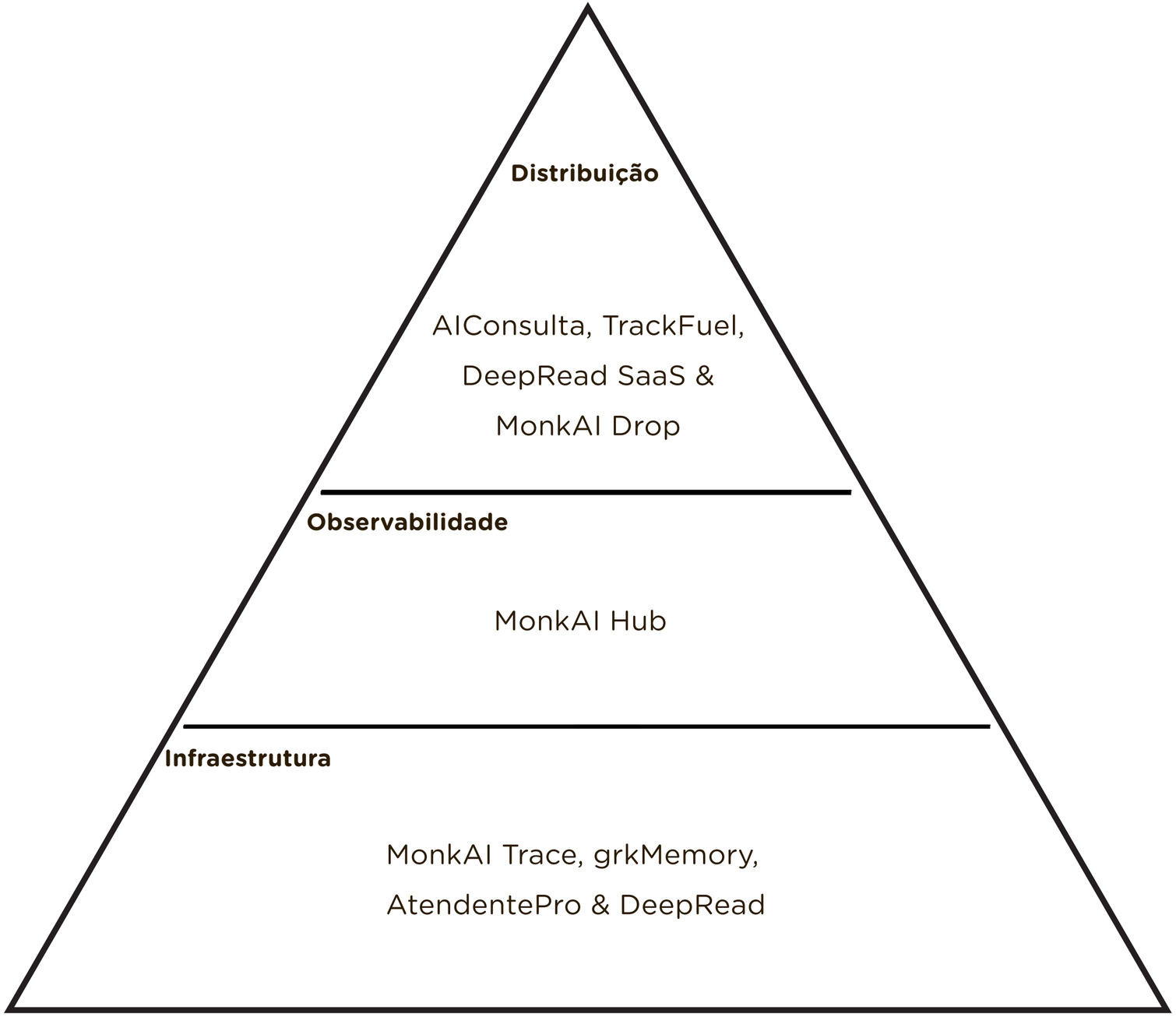
MONKAI

O que é MonkAI?

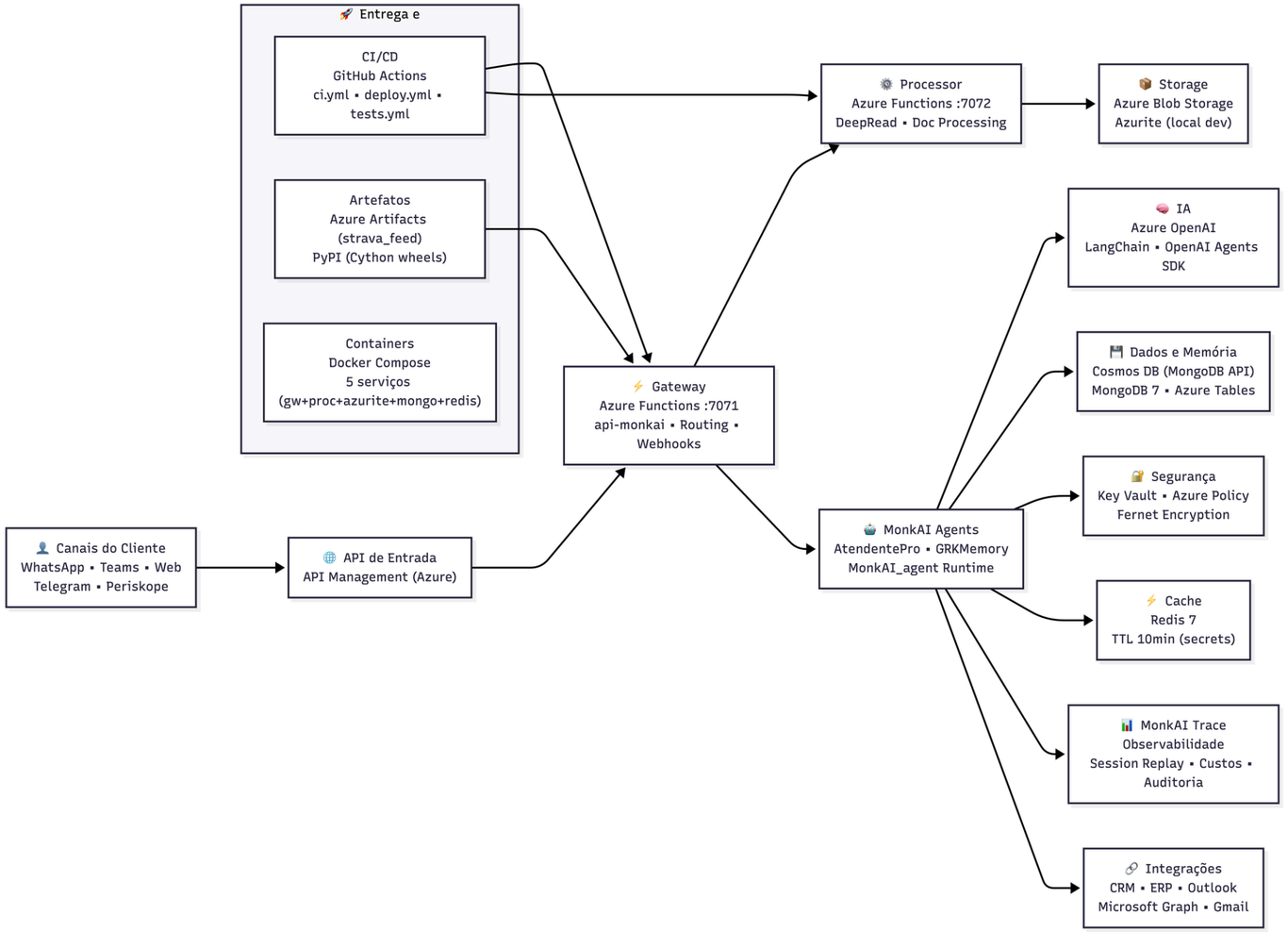
MonkAI é uma deeptech que oferece uma plataforma Agent-as-a-Service (AaaS) completa para empresas.

Com infraestrutura, produtos prontos ou customizáveis e governança, para operar e escalar agentes de IA em produção.



MonkAi Arquitetura (Multi Tenant)

A MonkAI roda no Azure, conectando canais (WhatsApp, Teams, Web) aos sistemas do cliente. Usa Azure OpenAI para automações, Cosmos e Blob para dados e Key Vault para segurança, com observabilidade ponta a ponta no MonkAI Trace (qualidade e custos).



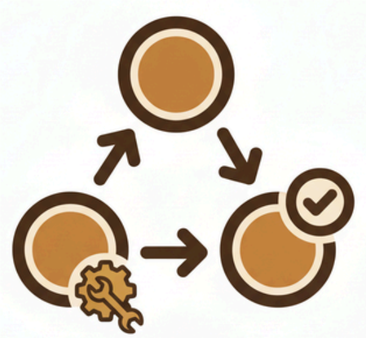
OBSERVABILIDADE

MonkAI Hub

O Hub oferece duas formas de visualização que garantem autonomia e confiança tanto para desenvolvedores quanto para a área de negócio.

Teste

validação

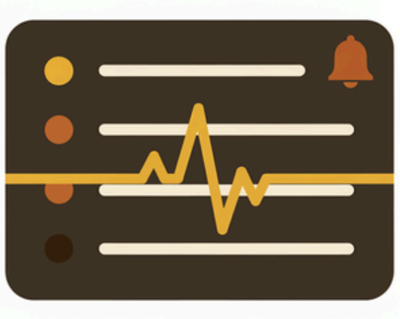


Fluxo

agentes

Conversas

insights



Monitoramento

observabilidade

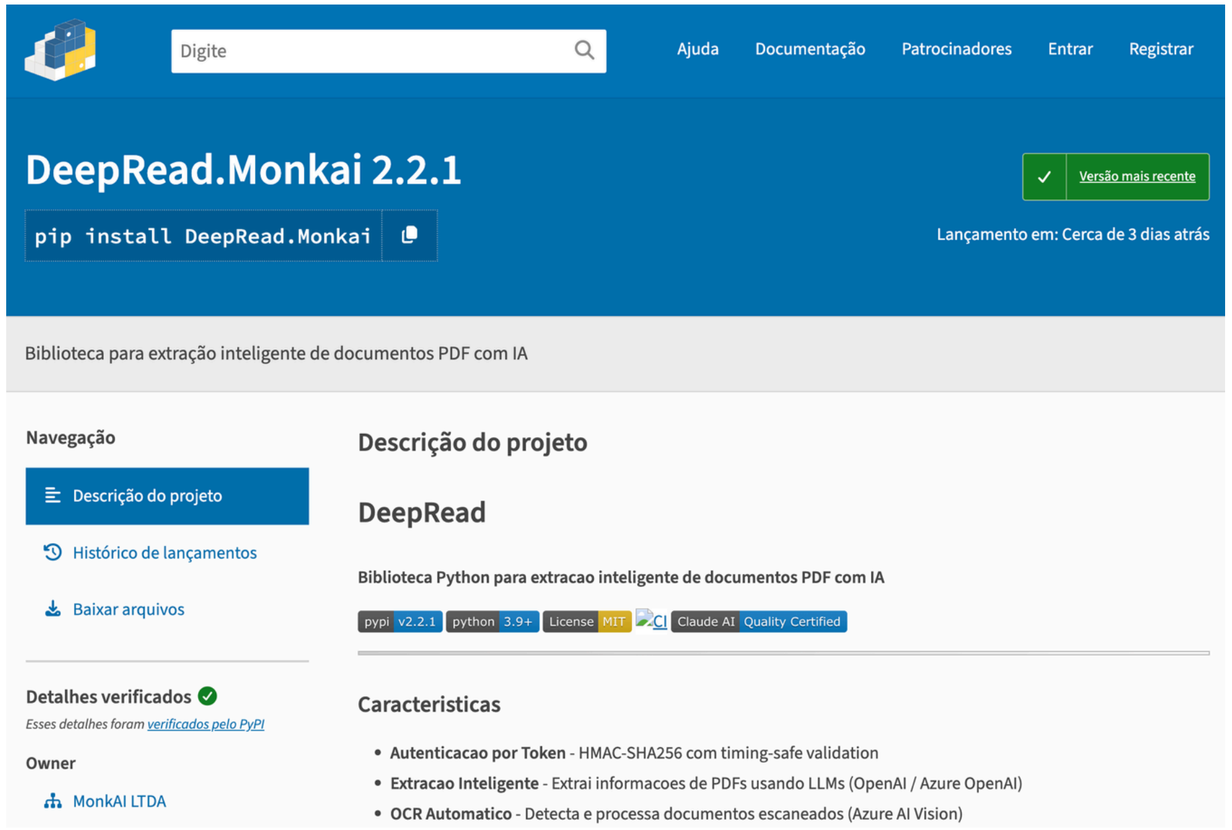
MonkAI Hub

Transforma agentes em sistemas auditáveis, otimizáveis e confiáveis — com controle total sobre os dados e as decisões.

INFRAESTRUTURA

DeepRead

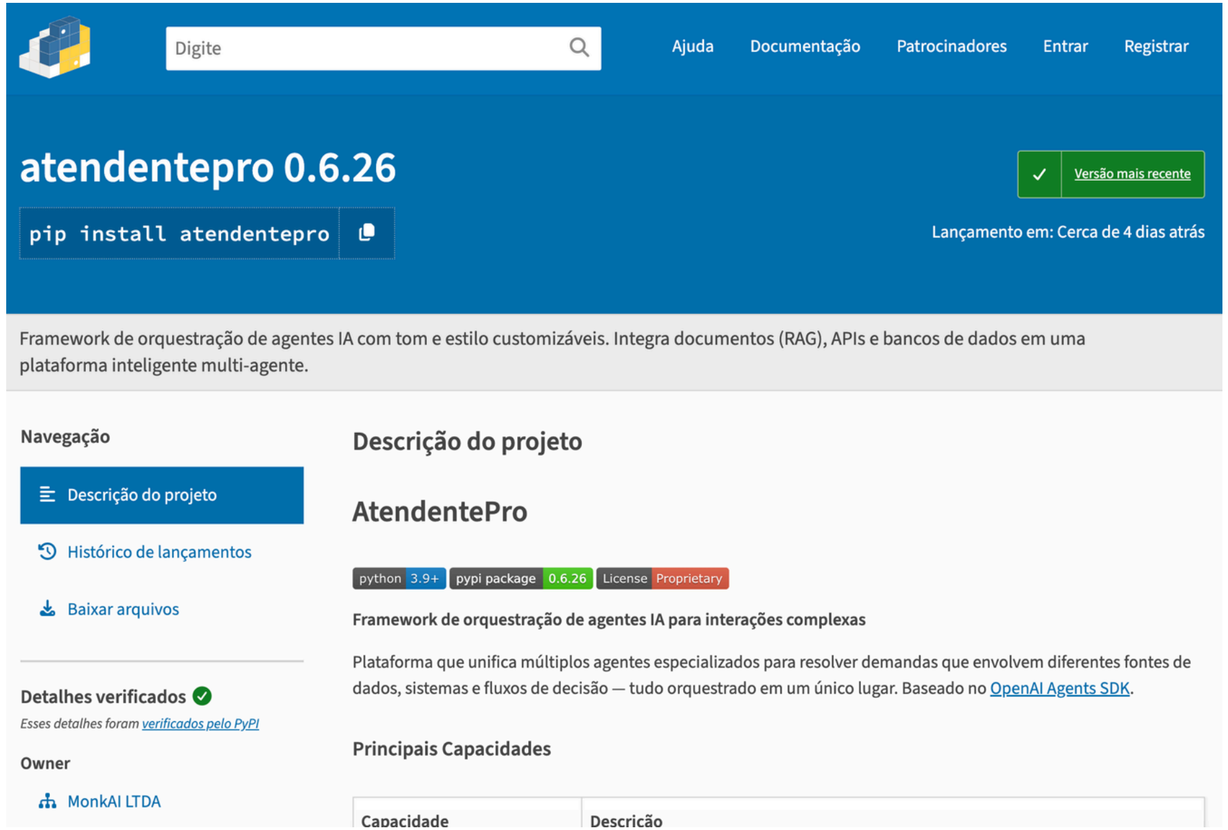
Biblioteca Python para extração inteligente de documentos PDF com IA e validação de poderes e informações no contrato junto à Receita Federal.



https://pypi.org/project/DeepRead.Monkai/

AtendentePro

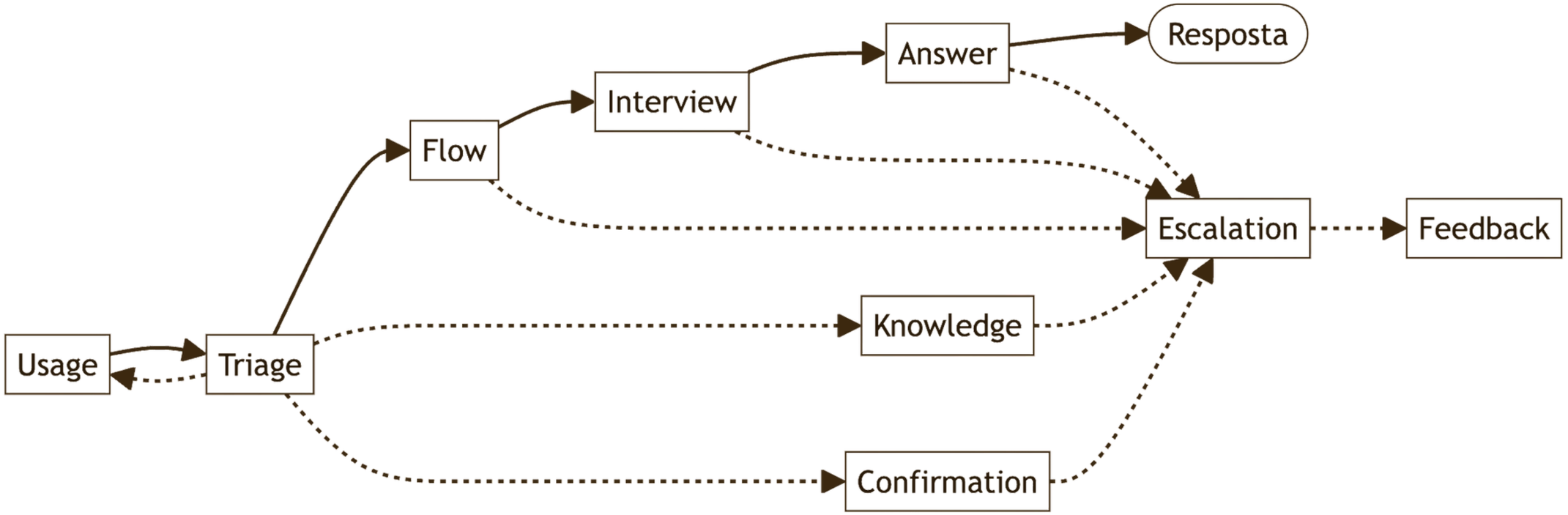
Framework de orquestração de agentes de IA para interações complexas. Plataforma que unifica múltiplos agentes especializados para resolver demandas que envolvem diferentes fontes de dados, sistemas e fluxos de decisão — tudo orquestrado em um único lugar.



https://pypi.org/project/atendentepro/

AtendentePro

A operação começa com a triagem da intenção do usuário e, a partir disso, o atendimento pode seguir para fluxos guiados, coleta estruturada de dados, respostas objetivas, consulta à base de conhecimento, confirmações ou escalonamento humano. Esse modelo reduz atrito, melhora a experiência e aumenta a taxa de resolução automática.



Linhas tracejadas: rotas alternativas comuns (roteamento, dúvidas, encerramento, tickets).

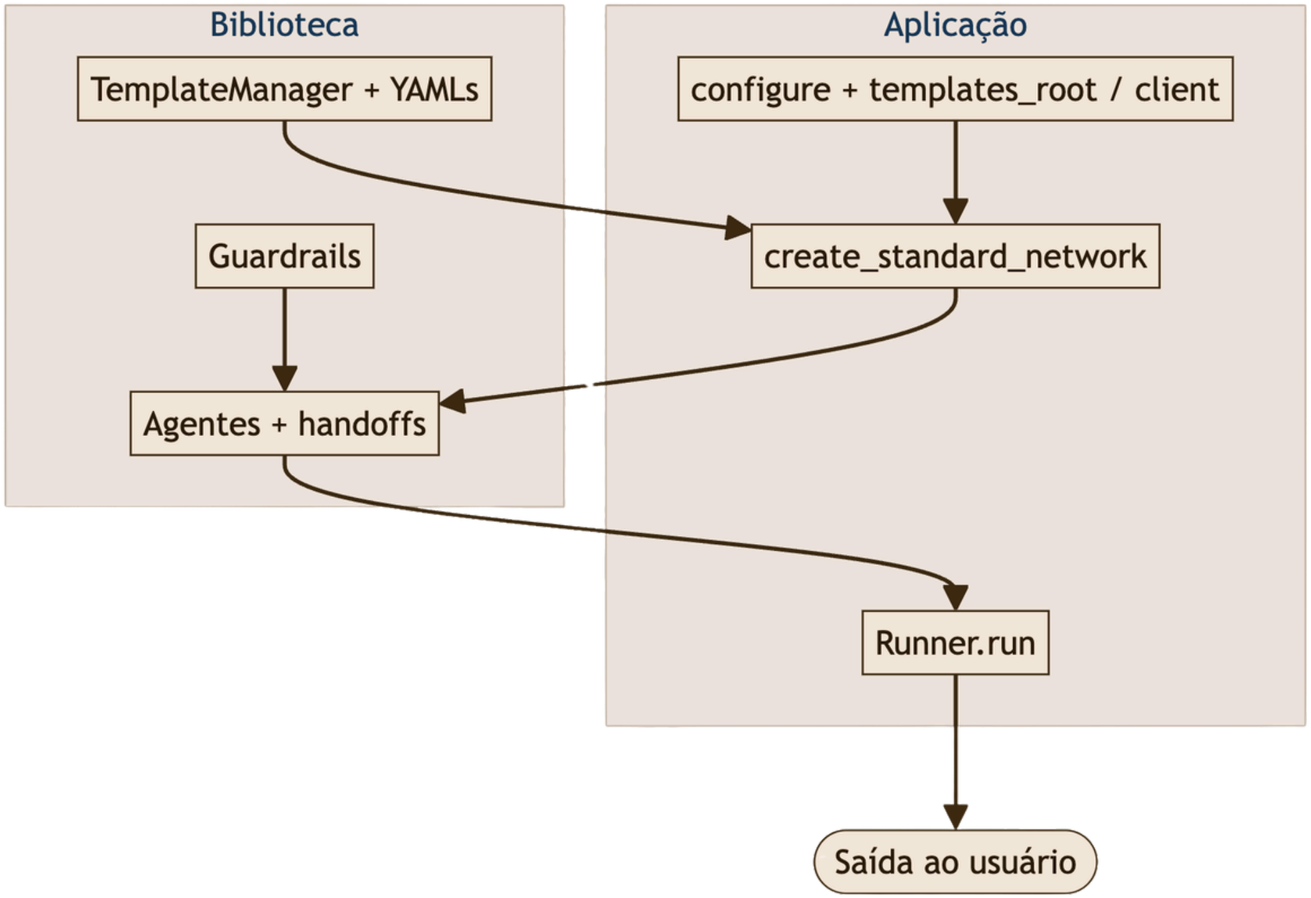
AtendentePro

Cada agente do AtendentePro possui uma função específica dentro da operação, como triagem, condução do fluxo, entrevistas estruturadas, resposta final, consulta de conhecimento, confirmação de dados, onboarding, suporte de uso, escalonamento e feedback. Essa divisão de responsabilidades permite maior qualidade no atendimento e mais controle sobre cada etapa da jornada.

Agente	Papel
Triage	Entrada: entender intenção e delegar.
Flow	Fluxo conversacional guiado.
Interview	Coleta estruturada de dados.
Answer	Respostas finais sintetizadas.
Knowledge	RAG / base de conhecimento.
Confirmation	Validações e confirmações.
Usage	Como usar o produto / tutoriais.
Onboarding	Boas-vindas e cadastro (opcional).
Escalation	Encaminhamento humano.
Feedback	Tickets e manifestações.

AtendentePro

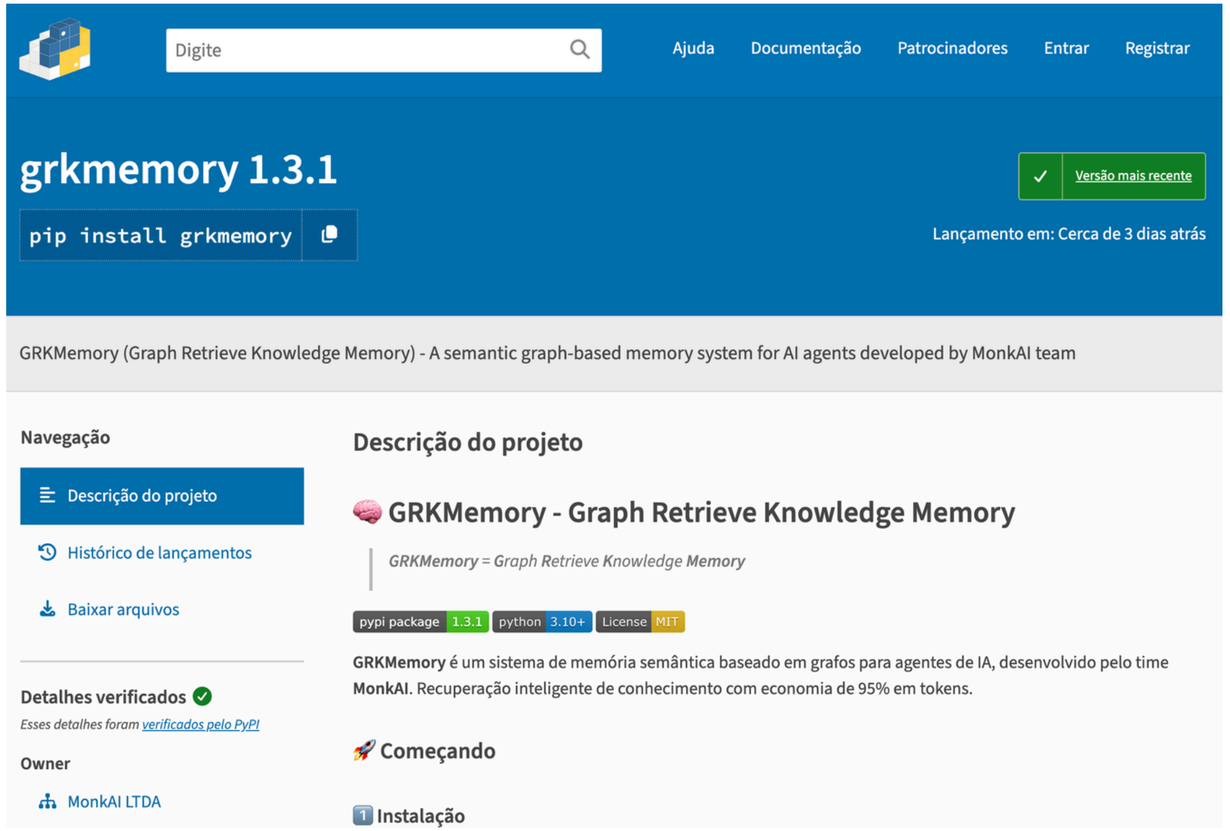
O AtendentePro combina uma biblioteca de templates, YAMLs, guardrails e agentes especializados para criar redes conversacionais padronizadas e seguras. Com isso, a aplicação consegue ser personalizada por cliente sem perder consistência operacional, escalabilidade e controle da experiência entregue ao usuário.



GRKMemory

Um sistema de memória semântica baseado em grafos para agentes de IA, desenvolvido pelo time MonkAI.

Recuperação inteligente de conhecimento com economia de 95% em tokens.



https://pypi.org/project/grkmemory/

GRKMemory

Exemplos como lidamos com o histórico das sessões, transformando em memórias estruturadas.

Estrutura do JSON

```
{
  "sessoes": [
    {
      "id": "sess_abc123",
      "timestamp": "2025-01-09T12:00:00",
      "summary": "Discussão sobre Python e IA",
      "tags": ["python", "ia", "programação"],
      "entities": ["Python", "OpenAI", "GPT"],
      "concepts": ["machine learning", "api"],
      "messages": [
        {"role": "user", "content": "..."},
        {"role": "assistant", "content": "..."}
      ]
    }
  ]
}
```

Estrutura do TOON (Token-Optimized Object Notation)

O mesmo conteúdo em TOON ocupa ~25% menos tokens, ideal para contexto de LLM:

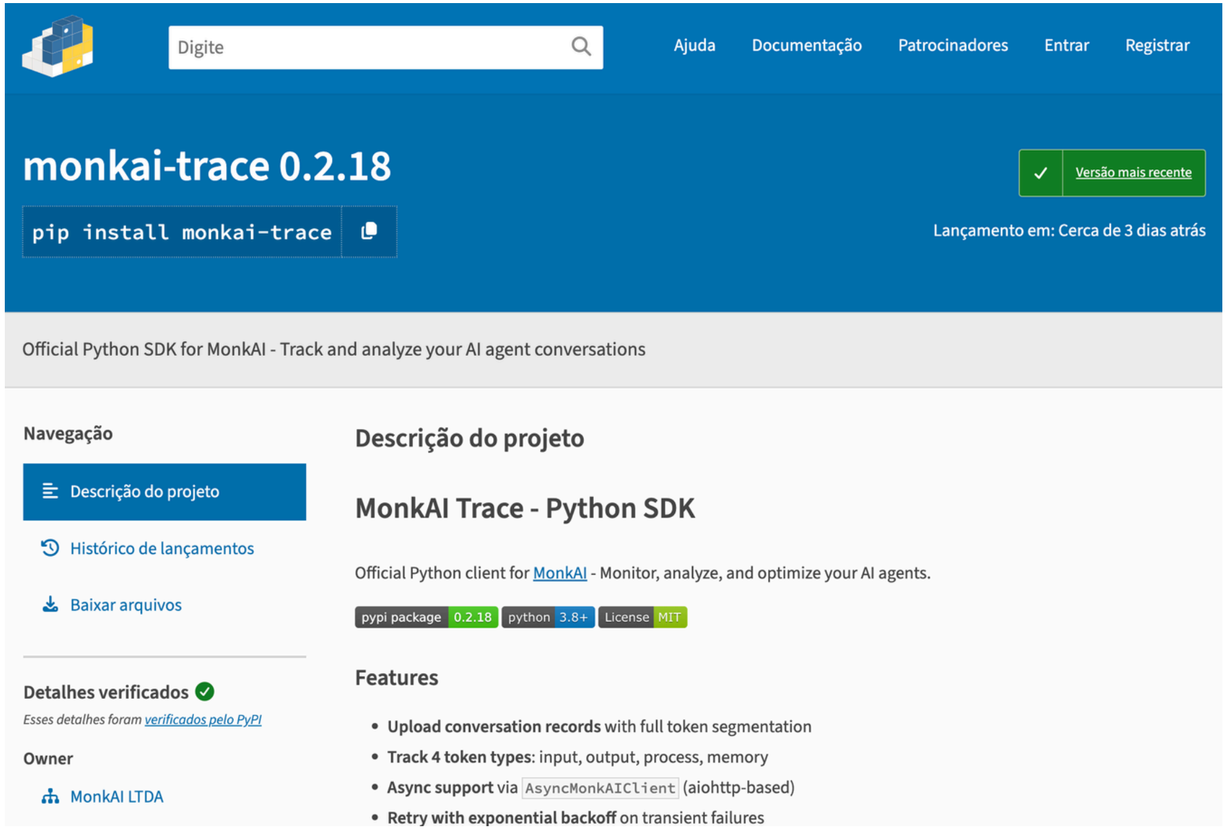
```
sessoes[1]:
  - id: sess_abc123
    timestamp: "2025-01-09T12:00:00"
    summary: Discussão sobre Python e IA
    tags[3]: python,ia,programação
    entities[3]: Python,OpenAI,GPT
    concepts[2]: machine learning,api
    messages[2]{role,content}:
      user,Vamos falar sobre Python
      assistant,Claro! O que você quer saber?
```

> ***Nota:*** *TOON elimina chaves, colchetes e aspas redundantes, compactando listas e tabelas em notação posicional. Instale com* `pip install toon_format`.

https://pypi.org/project/grkmemory/

MonkAI Trace

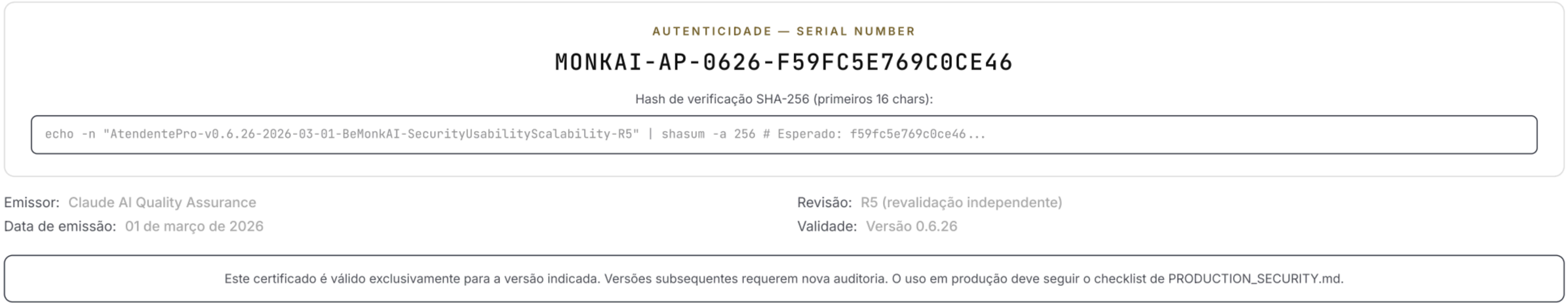
Cliente Python oficial para MonkAI – Monitore, analise e otimize seus agentes de IA.



https://pypi.org/project/monkai-trace/

Certificados de Qualidade

Realizamos auditorias de qualidade em nossos produtos da MonkAI, avaliando cada um deles quanto à **segurança**, **usabilidade** e **escalabilidade**. Emitido pelo Claude AI Quality Assurance Opus 4.6, alcançamos a nota **A** em todos os nossos produtos liberados.



https://www.monkai.com.br/certificados

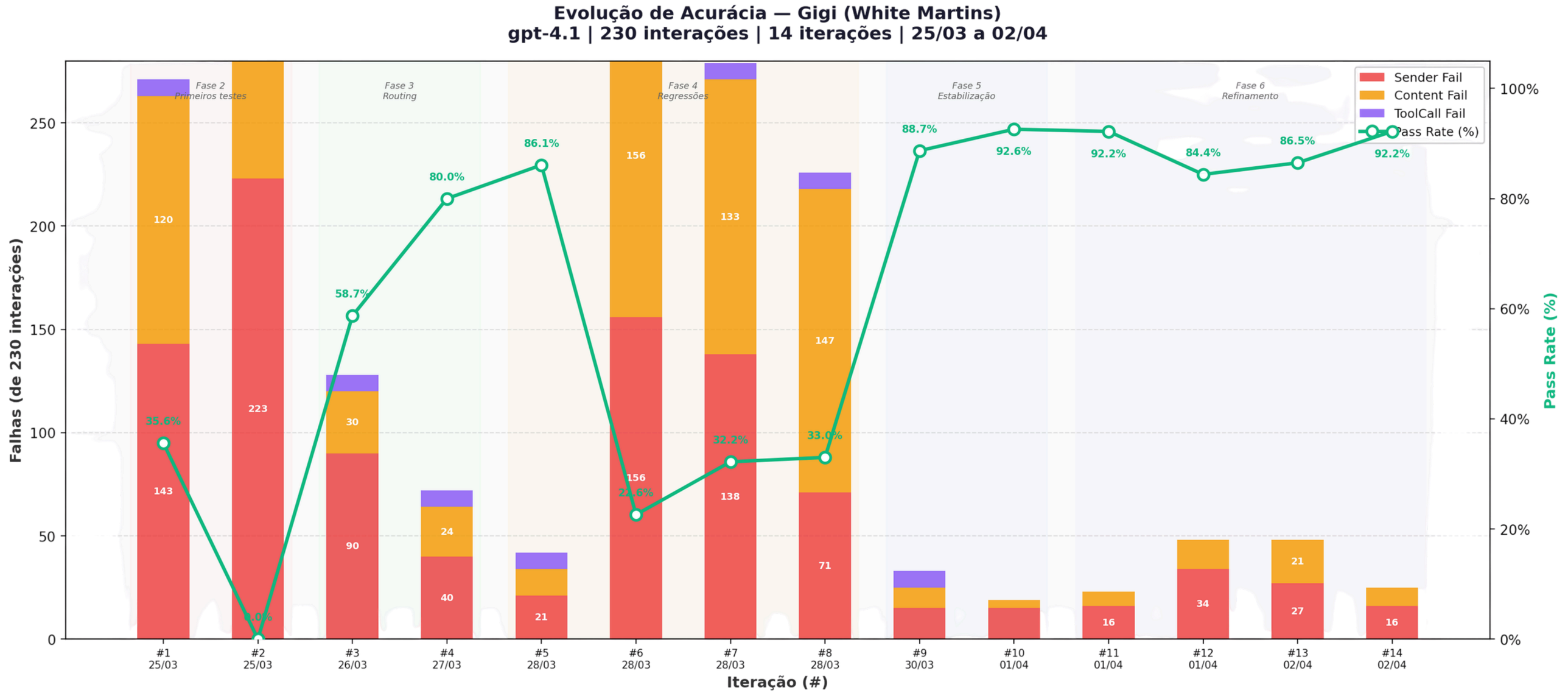
PRODUTOS

Distribuição

	vivo	White Martins	Vibra	EasyDr.	Nestlé	DeepRead Saas	TrackFuel	AIConsulta	MonkaiDrop
MonkAI Hub	✓	✓		✓	✓		✓	✓	
MonkAI Trace	✓	✓		✓	✓		✓	✓	
GrkMemory	✓	✓		✓	✓		✓	✓	
AtendentePro	✓	✓		✓	✓		✓	✓	✓
DeepRead	✓		✓	✓		✓			

CUSTO, QUALIDADE E VELOCIDADE:
COMO ESCOLHEMOS O MODELO CERTO

USE CASE - GIGI

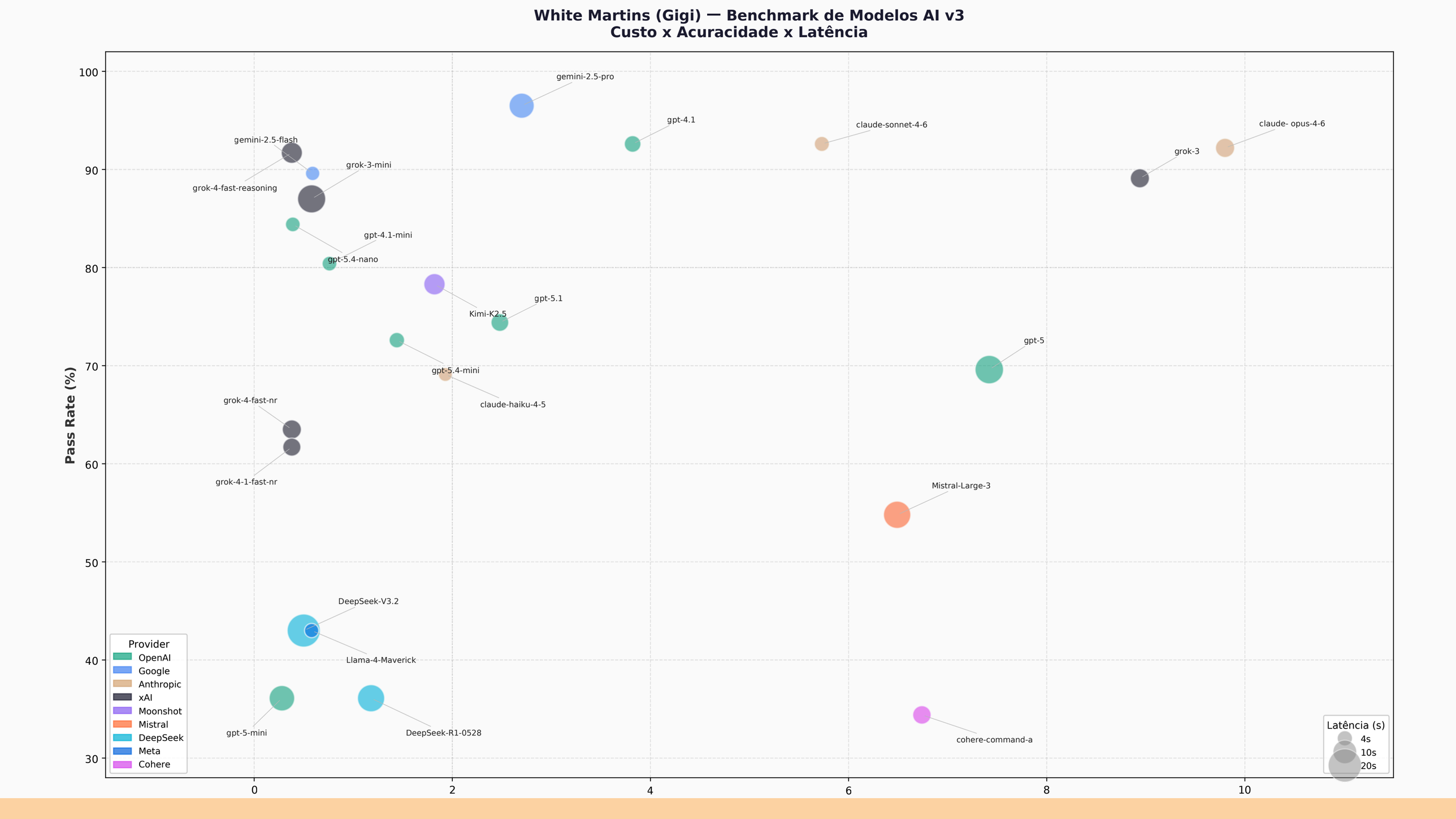

Evolução de Acurácia — Gigi (White Martins)
gpt-4.1 | 230 interações | 14 iterações | 25/03 a 02/04
Fase 2
Primeiros testes
Fase 3
Routing
Fase 4
Regressões
Fase 5
Estabilização
Fase 6
Refinamento
Sender Fail
Content Fail
ToolCall Fail
Pass Rate (%)
Falhas (de 230 interações)
Pass Rate (%)
Iteração (#)
#1 25/03
#2 25/03
#3 26/03
#4 27/03
#5 28/03
#6 28/03
#7 28/03
#8 28/03
#9 30/03
#10 01/04
#11 01/04
#12 01/04
#13 02/04
#14 02/04
35.6%
0.0%
58.7%
80.0%
86.1%
22.6%
32.2%
33.0%
88.7%
92.6%
92.2%
84.4%
86.5%
92.2%

White Martins (Gigi) — Benchmark de Modelos AI v3

Data: 2026-04-02 a 2026-04-05 | Bateria: 230 interacoes, 72 grupos de teste

Modelos testados (**23**):

- **gpt-4.1,**
- **gpt-4.1-mini,**
- **gpt-5,**
- **gpt-5.1,**
- **gpt-5-mini,**
- **gpt-5.4-mini,**
- **gpt-5.4-nano,**
- **claude-sonnet-4-6,**
- **claude-opus-4-6,**
- **claude-haiku-4-5,**
- **gemini-2.5-pro,**
- **gemini-2.5-flash,**
- **grok-3,**
- **grok-3-mini,**
- **grok-4-fast-reasoning,**
- **grok-4-fast-non-reasoning,**
- **grok-4-1-fast-non-reasoning,**
- **Kimi-K2.5,**
- **Mistral-Large-3,**
- **DeepSeek-V3.2,**
- **Llama-4-Maverick,**
- **DeepSeek-R1-0528,**
- **cohere-command-a**


White Martins (Gigi) — Benchmark de Modelos AI v3
Custo x Acuracidade x Latência
Pass Rate (%)
100
90
80
70
60
50
40
30
0
2
4
6
8
10
gemini-2.5-pro
gpt-4.1
claude-sonnet-4-6
claude- opus-4-6
gemini-2.5-flash
grok-3
grok-3-mini
grok-4-fast-reasoning
gpt-4.1-mini
gpt-5.4-nano
Kimi-K2.5
gpt-5.1
gpt-5
gpt-5.4-mini
claude-haiku-4-5
grok-4-fast-nr
grok-4-1-fast-nr
Mistral-Large-3
DeepSeek-V3.2
Llama-4-Maverick
gpt-5-mini
DeepSeek-R1-0528
cohere-command-a
Provider
OpenAI
Google
Anthropic
xAI
Moonshot
Mistral
DeepSeek
Meta
Cohere
Latência (s)
4s
10s
20s

Grupos de Performance

Modelo	Pass Rate	Latencia	Sender Fail	Content Fail	Observacao
gemini-2.5-pro	96.5%	11.5s	2	8	Melhor absoluto, latencia alta
gpt-4.1	92.6%	5.0s	15	4	Baseline solido, melhor instruction following
claude-sonnet-4-6	92.6%	4.1s	14	14	Empatado com gpt-4.1, mais rapido
claude-opus-4-6	92.2%	6.7s	16	10	Premium sem ganho sobre sonnet
grok-4-fast-reasoning	91.7%	8.1s	15	14	Excelente custo-beneficio
gemini-2.5-flash	89.6%	3.7s	17	23	Mais rapido dos lideres
grok-3	89.1%	6.6s	23	20	Solido mas caro

Group Pass Rate (grupo completo sem falhas)

Modelo	Interacoes Pass	Grupos Completos	Delta
gemini-2.5-pro	96.5%	**88.9%** (64/72)	-7.6pp
gpt-4.1	92.6%	**83.3%** (60/72)	-9.3pp
claude-sonnet-4-6	92.6%	**83.3%** (60/72)	-9.3pp
grok-4-fast-reasoning	91.7%	**80.6%** (58/72)	-11.1pp
gemini-2.5-flash	89.6%	**77.8%** (56/72)	-11.8pp
gpt-4.1-mini	80.4%	**72.2%** (52/72)	-8.2pp
gpt-5.4-nano	84.4%	**68.1%** (49/72)	-16.3pp

Testes mais difíceis (falham em múltiplos modelos líderes)

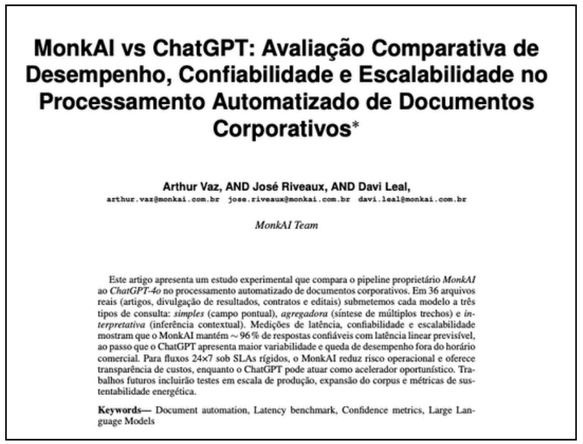
Test ID	Categoria	Falhas (de 8 modelos)	Observacao
205	Multi ServLig+AtivoOp+Indust	8/8	Fluxo mais complexo — todos falham em algum ponto
204	Multi Consumo+Comerc+Energia	8/8	Troca de contexto entre 3 categorias
201	Multi Comerc+Frete+Consumo	8/8	Frete (F1) e o IVA mais errado
203	Multi AtivoPj+Indust+Frete	8/8	Frete (F5) confunde todos os modelos
202	Multi AtivoOp+Energia+ServNaoLig	6/8	gemini-pro e grok-4-reasoning acertam
121	Usage Plataforma	8/8	Provavel problema no teste
200	Multi Energia+Indust+ServOp	5/8	Menos complexo, mais acertos

Recomendações

1. **Avaliar migracao para gemini-2.5-pro** — 96.5% supera todos os modelos, custo razoavel ($2.70/benchmark)
2. **Avaliar grok-4-fast-reasoning** — 91.7% a $0.38/benchmark, 10x mais barato que gpt-4.1
3. **Considerar gpt-5.4-nano para reduzir custo** — 84.4% a $0.39/benchmark, latencia de 3.9s
4. **Manter gpt-4.1 como fallback** — mais testado e estavel em producao
5. **Nao usar claude-opus-4-6** — mesmo resultado que sonnet-4-6 por quase 2x o custo
6. **Nao usar familia gpt-5.0/5.1** para multi-agent — instruction following insuficiente
7. **Nao investir em variantes non-reasoning** — perda de 28pp vs reasoning

MonkAI - Deep tech

A MonkAI é uma deep tech porque desenvolve tecnologia de base — de memória conversacional a frameworks de agentes — com pesquisa proprietária, eficiência comprovada e foco em infraestrutura e soberania dos dados.



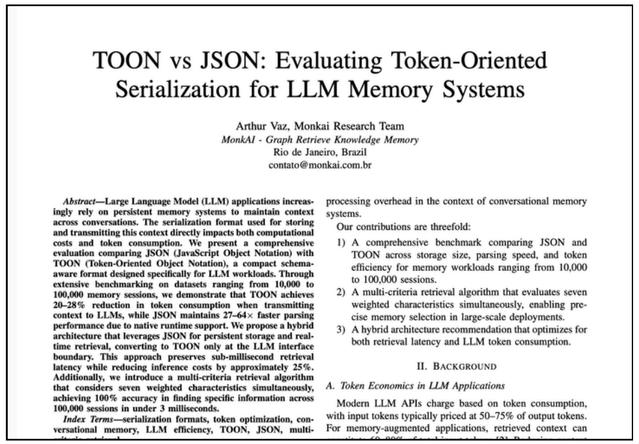
MonkAI vs ChatGPT: Avaliação Comparativa de Desempenho, Confiabilidade e Escalabilidade no Processamento Automatizado de Documentos Corporativos*

Arthur Vaz, AND José Riveaux, AND Davi Leal,
arthur.vaz@monkai.com.br jose.riveaux@monkai.com.br davi.leal@monkai.com.br

MonkAI Team

Este artigo apresenta um estudo experimental que compara o pipeline proprietário *MonkAI* ao *ChatGPT-4o* no processamento automatizado de documentos corporativos. Em 36 arquivos reais (artigos, divulgação de resultados, contratos e editais) submetemos cada modelo a três tipos de consulta: *simples* (campo pontual), *agregadora* (síntese de múltiplos trechos) e *interpretativa* (inferência contextual). Medições de latência, confiabilidade e escalabilidade mostram que o MonkAI mantém ∼ 96 % de respostas confiáveis com latência linear previsível, ao passo que o ChatGPT apresenta maior variabilidade e queda de desempenho fora do horário comercial. Para fluxos 24x7 sob SLAs rígidos, o MonkAI reduz risco operacional e oferece transparência de custos, enquanto o ChatGPT pode atuar como acelerador oportunístico. Trabalhos futuros incluirão testes em escala de produção, expansão do corpus e métricas de sustentabilidade energética.

Keywords— Document automation, Latency benchmark, Confidence metrics, Large Language Models



TOON vs JSON: Evaluating Token-Oriented Serialization for LLM Memory Systems

Arthur Vaz, Monkai Research Team
MonkAI - Graph Retrieve Knowledge Memory
Rio de Janeiro, Brazil
contato@monkai.com.br

***Abstract*—Large Language Model (LLM) applications increasingly rely on persistent memory systems to maintain context across conversations. The serialization format used for storing and transmitting this context directly impacts both computational costs and token consumption. We present a comprehensive evaluation comparing JSON (JavaScript Object Notation) with TOON (Token-Oriented Object Notation), a compact schema-aware format designed specifically for LLM workloads. Through extensive benchmarking on datasets ranging from 10,000 to 100,000 memory sessions, we demonstrate that TOON achieves 20–28% reduction in token consumption when transmitting context to LLMs, while JSON maintains 27–64× faster parsing performance due to native runtime support. We propose a hybrid architecture that leverages JSON for persistent storage and real-time retrieval, converting to TOON only at the LLM interface boundary. This approach preserves sub-millisecond retrieval latency while reducing inference costs by approximately 25%. Additionally, we introduce a multi-criteria retrieval algorithm that considers seven weighted characteristics simultaneously, achieving 100% accuracy in finding specific information across 100,000 sessions in under 3 milliseconds.**

***Index Terms*—serialization formats, token optimization, conversational memory, LLM efficiency, TOON, JSON, multi-**

processing overhead in the context of conversational memory systems.

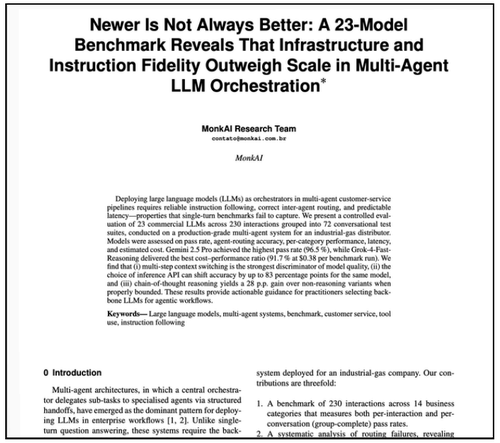
Our contributions are threefold:

1) A comprehensive benchmark comparing JSON and TOON across storage size, parsing speed, and token efficiency for memory workloads ranging from 10,000 to 100,000 sessions.
2) A multi-criteria retrieval algorithm that evaluates seven weighted characteristics simultaneously, enabling precise memory selection in large-scale deployments.
3) A hybrid architecture recommendation that optimizes for both retrieval latency and LLM token consumption.

II. Background

A. Token Economics in LLM Applications

Modern LLM APIs charge based on token consumption, with input tokens typically priced at 50–75% of output tokens. For memory-augmented applications, retrieved context can



Newer Is Not Always Better: A 23-Model Benchmark Reveals That Infrastructure and Instruction Fidelity Outweigh Scale in Multi-Agent LLM Orchestration*

MonkAI Research Team
contato@monkai.com.br

MonkAI

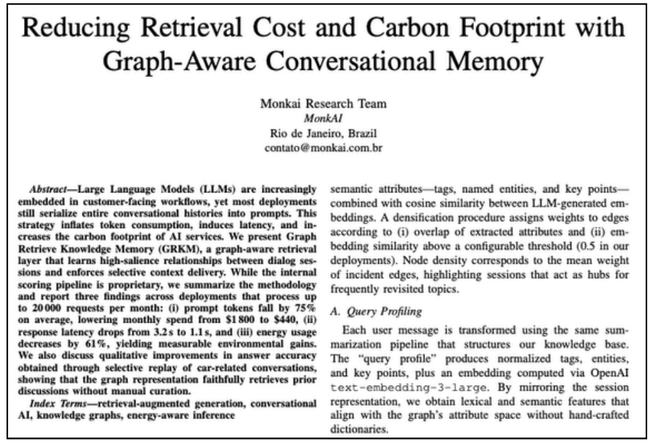
Deploying large language models (LLMs) as orchestrators in multi-agent customer-service pipelines requires reliable instruction following, correct inter-agent routing, and predictable latency—properties that single-turn benchmarks fail to capture. We present a controlled evaluation of 23 commercial LLMs across 230 interactions grouped into 72 conversational test suites, conducted on a production-grade multi-agent system for an industrial-gas distributor. Models were assessed on pass rate, agent-routing accuracy, per-category performance, latency, and estimated cost. Gemini 2.5 Pro achieved the highest pass rate (96.5 %), while Grok-4-Fast-Reasoning delivered the best cost–performance ratio (91.7 % at $0.38 per benchmark run). We find that (i) multi-step context switching is the strongest discriminator of model quality, (ii) the choice of inference API can shift accuracy by up to 83 percentage points for the same model, and (iii) chain-of-thought reasoning yields a 28 p.p. gain over non-reasoning variants when properly bounded. These results provide actionable guidance for practitioners selecting backbone LLMs for agentic workflows.

Keywords— Large language models, multi-agent systems, benchmark, customer service, tool use, instruction following

0 Introduction

Multi-agent architectures, in which a central orchestrator delegates sub-tasks to specialised agents via structured handoffs, have emerged as the dominant pattern for deploying LLMs in enterprise workflows [1, 2]. Unlike single-turn question answering, these systems require the backsystem deployed for an industrial-gas company. Our contributions are threefold:

1. A benchmark of 230 interactions across 14 business categories that measures both per-interaction and per-conversation (group-complete) pass rates.
2. A systematic analysis of routing failures, revealing



Reducing Retrieval Cost and Carbon Footprint with Graph-Aware Conversational Memory

Monkai Research Team
MonkAI
Rio de Janeiro, Brazil
contato@monkai.com.br

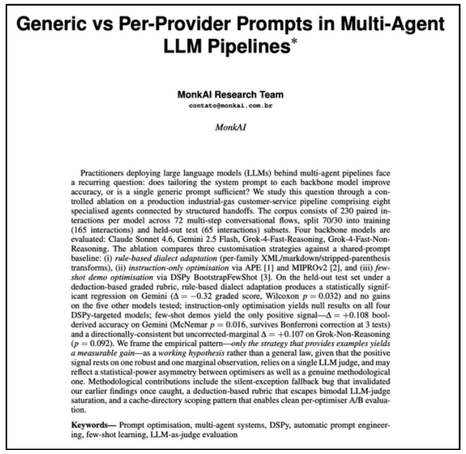
***Abstract*—Large Language Models (LLMs) are increasingly embedded in customer-facing workflows, yet most deployments still serialize entire conversational histories into prompts. This strategy inflates token consumption, induces latency, and increases the carbon footprint of AI services. We present Graph Retrieve Knowledge Memory (GRKM), a graph-aware retrieval layer that learns high-salience relationships between dialog sessions and enforces selective context delivery. While the internal scoring pipeline is proprietary, we summarize the methodology and report three findings across deployments that process up to 20 000 requests per month: (i) prompt tokens fall by 75% on average, lowering monthly spend from $1 800 to $440, (ii) response latency drops from 3.2 s to 1.1 s, and (iii) energy usage decreases by 61%, yielding measurable environmental gains. We also discuss qualitative improvements in answer accuracy obtained through selective replay of car-related conversations, showing that the graph representation faithfully retrieves prior discussions without manual curation.**

***Index Terms*—retrieval-augmented generation, conversational AI, knowledge graphs, energy-aware inference**

semantic attributes—tags, named entities, and key points—combined with cosine similarity between LLM-generated embeddings. A densification procedure assigns weights to edges according to (i) overlap of extracted attributes and (ii) embedding similarity above a configurable threshold (0.5 in our deployments). Node density corresponds to the mean weight of incident edges, highlighting sessions that act as hubs for frequently revisited topics.

A. Query Profiling

Each user message is transformed using the same summarization pipeline that structures our knowledge base. The "query profile" produces normalized tags, entities, and key points, plus an embedding computed via OpenAI `text-embedding-3-large`. By mirroring the session representation, we obtain lexical and semantic features that align with the graph's attribute space without hand-crafted dictionaries.



Generic vs Per-Provider Prompts in Multi-Agent LLM Pipelines*

MonkAI Research Team
contato@monkai.com.br

MonkAI

Practitioners deploying large language models (LLMs) behind multi-agent pipelines face a recurring question: does tailoring the system prompt to each backbone model improve accuracy, or is a single generic prompt sufficient? We study this question through a controlled ablation on a production industrial-gas customer-service pipeline comprising eight specialised agents connected by structured handoffs. The corpus consists of 230 paired interactions per model across 72 multi-step conversational flows, split 70/30 into training (165 interactions) and held-out test (65 interactions) subsets. Four backbone models are evaluated: Claude Sonnet 4.6, Gemini 2.5 Flash, Grok-4-Fast-Reasoning, Grok-4-Fast-Non-Reasoning. The ablation compares three customisation strategies against a shared-prompt baseline: (i) *rule-based dialect adaptation* (per-family XML/markdown/stripped-parenthesis transforms), (ii) *instruction-only optimisation* via APE [1] and MIPROv2 [2], and (iii) *few-shot demo optimisation* via DSPy BootstrapFewShot [3]. On the held-out test set under a deduction-based graded rubric, rule-based dialect adaptation produces a statistically significant regression on Gemini ($\Delta = -0.32$ graded score, Wilcoxon $p = 0.032$) and no gains on the five other models tested; instruction-only optimisation yields null results on all four DSPy-targeted models; few-shot demos yield the only positive signal—$\Delta = +0.108$ bool-derived accuracy on Gemini (McNemar $p = 0.016$, survives Bonferroni correction at 3 tests) and a directionally-consistent but uncorrected-marginal $\Delta = +0.107$ on Grok-Non-Reasoning ($p = 0.092$). We frame the empirical pattern—*only the strategy that provides examples yields a measurable gain*—as a *working hypothesis* rather than a general law, given that the positive signal rests on one robust and one marginal observation, relies on a single LLM judge, and may reflect a statistical-power asymmetry between optimisers as well as a genuine methodological one. Methodological contributions include the silent-exception fallback bug that invalidated our earlier findings once caught, a deduction-based rubric that escapes bimodal LLM-judge saturation, and a cache-directory scoping pattern that enables clean per-optimiser A/B evaluation.

Keywords— Prompt optimisation, multi-agent systems, DSPy, automatic prompt engineering, few-shot learning, LLM-as-judge evaluation

Nossos usuários

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ARTHUR LAMBLET VAZ