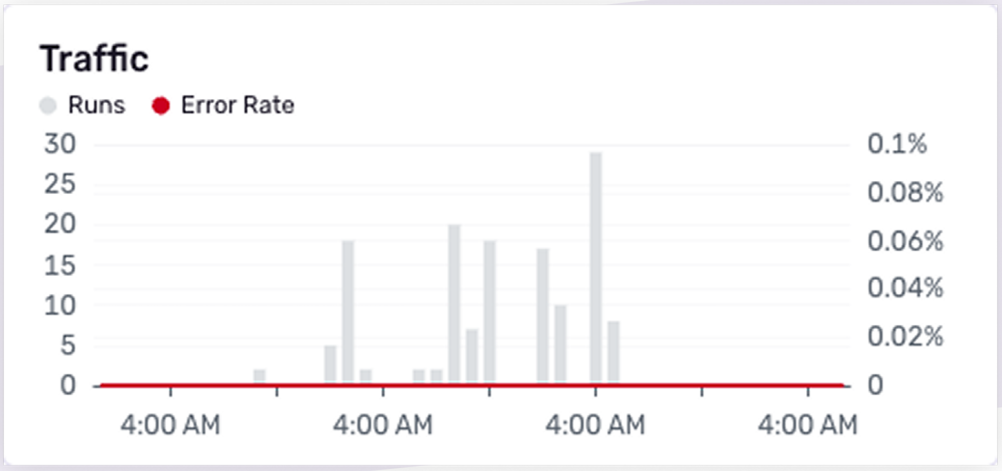
- **Reliability:** Is it working correctly?
- **Cost efficiency:** Are we spending within reaoson?
- **User experience:** Does it feel fast and responsive?



The metrics below map directly to those lenses, and to real failures you have probably seen: token spikes from a loop, a flaky vector DB dragging responses, or a quiet model change tanking output quality. They also align with common search terms like LLM evaluation metrics, LLM metrics, and LLM latency, so you can find the right guidance and help others find yours.

The 10 core LLM performance metrics to capture

Agent trafic (Runs per time window)



What & Why: Traffic volume is your heartbeat. A flatline suggests outage. A spike might mean a loop or flash crowd.

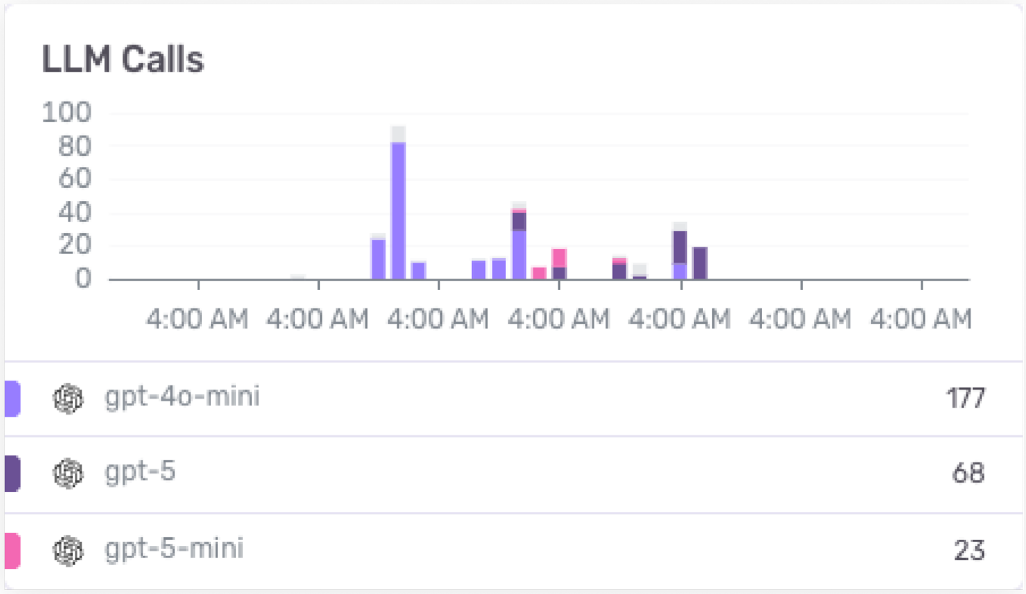
Tips:

- Plot runs per minute or hour
- Overlay deploys and feature flags
- Alert on flatlines and suddenly 10x jumps

Lens: Reliability, UX

A healthy pattern is a predictable daily shape with gentle growth after releases; investigate if traffic flatlines for 5 minutes, spikes 3x baseline for 10 minutes, or drops more than 50 percent outside quiet hours.

LLM generations (# of model calls by model)



🟪	gpt-4o-mini	177
🟪	gpt-5	68
🟥	gpt-5-mini	23

What & Why: Understand your model mix. A change in model routing can increase cost, latency, or failure rate.

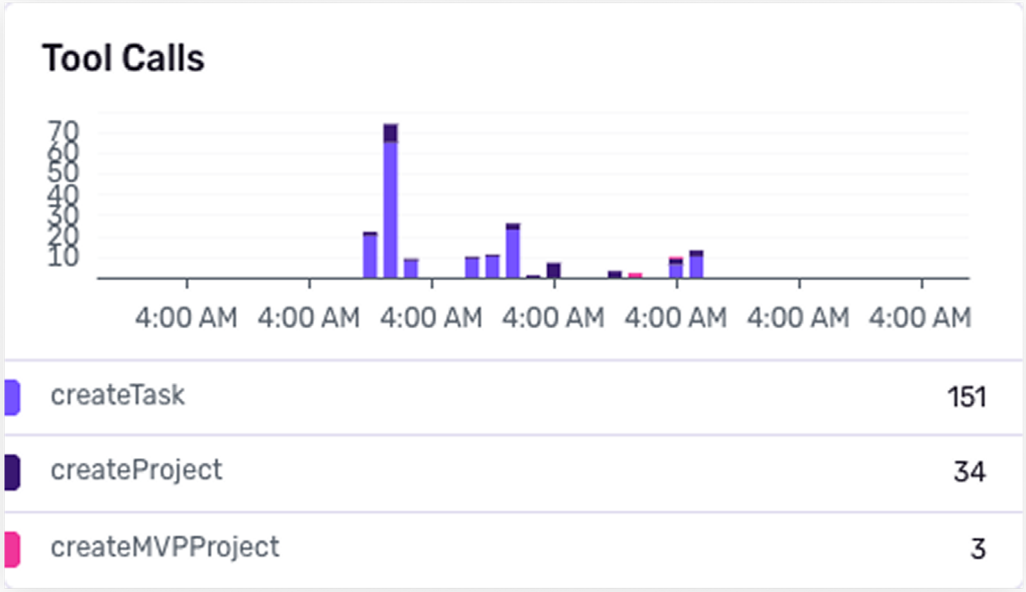
Tips:

- Bucket by model and version
- Alert on volume shifts or routing anomalies

Lens: Cost, Reliability

Under normal conditions, your routing mix is steady and changes only with deploys or flags; dig in if any model's share shifts more than 20 percent from the 7-day median or an unexpected version appears.

Tool calls and average duration



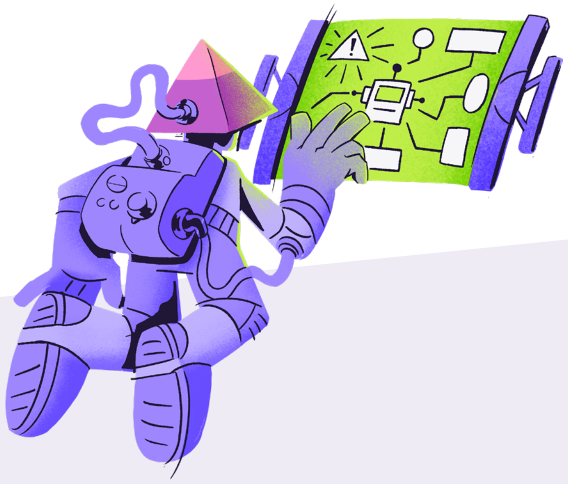
■	createTask	151
■	createProject	34
■	createMVPProject	3

What & Why: Tools like search APIs, vector DBs, and functions are common failure or slowness points.

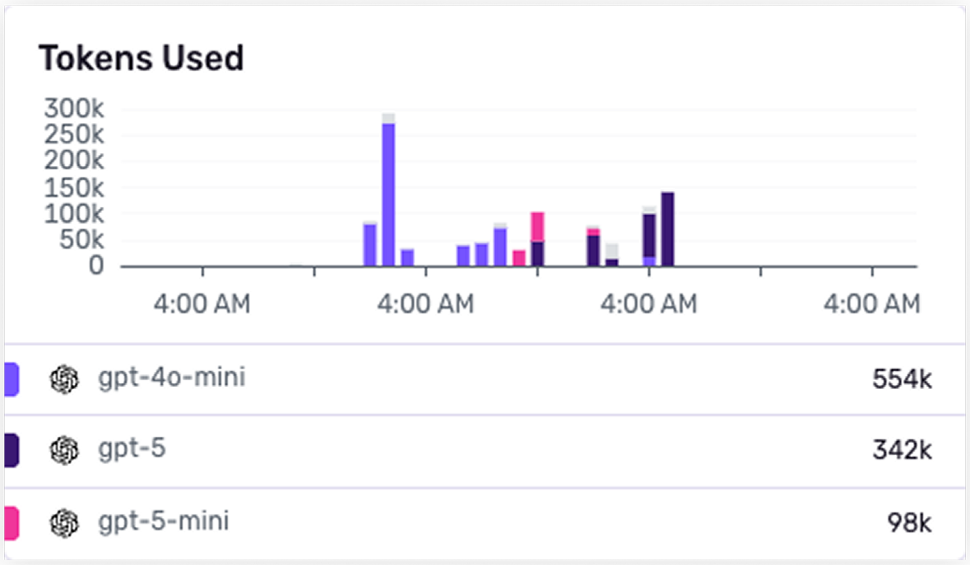
Tips:
- Capture tool call counts and durations
- Alert on spikes or timeouts

Lens: Reliability, UX

Aim for high success rates and a stable p95 duration; raise a flag if p95 climbs by 50 percent, timeouts exceed 1 to 2 percent, or new error classes cluster for a tool..



Token usage (Prompt, completion, total)



🟪	gpt-4o-mini	554k
⬛	gpt-5	342k
🟥	gpt-5-mini	98k

What & Why: Tokens directly drive cost and latency. Spikes often point to loops or prompt bugs.

Tips:

- Track tokens/request, per model
- Alert on outliers or hourly surges

Lens: Cost, UX

Typical behavior is stable tokens per request by route and model; investigate jumps of 50 percent, hourly token surges, or a growing tail near the 99th percentile.

LLM Cost (Aggregated Spend)

What & Why: Cost climbs with traffic, token bloat, or model swaps. Catch spend spikes early.

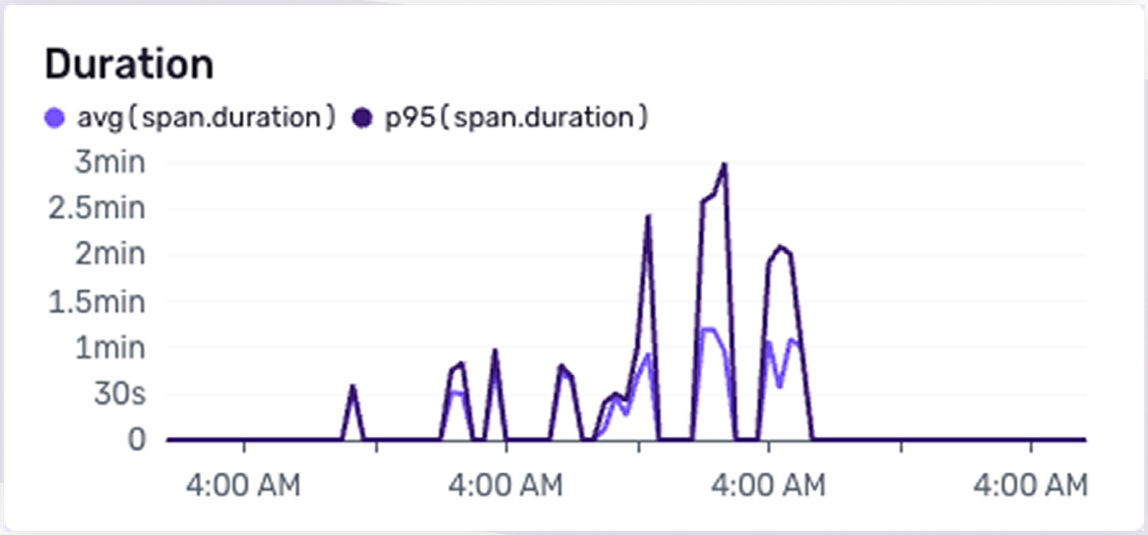
Tips:

- Calculate cost/model
- Alert when daily budget or per-request cost thresholds are exceeded

Lens: Cost

Cost looks healthy when per-request spend tracks your target and daily totals stay within budget; react if cost rises faster than traffic or per-request cost climbs after a prompt or routing change.

End-to-End latency (p50 / p95 + First token)



What & Why: Full response time matters but first-token latency is what the user feels.

Tips:

- Track p95, p99, and first-token latency
- Alert on regressions compared to weekly baseline

Lens: UX

Good UX shows a steady first-token time and p95 within your SLO, with p95 roughly 3 to 4 times p50 at most; watch for first-token increases while totals stay flat, or a 20 percent p95 regression versus a rolling baseline.

Critical step duration

What & Why: Break down generation into stages-retrieval, LLM call, post-processing. This isolates bottlenecks.

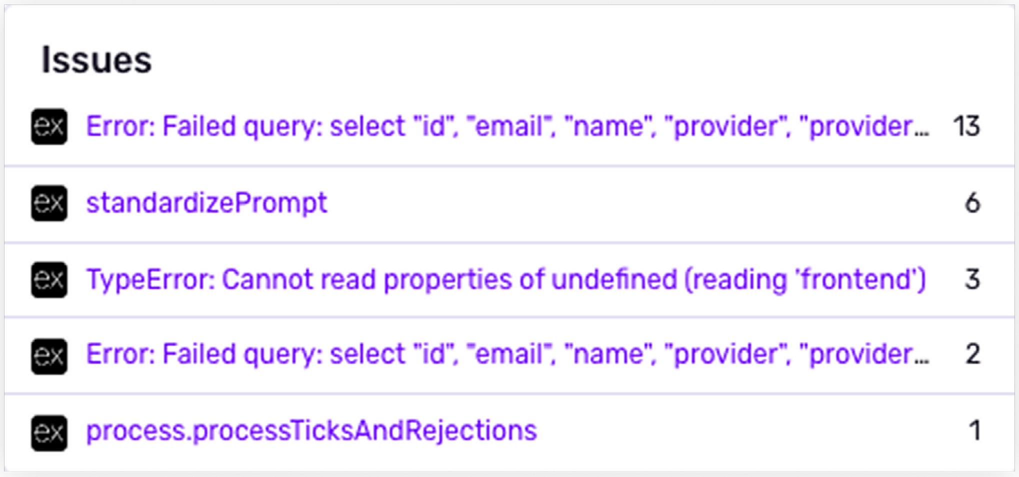
Tips:

- Use spans or structured logs per step
- Alert on max duration per stage

Lens: Reliability, UX

In a balanced run, no single stage dominates; investigate if one stage exceeds 60 percent of total time or its p95 jumps versus the 7-day baseline.

Error count and error rate



Issues

Error: Failed query: select "id", "email", "name", "provider", "provider...	13
standardizePrompt	6
TypeError: Cannot read properties of undefined (reading 'frontend')	3
Error: Failed query: select "id", "email", "name", "provider", "provider...	2
process.processTicksAndRejections	1

What & Why: Errors include tool call failures, JSON parsing errors, model timeouts, or misroutes.

Tips:

- Group by error class
- Alert on error % above threshold (e.g. 5%)

Lens: Reliability

Healthy systems keep error rate low and stable, with few parsing or timeout issues; act if overall errors exceed 5 percent or class-specific spikes appear, for example JSON parsing, timeouts, or 429s.

Agent invocations and nesting depth

What & Why: Multi-agent orchestration gets complex fast. High depth often signals runaway loops.

Tips:

- Track depth of calls per request
- Alert on depth > 3 or abnormal fan-out

Lens: Cost, Reliability

For controlled orchestration, depth stays between one and three and fan-out is bounded; dig in if depth exceeds three, invocations per request surge, or tokens rise without matching user traffic.

Handoffs (Agent -> Agent or human)

What & Why: Handoffs indicate poor coverage or user friction. Rising handoff rate is a quality red flag.

Tips:

- Log escalation events
- Alert on handoff % increase

Lens: UX, Reliability

The target is a low handoff percentage trending down over time; investigate week-over-week increases or clusters on specific intents, routes, or models.

Most modern LLM-observability tools (like Sentry) expose these with minimal config, below are some dashboards and alerts you can set up in Sentry to keep track of these.

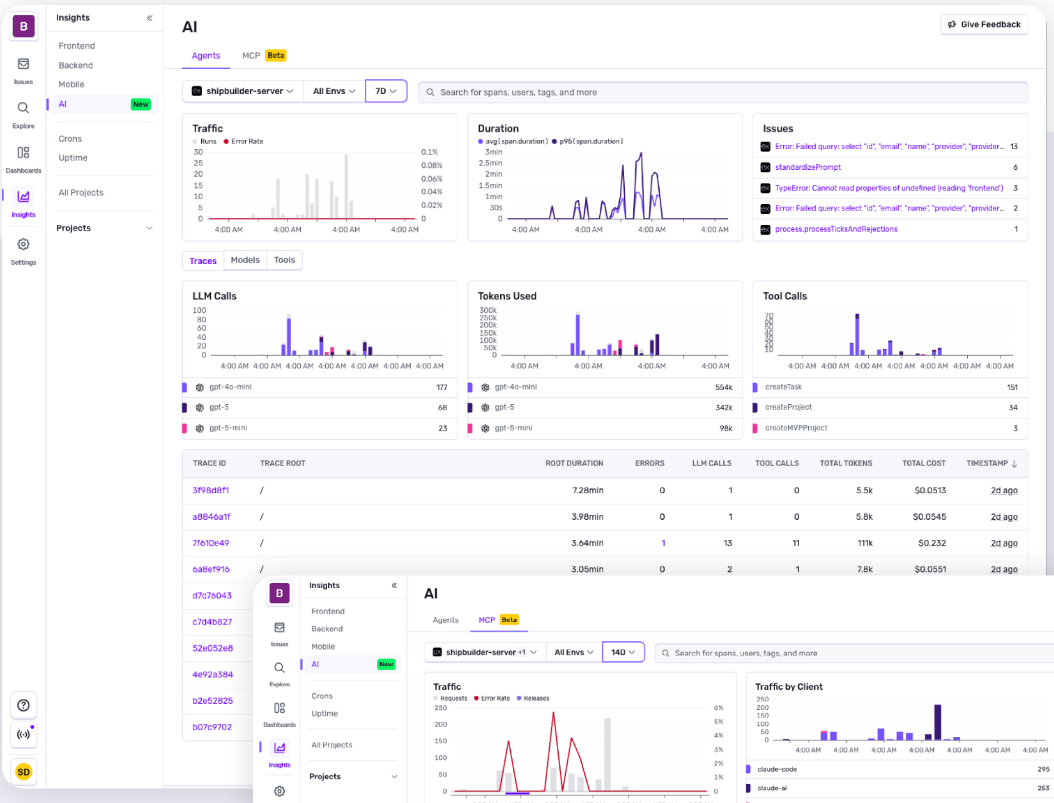
Getting started with Sentry's AI observability

Here is a minimal Node.js example using the Vercel AI SDK. Once enabled, Sentry's AI observability captures model calls, tool executions, prompts, tokens, latency, and errors. You can then build alerts and dashboards around the LLM metrics that matter.

```
import * as Sentry from "@sentry/node";

// Sentry init needs to be above everything else
Sentry.init({
  tracesSampleRate: 1.0,
  integrations: [Sentry.vercelAIIntegration()],
});

import { generateText } from "ai";
import { openai } from "@ai-sdk/openai";

// Your AI agent function
async function aiAgent(userQuery) {
  const result = await generateText({
    model: openai("gpt-4o"),
    prompt: userQuery,
    experimental_telemetry: {
      isEnabled: true,
      functionId: "ai-agent-main",
      recordInputs: true,
      recordOutputs: true,
    },
  });

  return result.text;
}
```

With this setup, each agent run links to a full trace. That makes it easy to confirm a fix, for example a slow span improves, and to watch for regressions with alerts for p95 latency, tokens per request, and error rate.

Your LLM ops cockpit: Dashboards and alerts to set on day one



Issues

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LLM Calls

gpt-4o-mini	177
gpt-5	68
gpt-5-mini	23

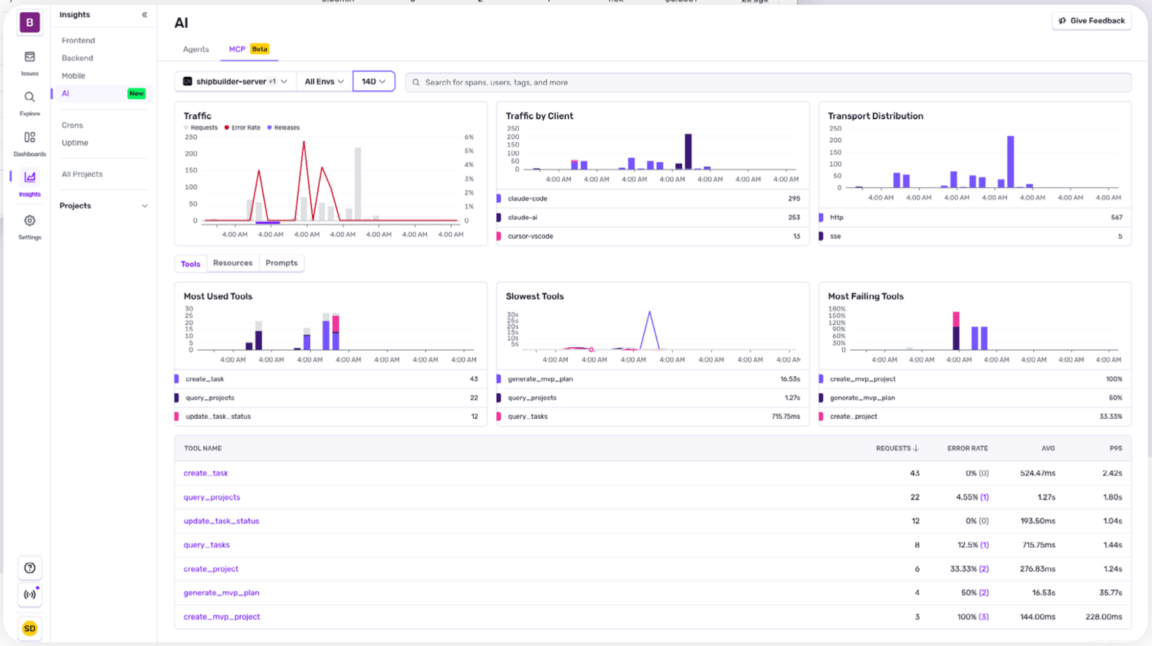
Tokens Used

gpt-4o-mini	554k
gpt-5	342k
gpt-5-mini	98k

Tool Calls

createTask	151
createProject	34
createMVPProject	3

TRACE ID	TRACE ROOT	ROOT DURATION	ERRORS	LLM CALLS	TOOL CALLS	TOTAL TOKENS	TOTAL COST	TIMESTAMP ↓
3f98d8f1	/	7.28min	0	1	0	5.5k	$0.0513	2d ago
a8846a1f	/	3.98min	0	1	0	5.8k	$0.0545	2d ago
7f610e49	/	3.64min	1	13	11	111k	$0.232	2d ago
6a8ef916	/	3.05min	0	2	1	7.8k	$0.0551	2d ago
d7c76043								
c7d4b827								
52e052e8								
4e92a384								
b2e52825								
b07c9702								



Traffic by Client

claude-code	295
claude-ai	253
cursor-vscode	13

Transport Distribution

http	567
sse	5

Most Used Tools

create_task	43
query_projects	22
update_task_status	12

Slowest Tools

generate_mvp_plan	16.53s
query_projects	1.27s
query_tasks	715.75ms

Most Failing Tools

create_mvp_project	100%
generate_mvp_plan	50%
create_project	33.33%

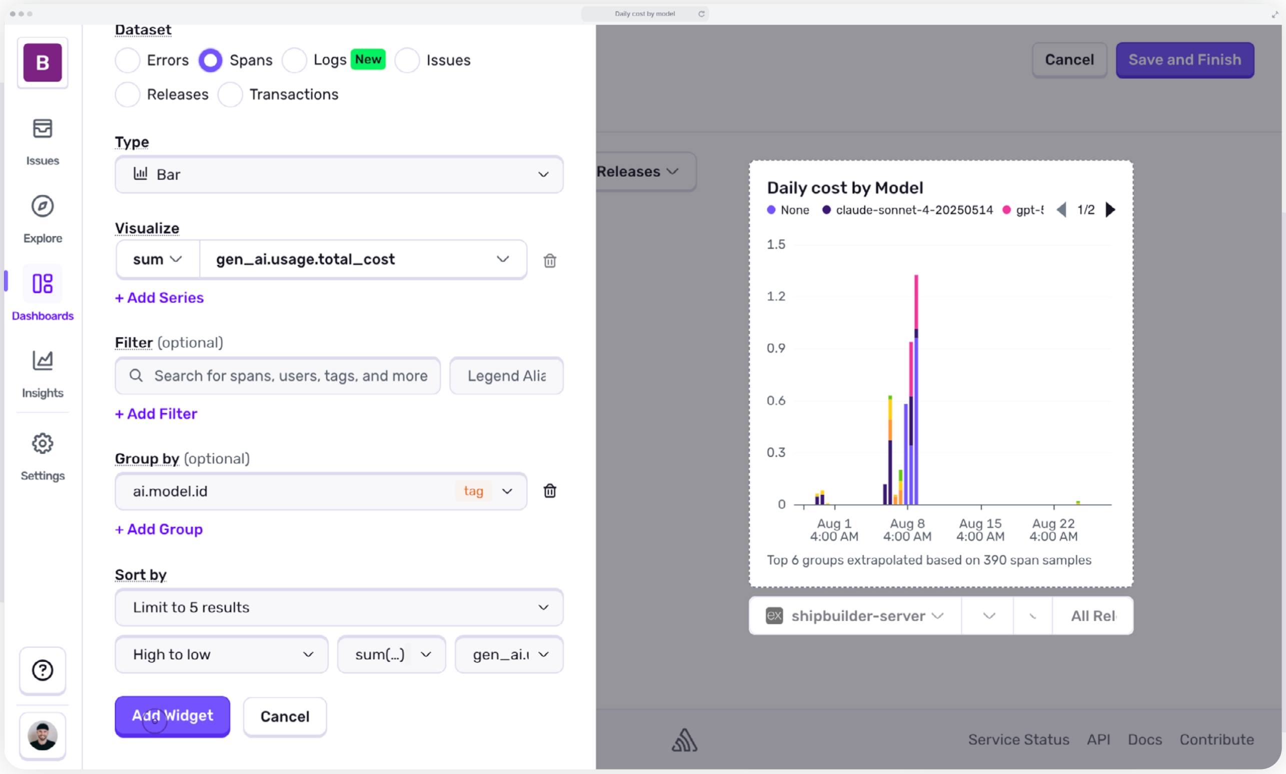
TOOL NAME	REQUESTS ↓	ERROR RATE	AVG	P95
create_task	43	0% (0)	524.47ms	2.42s
query_projects	22	4.55% (1)	1.27s	1.80s
update_task_status	12	0% (0)	193.50ms	1.04s
query_tasks	8	12.5% (1)	715.75ms	1.44s
create_project	6	33.33% (2)	276.83ms	1.24s
generate_mvp_plan	4	50% (2)	16.53s	35.77s
create_mvp_project	3	100% (3)	144.00ms	228.00ms

You can find more information about the different AI agents and MCP monitoring tools [in our documentation].

Beyond the default views we provide, here are a few examples of how you can instrument custom dashboards and alerts to help keep tabs on reliability, cost-efficiency, and user experience.

Daily cost by model

Having a clear understanding of cost across different models all in one single widget instead of going to the provider dashboards simplifies your operations. Pair it with an alert for high spend instead of waiting for the bill to come in at the end of the month.


Dataset
Errors [✓ Spans] Logs New Issues
Releases Transactions

Type
Bar

Visualize
sum gen_ai.usage.total_cost
+ Add Series

Filter (optional)
Search for spans, users, tags, and more | Legend Alia
+ Add Filter

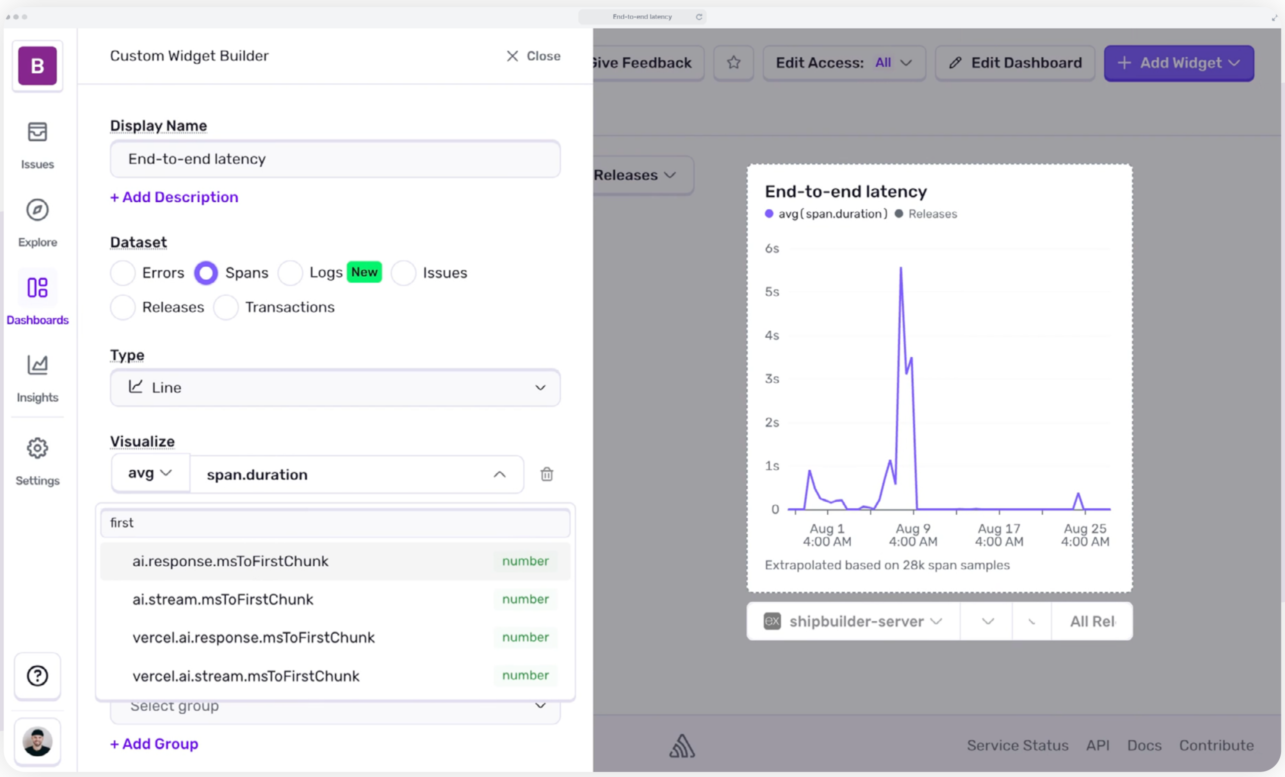
Group by (optional)
ai.model.id tag
+ Add Group

Sort by
Limit to 5 results
High to low | sum(...) | gen_ai.

End-to-end latency

Beyond cost it’s also really important to understand how each model is performing. The 3 data points that are useful to understanding user experience are:

- Average AI response milliseconds to first chunk: how long it took before you got the payload from the LLM
- P50 AI response milliseconds to finish: general user experience of a complete LLM response
- P95 AI response milliseconds to finish: gives insight into anomalies you might want to look into



Custom Widget Builder

Display Name: End-to-end latency

+ Add Description

Dataset: Errors [✓ Spans] Logs New Issues Releases Transactions

Type: Line

Visualize: avg span.duration

first

ai.response.msToFirstChunk	number
ai.stream.msToFirstChunk	number
vercel.ai.response.msToFirstChunk	number
vercel.ai.stream.msToFirstChunk	number

Select group

+ Add Group

Quick wins that pay off immediately

- Overlay deploys and flags so KPI spikes line up with changes, which speeds up root cause analysis.
- Start with tokens, cost, p95 latency, and error-rate alerts to catch costly regressions with minimal noise.
- Keep operational telemetry, not prompts or outputs, so you meet privacy needs without losing the metrics your alerts depend on.

Other LLM metrics you'll probably also want to track

- Hallucination and factual accuracy rate
- Toxicity and bias scores
- Retrieval precision and recall for RAG
- User sentiment, thumbs up or down, CSAT
- Hardware utilization, CPU and GPU
- Prompt quality and versioning
- Policy violation counters

Next steps to keep LLMs in check

You do not need dozens of charts. You do need the right performance metrics for AI agents: traffic, tokens, cost, latency, including first-token latency, errors, and a few orchestration signals. Audit your current observability setup against these LLM evaluation metrics, plug the gaps, and set a few sane alerts. If you already use Sentry for errors or traces, enable AI Agent Monitoring and see these dashboards in your own app. You can also check out or documentation for AI observability.

Take a quick tour of our Agent Monitoring Sandbox to get a feel for how Sentry can provide visibility into your AI agents, performance, costs, and user interactions.