ChatGPT

Root Cause Analysis

Single Provider Hitting Rate Limits: The error indicates that OpenClaw only had one upstream LLM configured ("openai-codex/gpt-5.3-codex") and it hit a usage cap [1]. OpenClaw's Codex integration uses a ChatGPT (OpenAI) subscription via OAuth [2]. ChatGPT Plus and similar subscriptions impose rate limits (e.g. limited messages per hour), so heavy use causes 429 "rate_limit" errors. When this happens, OpenClaw marks that provider profile as in *cooldown* and won't use it until the cooldown expires [3] [4]. In your case, with only one model available, there were no alternatives to failover to, leading to the *FailoverError*. This is a known issue – OpenClaw users have reported hitting Codex (ChatGPT) limits and seeing the agent "cool down" until the window resets [1]. The **free/shared** nature of OpenClaw's Codex connector means it's bounded by OpenAI's limits (unless you add your own API key or subscription). OpenClaw's docs explicitly warn that if a provider hits a quota or rate limit, you should configure a fallback model so the agent can continue responding [5].

No Fallbacks or Caching: The architecture has *zero resilience* once the single LLM fails. OpenClaw *can* rotate between multiple auth profiles or models, but here there was only one configured. With no secondary model or local fallback, the request just times out. There's also no caching layer – every similar user query goes to the LLM fresh, increasing call volume. Without caching or a broader deterministic intent handler, even repetitive or simple requests always hit the LLM, burning through your rate limits unnecessarily.

Lack of Throttling and Backoff: At the application layer, requests weren't being throttled or queued. Your `.env` shows a flat retry mechanism (3 retries at 2s base delay) but no exponential backoff or adaptive delay. So when the LLM started returning rate-limit errors, the app likely retried immediately, which wouldn't help – the OpenClaw profile remained in cooldown for at least 1 minute by design [3]. This immediate retry could even exacerbate the issue by hammering the provider. There's no logic to defer new LLM requests until the cooldown elapses or to inform the user to wait.

WSL2 Subprocess Overhead: Every Lane 2 request spawns a new Node.js process via WSL (`wsl.exe -e bash -lc "<node> openclaw.mjs agent …"`). This cold-start adds latency (~seconds) and possibly an extra authentication handshake for the Codex OAuth each time. That overhead doesn't directly cause the *rate-limit*, but it **wastes time** and might be forcing each request into a fresh ChatGPT session rather than a warm session. It's possible the repeated session starts trigger stricter limits (e.g. OpenAI might throttle rapid new sessions). At minimum, the overhead inflates end-to-end latency and increases the chance a request hits the 30s timeout. In summary, the "reasoning lane" was all-or-nothing: one provider, no backup, no local model, no request optimization – so a single point of failure (OpenAI Codex) brought the entire lane down [1].

Ranked Solution List (Most Impactful First)

Below are **several solutions** to improve resilience, ranked from highest impact to lowest. Each solution includes a description, complexity, cost, expected reliability boost, and specific implementation tips (with libraries/tools). Together, they address all categories (A–E) you mentioned.

1. Integrate a Local LLM as a Fail-Safe (Category B – *Local Inference*)

Description: Run a capable **local** language model on your RTX GPU and use it as a fallback (or even primary for certain queries). This eliminates dependence on external APIs for basic reasoning. For example, you might run a Llama2 or Code Llama model locally. When the cloud LLM is unavailable (rate-limited or offline), the system automatically routes requests to the local model. You could configure OpenClaw to include a local model in its failover chain, or handle this in your Python app by catching OpenClaw failures and querying a local model directly.

- **Complexity:** *Medium-High.* You'll need to set up a local inference backend. E.g. install **LM Studio** or **Ollama** (which can serve LLMs locally), or use a library like `llama-cpp-python` to run a GGML model in Python. Configuration is somewhat involved: you must download a model (which can be tens of GBs), ensure it fits in GPU VRAM (quantized models like 4-bit help), and potentially adjust prompts for the smaller model. Integrating with OpenClaw means editing its config to add a local provider. Alternatively, integrating at the app level means writing Python code to load and query the model.
- **Cost:** *Free (after hardware).* Running the model on your existing GPU costs no API fees – just electricity. The models themselves are open-source (e.g. Meta's Llama 2, CodeLlama, MiniMax M2.1, etc.), so no subscription needed [6] [7]. The main "cost" is GPU memory and some disk space for model files.
- **Reliability Improvement:** *High.* A local model provides an **always-available** fallback. Even if all external services rate-limit or go down, Lane 2 can still produce responses (albeit possibly less advanced). This dramatically reduces "no reply" failures – the app can always attempt an answer. It also improves latency for fallback cases (no network calls). However, the quality of responses will depend on the model – a smaller local model might not handle complex instructions as well as GPT-4, so this is best used as a fail-safe or for simpler queries.
- **Tools/Libraries:** For serving a model to OpenClaw, **LM Studio** is a good option – it has an OpenAI-compatible HTTP server mode [8]. You could run LM Studio with a model like "MiniMax M2.1" or a Llama2 variant; OpenClaw can then treat it like an OpenAI endpoint. Another route is **Ollama** (which serves models at `localhost:11434/v1`). OpenClaw supports Ollama as a provider (you just point the baseUrl to the Ollama API) [9] [10]. If integrating in Python, libraries like `transformers` or `llama_cpp` can load a local model. For example, using `llama_cpp`:

```
from llama_cpp import Llama
llm = Llama(model_path="path/to/ggml-model.bin", n_threads=8)
result = llm("Q: " + user_query + "\nA:")  # simple prompt
answer = result["choices"][0]["text"]
```

This snippet loads a quantized model and queries it. You'd replace `user_query` with the text and adjust the prompting format as needed for your model.

- **Architecture Sketch:** *Option A:* **OpenClaw fallback integration** – Add a provider in `~/.openclaw/openclaw.json` for the local model. For example, if using Ollama:

```
"models": {
  "providers": {
```

```
    "ollama": {
      "baseUrl": "http://127.0.0.1:11434/v1",
      "apiKey": "dummy-key",
      "api": "openai-completions",
      "models": [ { "id": "Llama-2-13b-chat", "name": "Llama2 13B Chat" } ]
    }
  }
},
"agents": {
  "defaults": {
    "model": {
      "fallbacks": ["ollama/Llama-2-13b-chat"]
    }
  }
}
```

(OpenClaw requires an `apiKey` field even if not used, hence the dummy key [11].) With this, if the primary model is unavailable, OpenClaw will call the Ollama local model next [12]. *Option B:* **Application-level fallback** – Keep OpenClaw as-is for primary, but modify your Python code in `jarvis_desktop_openclaw.py` to intercept failures. For instance, if OpenClaw returns the "All models failed" error, instantiate a local model (as in the Python snippet above) and generate a response. Then display that in the UI with a note like "[Local AI reply]". This requires ensuring the local model has some instructions about the Ableton control domain (you might need to prime it with a system prompt about Ableton commands).

By implementing a local LLM, your app gains an offline brain. OpenClaw's docs note that small local models have limitations (smaller context windows, higher prompt-injection risk) [7], so use the largest model you can accommodate, and perhaps reserve it for straightforward tasks. For example, the local model could handle "simple intent → tool" mapping (like *"make track louder"* into an OSC command) while complex multi-step reasoning still goes to the cloud LLM when available.

2. Add Multiple LLM Providers & Model Fallbacks (Category A – *Provider Fallback Strategies*)

Description: Configure **multiple LLM providers** so that if one is rate-limited, OpenClaw automatically fails over to another. Instead of relying solely on OpenAI Codex, you can add providers like Anthropic Claude, OpenRouter, Google Gemini, etc., and list backup models in the fallback chain. OpenClaw will try each in order until one responds [12]. This diversifies the "reasoning lane" so it's not all-or-nothing. For example, you might set Anthropic Claude Instant as the secondary, and a free OpenRouter model as tertiary. If GPT-5.3 (OpenAI) is in cooldown, OpenClaw will seamlessly try Claude; if Claude hits its limit, it might try an open-source model via OpenRouter, etc.

- **Complexity:** *Medium.* On the simpler end, you can add providers via the OpenClaw config JSON or CLI without writing new code. For instance, to add Anthropic, you'd supply an API key or Claude "setup token" (if you have a Claude Pro account) and update `agents.defaults.model.fallbacks`. To use **OpenRouter**, you'd get an OpenRouter API key (they act as a gateway to many models) and configure OpenClaw's OpenRouter provider. Each

additional provider has its auth method (API key, OAuth login, etc.), so setup involves following docs for each. Overall, it's configuration work and testing – no heavy coding, but not "plug-and-play" either. OpenClaw's wizard or CLI can aid in adding auth profiles (e.g. `openclaw models auth add …`). Expect some trial and error to ensure each provider is properly authenticated and reachable.

- **Cost:** *Varies – potentially cheap.* If you choose **free/cheap providers** for backups, you can keep costs low. For example, **OpenRouter** offers some free tier models (you can append `:free` to certain model IDs to use community-provided models at no cost [13]). You could also use **Qwen** (Tencent's model) via their free OAuth plugin – Qwen offers a daily free quota [14]. These options cost $0 but may have usage limits. If you add a provider like Anthropic or Google, you'll incur their token fees or need a subscription (Claude Pro, etc.). However, you can prioritize free/cheap models in the fallback chain for cost control. For instance, set primary to your high-quality model and a free model as last-resort fallback to avoid paying if everything else fails.
- **Reliability Improvement:** *High.* A broader provider pool means **no single point of failure**. Each model has its own rate limits, so hitting one limit doesn't incapacitate the system. OpenClaw's failover logic will rotate through auth profiles and then move to the next model chain automatically [15] [3]. For example, if OpenAI returns a 429, that profile goes into a short cooldown and OpenClaw immediately tries the next model on the list [3] [12]. This greatly reduces the chance of getting "All models failed" – you'd have to exhaust **all** configured providers' limits to hit a dead-end. It also improves uptime during provider-specific outages (if OpenAI or Anthropic has an outage, your agent can fall back to another).
- **Tools/Libraries:** Primarily this involves **OpenClaw's configuration**. Key settings are in `~/.openclaw/openclaw.json` (or `agents/<agent>/agent.json`). You'll use fields:
- `models.providers` – to define each provider (API endpoints, keys, model IDs).
- `agents.defaults.model.primary` and `agents.defaults.model.fallbacks` – to set the main model and an ordered list of fallback models. For example:

```
"agents": {
  "defaults": {
    "model": {
      "primary": "openai-codex/gpt-5.3-codex",
      "fallbacks": [
        "anthropic/claude-instant-1",
        "openrouter/meta-llama/llama-3.2-3b-instruct:free"
      ]
    }
  }
}
```

This chain would try OpenAI Codex first, then Claude Instant, then an OpenRouter-hosted Llama 3B model (free) [13]. You'd need to ensure credentials for each: e.g. set `ANTHROPIC_API_KEY` in `~/.openclaw/.env` or use `openclaw models auth paste-token --provider anthropic` for Claude [16], and set `OPENROUTER_API_KEY` for OpenRouter (if required by that model – free ones still typically require an account/key).

OpenClaw's documentation and community guides (like LumaDock's tutorial on *free AI models for OpenClaw* [17]) provide examples of adding providers. Another useful tool is **LiteLLM** or **OpenRouter** *as a proxy* – see

Solution 3. But without going to a separate proxy service, you can already list multiple models directly in OpenClaw as above. - **Pseudocode/Workflow:** No significant code changes in your Python app; most work is in config. Pseudocode for how the request flows after setup:

```
user_message -> OpenClaw (main agent) -> try model1 (OpenAI Codex)
                                  if rate_limit -> cooldown model1, try model2
(Claude)
                                  if fails -> try model3 (OpenRouter free model)
                                  if succeeds -> return answer
                                  if all fail -> OpenClaw returns error
```

OpenClaw internally handles the rotation and cooldown timers [3] [18]. You can verify the chain by running `openclaw models status --json` to see available models and profiles, and ensure none are marked unusable.

This approach addresses the **provider fallback** aspect head-on. In practice, even adding one fallback (say, Claude Instant) will hugely improve reliability – e.g., one user noted that with Claude as backup, their agent could keep responding while GPT was in cooldown [5]. Just be mindful of each provider's terms (some "free" tiers reset daily or have their own limits). By mixing and matching, you can achieve essentially uninterrupted service: when one provider says "please wait," another takes over the load.

3. Use an LLM Gateway/Proxy for Smart Routing (Category A/E – *Provider Fallback via Proxy*)

Description: Deploy an **AI gateway proxy** like **LiteLLM** (open-source) or use a hosted aggregator like **OpenRouter** to manage multiple model backends for you. This is a more advanced twist on solution 2: instead of OpenClaw explicitly juggling 3-4 providers, you point OpenClaw at *one* proxy server (local or cloud) which in turn routes requests to different models based on rules you define. The proxy can implement load-balancing, dynamic failover, and even cost-based routing (e.g., use a cheaper model for short/simple queries and a powerful model for complex ones). Essentially, OpenClaw will think it's hitting a single "OpenAI-compatible" API, but that API is your LiteLLM service which then fans out to multiple providers or local models.

- **Complexity:** *Medium.* Setting up **LiteLLM Proxy** locally requires installing the Python package (`pip install "litellm[proxy]"`) and running the proxy server, or using a Docker container. You'll need to configure it with your provider API keys or endpoints. For example, LiteLLM allows defining multiple upstream keys for OpenAI, Anthropic, etc., and can auto-rotate or failover between them [19]. You also can define routing rules (like "if prompt contains code, use Code model"). The complexity is in initial configuration – once set, OpenClaw sees it as a standard OpenAI API. If using the hosted **OpenRouter** service, complexity is lower (just get an API key from openrouter.ai and choose models), but you rely on their uptime. In both cases, you must ensure the proxy is running continuously (if self-hosted).
- **Cost:** *Free (for the proxy).* LiteLLM is open-source and free to run [20]. The cost comes from whichever upstream models you use (it doesn't magically make GPT-4 free – you either bring your API keys or use free models). However, a proxy lets you **enforce policies** to control cost. For instance, you can configure it to route all requests under 100 tokens to a *free* model, or to use a 3rd-party model that's

cheaper than OpenAI if response quality would be similar. OpenRouter's hosted proxy is free to use, but certain premium models require you to attach your own keys or purchase credits. The benefit is you can start with their free-tier models and only pay for upscale models when needed.

- **Reliability Improvement:** *High.* A well-configured proxy can **dynamically manage rate limits** and provider failures without your app even noticing. LiteLLM, for example, supports load-balancing and will cycle through multiple keys or providers behind the scenes [21]. If one provider goes down or hits a limit, the proxy can automatically retry on another. You can also set up *circuit breakers* – e.g., if GPT-4 fails twice, don't call it again for X minutes – at the proxy level. This means fewer error conditions bubble up to OpenClaw or your app. Essentially, you outsource the multi-provider juggling to a dedicated layer that's designed for it [22] [23]. Reliability goes up not only via failover, but also because you can **rate-limit centrally** (LiteLLM can apply a token bucket, etc., so you don't overload any single API). The proxy becomes the single integration point, which simplifies your OpenClaw config (just one provider entry).
- **Tools/Libraries: LiteLLM** is a prime choice for self-hosting. It exposes an OpenAI-compatible HTTP endpoint (by default at `http://localhost:4000/v1`) [21] [24]. You'd configure OpenClaw like:

```
"models": {
  "providers": {
    "openai": {
      "baseUrl": "http://127.0.0.1:4000/v1",
      "apiKey": "${LITELLM_API_KEY}",
      "api": "openai-completions"
    }
  }
},
"agents.defaults.model.primary": "openai/gpt-3.5-turbo"  // example model
name
```

Here, OpenClaw thinks it's calling OpenAI's API, but `baseUrl` is redirected to your LiteLLM proxy. (LiteLLM can accept any string as an API "key" for simple auth – you might set `LITELLM_API_KEY` to a secret for the proxy, or if you disable auth on the proxy, just put a dummy string.) Inside LiteLLM, you'll configure upstream providers. For instance, in a `litellm.yaml` you might list multiple OpenAI keys (to rotate to avoid per-key rate limits) and an Anthropic key as a fallback, etc. LiteLLM's docs show how to enable **routing and fallback rules** easily [25]. Another tool is **Lynkr** (an open-source "security proxy" that can filter requests) – it can sit in front of LiteLLM for content sanitization if needed [26], though that's optional for your use-case.

If you don't want to self-host, **OpenRouter** is the cloud alternative. You'd put `openrouter` as the provider in OpenClaw. For example:

```
"agents.defaults.model.primary": "openrouter/gpt-4",
"models": {
  "providers": {
    "openrouter": {
      "apiKey": "${OPENROUTER_API_KEY}",
      "api": "openai-chat",
```

```
      "baseUrl": "https://openrouter.ai/api/v1"
    }
  }
}
```

OpenRouter will then handle whether to use GPT-4 or fallback to other models based on their routing (you can specify a chain in the OpenRouter request or use their model aliases). OpenRouter also offers community models like `meta-llama/llama-2-7b:free`, etc., which cost nothing to use [13]. - **Architecture Sketch:** With a proxy in place, the flow is:

```
App -> OpenClaw (calls provider "X") -> Proxy (LiteLLM/OpenRouter) -> chosen LLM
                   ↳ if fail, proxy retries with next model/key
                   ↳ if success, returns to OpenClaw -> App
```

For example, you send a request to `proxy` (via OpenClaw). LiteLLM sees it's a chat completion; you've configured it to try GPT-4 first, but if it hits a rate limit error or >5s delay, then fall back to GPT-3.5 or Claude, etc. The proxy responds with the result from whichever model succeeded. OpenClaw and your app just see a successful response. This **decouples** the failover logic from your app. It also means you can tweak the routing policy externally (e.g., update the proxy config to use a new model) without changing the app or OpenClaw config at all [27] [28].

In summary, a proxy gateway is like introducing a smart traffic manager for LLM requests. It's more to maintain (another service running in background), but since you're open to background processes, this could significantly improve both reliability and control. You could start with OpenRouter for simplicity (no server to run), and later move to a self-hosted LiteLLM when you want maximum control over routing and keys. This solution, combined with solution 2, means OpenClaw could have *one primary provider (the proxy)* and that proxy in turn fans out to many models – a very robust setup [23] [19].

4. Implement Request Caching and Optimization (Category C – *Caching & Context Optimization*)

Description: Introduce a caching layer and optimize prompts to reduce unnecessary LLM calls. **Semantic caching** means if the user asks something substantially similar to a past query, the system reuses the previous LLM result instead of calling the LLM again. This can be done by storing embeddings of user queries and doing a similarity lookup. Additionally, you can pre-process user input to catch more cases with the deterministic lane or compress what you send to the LLM (reducing token load and chance of hitting rate limits).

- **Complexity:** *Medium.* Caching requires designing a storage for past queries and answers, plus a method to compare new queries to old ones. You can leverage existing libraries: e.g. use **LangChain's** caching utilities or implement a custom cache with a vector database (FAISS, Annoy, etc.). The basic steps: whenever the LLM returns a result, compute an embedding for the user's request (a vector representation of its meaning) and save it with the result. On a new request, compute its embedding and find the nearest stored vector; if it's above a similarity threshold (meaning *"we've seen something like this before"*), then skip calling the LLM and reuse the cached answer (maybe with a note that it's a past result). You'll need an embedding model – OpenAI offers

embedding APIs, or you can use a local one (SentenceTransformers has models like `all-MiniLM-L6-v2` which runs quickly on CPU). Implementation means integrating this into your pipeline in Python, which is additional code but straightforward logic. Prompt/context optimization might involve trimming irrelevant context from what you send into OpenClaw's LLM prompt or splitting complex multi-part questions so that simple parts can be answered deterministically.

- **Cost:** *Free/cheap.* Storing embeddings and texts is essentially free (just disk/memory). If you use OpenAI's embedding API, there's a small cost per input token, but you could use a local embedding model to avoid costs entirely. The infrastructure for caching (like a lightweight database or even a JSON file for small scale) is free. So this is mostly a development time cost, not runtime expense. By **saving API calls**, caching directly **saves money and quota** – as noted in LangChain's docs, it reduces the number of repeated calls, saving you tokens and speeding up responses [29] [30].
- **Reliability Improvement:** *Moderate to High.* Caching doesn't make the LLM *more capable*, but it **avoids redundant queries**, which in turn means you're *less likely to hit rate limits*. If, for example, you often give similar commands like *"make the vocals warmer"* across sessions, after the first successful LLM resolution, subsequent ones can be handled instantly from cache. This reduces load on the external LLM and keeps responses fast. It's a **preventative** measure: by cutting total LLM calls (especially back-to-back calls), you reduce the chance of triggering provider cooldowns. Also, if the LLM service is down, you might still answer some queries from cache, improving perceived reliability. The caveat is that cached answers might be stale or not perfectly context-specific if the project state changed – you'd need to invalidate or tag cache entries accordingly (e.g., include Ableton project state info in the cache key if relevant).
- **Tools/Libraries:** For **semantic search**, you can use **FAISS** (Facebook AI Similarity Search) or **Annoy** (Approximate Nearest Neighbors) to store and query embeddings efficiently. Alternatively, a simple approach: use `numpy` to compute cosine similarity between vectors stored in-memory if the cache size is small. To get embeddings: libraries like **SentenceTransformers** (`pip install sentence-transformers`) offer easy-to-use models. Example code:

```
from sentence_transformers import SentenceTransformer
import numpy as np

model = SentenceTransformer('sentence-transformers/all-MiniLM-L6-v2')
# Build cache as a list of (embedding, user_query, llm_result)
cache = []

def cache_lookup(new_query, threshold=0.8):
    vec = model.encode(new_query)
    best_score = 0; best_answer = None
    for emb, old_q, result in cache:
        score = np.dot(vec, emb) /
(np.linalg.norm(vec)*np.linalg.norm(emb))
        if score > best_score:
            best_score = score; best_answer = result
    if best_score >= threshold:
        return best_answer
    return None
```

```
def cache_store(query, answer):
    cache.append((model.encode(query), query, answer))
```

In this pseudocode, `cache_lookup` finds the most similar past query. If it's above some threshold, we reuse the answer. `cache_store` saves new Q&A. In practice, you'd want to persist this cache (e.g., to disk using SQLite or a simple JSON) so it survives app restarts. LangChain provides a `SQLiteCache` you can use out of the box for exact prompt matching, and you could extend it for semantic matches [31].

For **expanding deterministic Lane 1**, consider adding an **intent classifier**. A quick solution: use a small **Naive Bayes or keyword-based classifier** to catch more commands. For example, if the regex parser fails, you could have a list of known verbs/effects and do a fuzzy match. Even using an LLM in classification mode (with a prompt like "Classify this user request into categories: {list} or 'other'") could decide if a query is a straightforward Ableton command, and then route it accordingly without full reasoning. Because such a classifier prompt is much shorter than a full agent prompt, you could use a cheaper or local model for it. The key is to intercept queries before they hit OpenClaw: if the query is something like "load a piano preset on track 5", you *know* the structure – you can directly call Lane 1 code to do that, even if the wording didn't exactly match your regex. This may involve writing a bit more parsing logic or using ML to map synonyms ("load" ~= "add", "preset" ~= "instrument rack", etc.). Over time, as you see common phrases that trigger Lane 2 needlessly, you can add them to Lane 1 handling.

- **Architecture Changes:** You'd integrate caching in the Python app around the OpenClaw call. For example:

```
user_input = get_input()
cached = cache_lookup(user_input)
if cached:
    display_answer(cached + " (cached)")
else:
    # If not a deterministic command:
    if not parse_local_tool_intent(user_input):
        answer = call_openclaw(user_input)
    else:
        answer = execute_deterministic(user_input)
    display_answer(answer)
    if source_of_answer_was_llm(answer):
        cache_store(user_input, answer)
```

This ensures that repeated or semantically similar requests short-circuit the LLM. You might also incorporate **prompt compression**: if Ableton's state (track names, device list) is included in every query context, see if you can limit it (perhaps only send the specific track/effect in question to the LLM, rather than full session info). Shorter prompts = fewer tokens used = less chance of hitting token rate limits. OpenClaw does some context management (it won't always stuff entire history thanks to its memory search), but any optimizations on what *you* prepend (like tool descriptions or additional instructions) can help.

In summary, caching and optimization won't entirely eliminate hitting provider limits, but they *delay* and *reduce* it. Think of it as **pressure relief** on the LLM: your app becomes smarter about when it truly needs the "big brain." Over time, as your cache grows and deterministic coverage expands, the reasoning lane is invoked less frequently, making rate-limit errors a rarity.

5. Rate Limit Management & Queueing in the App (Category D – *Graceful Degradation on Rate Limits*)

Description: Add logic to handle rate limiting at the application level. Rather than hammering the LLM (and getting 429 errors), the app can **throttle requests** (ensure a safe interval between calls), implement an **exponential backoff** for retries, and maintain a **queue** if multiple queries come in too quickly. Also utilize a **circuit breaker** pattern: if the LLM fails due to rate limit, don't immediately retry the same action over and over – instead, trip a breaker that pauses LLM calls for a short period or until a manual reset, and give the user a friendly message.

- **Complexity:** *Low to Medium.* This mostly involves coding some wrappers around your LLM call function (`call_openclaw`). For example, you can use Python's `time` module or `asyncio` to delay calls. A simple token-bucket algorithm can be implemented with a counter that resets every minute. Or even easier, keep a timestamp of the last call and if a new call comes too soon, `sleep()` for a bit. The retry logic you have can be improved to exponential backoff with jitter – e.g., after first failure, wait 2s, after second, wait 4s ± some random, etc., up to maybe 30s. Python's `retry` library or writing a loop with `time.sleep` can accomplish this. Implementing a request **queue** might involve spinning a background thread or using an asyncio event loop: incoming requests get put into a queue, and a worker pulls from it at a controlled rate. This ensures if a user (or some automated process) triggers many requests, they'll be processed one at a time, and you can even assign priority (e.g., if a "critical" command comes, handle it before a less important one).
- **Cost:** *Free.* This doesn't require any external service – it's just code. It might slightly impact user experience (introducing waits), but those waits are better than hitting an error. No ongoing cost.
- **Reliability Improvement:** *Moderate.* This solution doesn't give your system new abilities, but it **prevents self-inflicted issues**. By pacing the calls, you avoid tripping the provider's rate limits in the first place. For instance, if OpenAI's limit allows, say, 3 requests per second and your app normally wouldn't hit that – fine. But if a user does something that triggers 5 quick consecutive LLM queries (maybe an automated macro or a bug causing a loop), a rate limiter in your app will catch that and serialize or slow them. This can stop you from ever seeing the cooldown state. The **exponential backoff** on retries means that if you *do* hit a limit, the second attempt comes after a grace period, giving the provider time to reset a quota window. That increases the chance the retry succeeds rather than immediately failing again. A **circuit breaker** improves reliability by not wasting time on hopeless retries – e.g., if you know the LLM will be in cooldown for 60 seconds, you can fail fast and inform the user "LLM is busy, retrying in a minute…" instead of them staring at a spinner. Overall, these measures **turn hard failures into graceful delays**.
- **Tools/Libraries:** This can be done with basic Python. However, there are utilities like **tenacity** or **backoff** libraries that provide decorator-based retry with backoff. For example, using `tenacity`:

```
from tenacity import retry, stop_after_attempt, wait_exponential,
retry_if_exception_type
```

```
class RateLimitError(Exception): pass

@retry(reraise=True, stop=stop_after_attempt(5),
wait=wait_exponential(min=2, max=30),
retry=retry_if_exception_type(RateLimitError))
def call_openclaw_with_backoff(prompt):
    result = call_openclaw(prompt)
    # If OpenClaw returned a rate-limit or timeout error:
    if "rate_limit" in result.error_message:
        raise RateLimitError()
    return result
```

This will automatically retry with exponential delays (2s, 4s, 8s, etc.) up to 5 attempts. You could also add jitter by using `wait_exponential(min=2, max=30, exp_base=2, jitter=1)`. If all attempts fail, you catch the exception and handle it (e.g., inform user).
For a **queue**, Python's `queue.Queue` in a separate thread is straightforward:

```
import queue, threading, time
q = queue.Queue()
def worker():
    while True:
        prompt = q.get()  # blocks until item available
        try:
            result = call_openclaw_with_backoff(prompt)
            display_result(result)
        except Exception as e:
            display_error(e)
        finally:
            q.task_done()
        time.sleep(0.5)  # ensure at least 0.5s between calls
threading.Thread(target=worker, daemon=True).start()
# ... later, to use the queue:
def submit_request(prompt):
    q.put(prompt)
```

This spawns a thread that processes one LLM request at a time with a 0.5s gap between them. You might tune that gap based on the provider's rate (or make it dynamically adjust if you get a rate error). The `submit_request` would be called instead of directly invoking `call_openclaw`. In a Tkinter app, you'd tie the UI input to `submit_request`, and perhaps disable the Send button if the queue is too full or the breaker is open.

- **Integration points:** You can enhance your existing retry loop by increasing the base delay and multiplying it after each failure, rather than a fixed 2s. Also consider **tracking the error message**: OpenClaw's error said "provider is in cooldown (rate_limit)". You could parse that and immediately decide to pause further attempts. For example, if you catch a cooldown message, you could start a timer in the app that blocks any new LLM calls for, say, 60 seconds (and inform the user "AI is cooling

down, please wait…"). This is the circuit breaker effect – it prevents flooding the provider while it's in a deny state. After the time passes, you reset the breaker and allow calls again. This could be as simple as a global flag `llm_available=True/False` that you set False when cooldown is hit, and use `threading.Timer(60, reset_flag)` to flip it back after a minute.

Proper rate limit management in the app ensures that even under heavy usage, you **stay within safe call rates**. It complements OpenClaw's own cooldown mechanism: rather than blindly letting OpenClaw trigger exponential backoff on its side, your app will proactively avoid getting to that point. It also improves user experience by making any wait states explicit and bounded (e.g., a progress bar or countdown when the system is busy). By adopting these patterns, you transform a potential *infinite hang* or repeated error into a controlled delay with feedback, which is a big reliability and usability win.

6. Run OpenClaw as a Persistent Service (Architectural Tweaks) (Category E – *Architectural Improvements*)

Description: Modify the way you invoke OpenClaw so that it isn't a cold new process for each request. Instead, run OpenClaw's **Gateway** in the background (a persistent Node.js service) and send requests to it via a lightweight method (could be an HTTP call, WebSocket, or a local CLI call that connects to the running service). This removes the WSL startup overhead per query and can maintain a warm session in memory.

- **Complexity:** *Medium.* On Windows 11 with WSL2, you can set up OpenClaw to run as a **systemd user service** (the onboarding wizard can install it as a daemon in WSL [32]). That means OpenClaw is always running in the background. The challenge is how your Python app communicates with it. OpenClaw's Gateway listens on `localhost:18789` by default for its control UI and agent connections [33]. This is a WebSocket/HTTP endpoint. One approach: use **OpenClaw's CLI** in client mode – e.g., `openclaw chat "<message>"` might send a message to the running agent instead of spawning a new one (OpenClaw CLI is aware if the gateway is running and will route commands to it, though documentation is sparse on specific CLI commands for that). If a direct CLI doesn't exist for sending a message, you could interface at the WebSocket level (this is more advanced: essentially mimic what the web dashboard does – send the message JSON over a socket and wait for response). Alternatively, OpenClaw might have a RESTful hook you can POST to (some community discussions hint at hooking OpenClaw via HTTP, but not officially documented). If that's complex, a simpler tactic: **keep one subprocess open**. You could spawn `openclaw.mjs agent --json --message` *once* and keep its STDIN/STDOUT piped, sending multiple messages in a single session (not sure if the CLI supports interactive mode, but if it did, that'd be ideal).
- **Cost:** *Free.* This is purely an architectural change. If anything, it saves you cost by possibly preserving session context (so the LLM might not need as much prompt info every time) and by being able to stream responses (so you could potentially cancel early if not needed). No new services or fees.
- **Reliability Improvement:** *Moderate.* While this doesn't directly address rate limits, it improves overall **performance and stability**. A persistent gateway means no Node.js startup lag, which reduces the chance of hitting your 30s timeout for legitimate responses. It also avoids repeated OAuth handshakes to OpenAI (which might have been happening on each new process). Keeping a single session open could allow the agent to reuse conversation context rather than starting fresh each time (depending on how you handle sessions). That could indirectly reduce token usage per request (since OpenClaw can reference prior steps from memory instead of re-reasoning from scratch), which in turn might lower API usage. Additionally, fewer moving parts (not spawning a new OS process every time) means fewer things to go wrong on the system side. It essentially aligns with

how OpenClaw is intended to run (as a long-running service) [34] [35]. If the gateway is persistent, you can also leverage features like streaming responses easily.

- **Tools/Implementation:** You can enable the **OpenClaw Gateway** in WSL. For example, run `openclaw gateway start` or set up the systemd service (the wizard can do `openclaw onboard` -> "daemon install"). Once it's running, test sending a message via the OpenClaw CLI:

```
$ openclaw say --agent main "Hello, OpenClaw"
```

(The exact command might be `openclaw agent main --message "..."`; consult `openclaw --help` for any send/chat command). If such a command connects to the running instance, it should return a response quickly. In Python, you'd then call this CLI without the heavy startup. For instance:

```
import subprocess, json
def query_openclaw(msg):
    result = subprocess.run(
        ["wsl", "-e", "openclaw", "agent", "main", "--json", "--message",
msg],
        capture_output=True, text=True, timeout=10
    )
    data = json.loads(result.stdout)
    return data["content"]  # or however the JSON is structured
```

In this snippet, `openclaw agent main` is assumed to send the message to the main agent on the running gateway (and `--json` yields machine-readable output). Since the gateway is already running, this subprocess call is lightweight – it's just sending an RPC to the service and getting the JSON. You can further optimize by using Python's `requests` or `websockets` library to hit the endpoint directly. For example, if you open `http://localhost:18789` in a browser, you get the Control UI; digging into that, the network calls may show a WebSocket handshake. You could connect a WebSocket client in Python to `ws://localhost:18789/agents/main` (for instance) and send a message payload. This is advanced, but possible if you want real streaming. Given your timeframe, using the CLI in client mode is probably fine.

- **Architecture changes:** Instead of starting a new Node for each message, you start one at app launch (or rely on the system service). This might involve moving initialization earlier (so that by the time the user sends a query, the gateway is up and ready). You might do this in a background thread on app start: e.g., call `subprocess.Popen(["wsl", "-e", "openclaw", "gateway", "start"])` and wait a few seconds for it to come online. Once running, subsequent calls use the lightweight method. You should also handle gateway downtime: if your app tries to send a message and the gateway isn't responding (maybe it crashed), you might catch that and attempt to restart it (or alert the user). But overall, this yields a more **responsive and robust** Lane 2 pipeline.

In essence, this solution is about **eliminating unnecessary overhead and maintaining state**. It pairs well with all the above improvements: you can still use multi-provider fallbacks, local models, etc., but now everything runs through one always-on OpenClaw instance. You'll spend less time launching processes and more time actually getting answers. While the direct impact on the rate-limit issue is indirect, it contributes to a smoother system where timeouts are less likely and throughput is steadier.

Recommended Implementation Order

To maximize impact quickly, you can tackle these solutions in phases:

Phase 1: Quick Wins (< 1 day)
Start by addressing the *low-hanging fruit* that require minimal development but yield immediate resilience gains:

- **Add a fallback model in OpenClaw (Solution 2):** Even if it's just one, do this first. For example, configure **Anthropic Claude Instant** or an **OpenRouter free model** as your fallback. This might be as simple as adding a few lines to OpenClaw's config and setting an environment variable for an API key. Testing this in isolation (via `openclaw chat` CLI) will confirm it works. This change alone means the next time Codex hits a limit, your app should get a response from the other model instead of failing [12]. It's a high impact for relatively low effort.
- **Improve retry/backoff logic (Solution 5 partial):** You can tweak your Python retry loop in **minutes**. For example, change it to exponential backoff: if attempt 1 fails, wait 2s; attempt 2 fails, wait 4s, etc. Also add a check for the `"rate_limit"` error message – if seen, do not spam immediate retries. As an interim quick fix, you might simply catch the known error and sleep for 60 seconds before retrying. This ensures that if a cooldown occurs, your app will wait and possibly succeed on the next try rather than giving up after 45s. It's a few lines of code change.
- **Pre-warm OpenClaw (Solution 6 partial):** Instead of waiting for the first user query to spawn OpenClaw, launch it at application startup. For now, even if you keep using the same subprocess method, doing it early means by the time the user asks something, the Node process might have already loaded models or done auth. This can be as simple as triggering a dummy query ("Hello") on startup and discarding the result, or actually running `openclaw gateway start` in the background as you launch the app. It's not a full persistent integration yet, but it sets the stage and can shave off initial latency.

These quick wins can likely be done in one day or less, and they directly tackle the immediate pain (the rate-limit failures). After Phase 1, your system should already be more robust: a backup model to catch failures, and smarter wait/retry behavior to avoid immediate timeouts.

Phase 2: Medium Improvements (1–3 days)
Next, focus on changes that need moderate effort but substantially boost reliability and performance:

- **Integrate a Local LLM (Solution 1):** Depending on the model size, downloading and setting up could be a few hours. You mentioned having an RTX-class GPU; a 7B or 13B parameter model with 4-bit quantization could be a good target (needs ~8–16 GB VRAM). Try using LM Studio or Ollama to simplify running the model. In this phase, you might first get the local model running **outside** the app (e.g. test prompts in LM Studio's UI or via Ollama's CLI). Then configure OpenClaw to use it as a fallback provider [9]. This integration and testing might take a day or two to refine (ensuring the

responses are useful for your use-case). Alternatively, implement it as an app-level fallback if that's easier to prototype (e.g., use `llama_cpp` in Python when OpenClaw fails). The local LLM gives you an offline safety net – aim to have it operational in Phase 2.

- **Persistent OpenClaw Service (Solution 6):** Set up the OpenClaw gateway as a background service in WSL2. This might involve enabling systemd in WSL (if not already) and configuring the openclaw service. The OpenClaw docs for Linux/WSL cover running it as a systemd user unit [32]. Once it's running, modify your Python calls to connect to it (test out the `openclaw agent --message` approach). This will likely take some experimentation to get right. Allot time to ensure that the Python app can indeed send/receive from the persistent service. The benefit will be immediate in terms of latency and avoiding Node restarts.
- **App-layer Queue/Priority (Solution 5 extended):** If your use-case involves parallel or rapid-fire requests (or you plan to allow multiple queries queued up), implement the request queue at this stage. Use the threading or asyncio approach to ensure only one LLM call happens at a time (or whatever rate you decide). Also implement a simple priority mechanism if needed: e.g., user-triggered actions vs. internal background questions could be prioritized. Given that Ableton control commands are usually user-driven one at a time, this might be optional – but it's good to have the scaffolding in case of future expansion.

By the end of Phase 2, you'll have a **multi-layered defense**: multiple providers (Phase 1) + a local model, all accessible through a continuously running gateway, managed by a smarter application layer. This dramatically reduces downtime. Even if one piece is slow or failing, another picks up the slack automatically.

Phase 3: Full Resilience (1–2 weeks)
In this phase, you polish and extend the robust features, tackling more complex optimizations:

- **Semantic Caching System (Solution 4):** Implement the full caching mechanism with a vector store. This involves choosing an embedding model (try a small one locally first for speed). Set up the infrastructure to save and load the cache (maybe use SQLite for persistence). Then integrate it into the app's workflow as described. You'll need to tune the similarity threshold so that only genuinely similar queries hit cache. Over a week, you can gather real usage data to refine this – e.g., see if it's effectively catching repeats. Also, create a mechanism to invalidate cache entries that are no longer valid (if the Ableton project changes significantly, some cached actions might not apply – you could key the cache on the Ableton project name or a session ID so you don't reuse actions across different project contexts erroneously).
- **Expand Deterministic Intent Coverage (Solution 4 adjunct):** Analyze what kinds of natural language requests have been going to the LLM and identify patterns that could be handled with rule-based logic. For instance, if users often say "turn **up** the volume on track X", maybe your regex was only catching the word "increase" before – you can add synonyms. If they ask for "something" that implies a known macro (like "make the drums punchier"), you could directly map that to a specific chain of effects if you know one. You might implement a small classifier as discussed (could even use a simple machine-learning model trained on a few examples of each intent). This effort can be spread out – you don't need a full ML pipeline; even incremental improvements help (every request diverted from LLM is a win).
- **LLM Proxy & Advanced Routing (Solution 3):** If you choose to adopt a proxy like LiteLLM, this would be the time to do it. This is somewhat optional if Solution 2 (multiple direct providers) is working well for you. But for ultimate flexibility, setting up LiteLLM and moving all provider logic there could be a project in itself (~1 week to thoroughly test in your environment). You'd configure it to use your API keys and maybe add rules (e.g., if the user's message is very long, automatically

route to a model with a larger context window). Since you expressed comfort with background processes, you can run LiteLLM in the background (maybe as a Docker container or a service on Windows). After confirming it routes correctly (you can simulate requests with curl or their Python SDK), re-point OpenClaw to it as the single provider. This essentially centralizes the multi-provider fallback in one place and might simplify OpenClaw config (no need for many entries there).

- **Monitoring & Circuit-Breaking:** In a fully resilient setup, you might add monitoring to track usage and auto-adjust. For example, your app could log each LLM call and response time. If it notices consecutive failures or slowdowns, it could proactively switch the active model (maybe even instruct OpenClaw to use a different default via a command or an agent message like `/model switch`). While not trivial, OpenClaw *does* allow runtime switching of models per session (via slash commands or API) [36]. You could script the agent to do this automatically if one provider is flaking out (kind of an auto-circuit breaker at the session level). This is an advanced improvement that could be explored in this phase if needed.

Phase 3 is about **fine-tuning and future-proofing**. At this point, outright failures should be rare. The focus shifts to efficiency (caching speeding things up, minimizing external calls to save cost) and maintainability (having a proxy where you can swap models easily, having monitoring to catch any new failure modes early).

By following this phased roadmap, you start with changes that give immediate relief (so you can reliably use your app day-to-day), then layer on more robust solutions that require more effort. This ensures you're never stuck in a long development cycle without improvements in the interim. Each phase builds on the previous, and you can stop at any point if reliability is "good enough" for your needs.

OpenClaw Configuration Guidance

To specifically help with configuring OpenClaw for resilience:

- **Adding Multiple Providers/Models:** OpenClaw uses a JSON (or JSON5) config located at `~/.openclaw/openclaw.json` (global defaults) and per-agent overrides in `~/.openclaw/agents/<agentId>/agent.json`. To add providers, edit the `models.providers` section. For each provider, you give it a name and the necessary info for API access. For example, to add OpenRouter as a provider (with an OpenAI-compatible API):

```
"models": {
  "providers": {
    "openrouter": {
      "baseUrl": "https://openrouter.ai/api/v1",
      "apiKey": "${OPENROUTER_API_KEY}",
      "api": "openai-chat",
      "models": [
        { "id": "meta-llama/llama-2-7b-chat:free", "name": "Llama2 7B Chat
(Free)" },
        { "id": "openai/gpt-4", "name": "GPT-4" }
      ]
    }
```

```
  }
}
```

This defines a provider "openrouter" with two model options. The environment variable `OPENROUTER_API_KEY` should be set in your `~/.openclaw/.env` file (or Windows env) to your OpenRouter key. Similarly, to add Anthropic:

```
"providers": {
    "anthropic": {
       "apiKey": "${ANTHROPIC_API_KEY}",
       "api": "anthropic",
       "models": [
         { "id": "claude-instant-1", "name": "Claude Instant 1" },
         { "id": "claude-2", "name": "Claude v2" }
       ]
    }
}
```

And ensure `ANTHROPIC_API_KEY` is in the env or use the OAuth "setup token" method if no API key (OpenClaw's wizard can handle that via `openclaw models auth login --provider anthropic`, which stores a token profile) [37]. After editing, you can run `openclaw models list` to see all models and `openclaw models status` to verify auth. OpenClaw will list profiles like `anthropic:default` if your key/token is loaded.

- **Configuring Failover Chains:** The failover order is set by `agents.defaults.model.fallbacks`. This is an **ordered list** of model identifiers (including provider prefix). The "primary" model is set by `agents.defaults.model.primary` (or by the default chosen during onboarding). To add fallbacks, list them in the order you want. As an example:

```
"agents": {
  "defaults": {
    "model": {
      "primary": "openai-codex/gpt-5.3-codex",
      "fallbacks": [
         "anthropic/claude-instant-1",
         "openrouter/meta-llama/llama-2-7b-chat:free",
         "ollama/Llama-2-13b-chat"
      ]
    }
  }
}
```

This tries Codex first, then Claude, then an OpenRouter Llama2, then a local Ollama model. You can include local models in the chain as shown (just ensure the provider and model id are defined under

`models.providers`). OpenClaw's failover works as documented: it will attempt all auth profiles of the primary provider first (rotation within provider), and if none succeed, it moves to the next model in the list [15]. **Important:** If you add something like Google Gemini to the list but don't actually provide credentials, the failover will still try it and then error. So only list fallbacks you've configured. If you inadvertently do so, remove or disable that model in config to avoid spurious "No API key for provider X" errors [38] [39].

- **OpenClaw HTTP/WebSocket Mode:** Yes, OpenClaw Gateway exposes a local HTTP/WebSocket interface. By default it's on port 18789 (and only bound to localhost unless you configured otherwise). The Control UI uses this interface. While not officially documented as a public API, it's possible to interact with it. Typically, the web UI opens a WebSocket to `ws://localhost:18789/agent/<agentId>/stream` (or a similar endpoint) to send user messages and receive streaming responses. If you wanted to avoid the CLI and hit this directly, you'd need to mimic the protocol. OpenClaw messages are likely JSON with fields like `{"id": "...", "type": "user", "text": "your message"}` and the response comes back as a stream of tokens. This is non-trivial without an SDK. However, **OpenClaw's CLI is aware of the Gateway** – when the gateway is running, commands like `openclaw agents list` or `openclaw chat ...` will interface with it rather than spawning a new agent. So the simplest way to use HTTP mode is actually to run the gateway in the background and keep using CLI commands (they'll be faster because they hit the live service). There isn't an official REST API documented for sending a chat in one go (OpenClaw is meant to be multi-turn, stateful). If you really need a programmatic interface, consider using the **AIMLAPI** integration or *bridging OpenClaw into an SDK* – but that likely requires an API key for aimlapi.com and is more for cloud usage [40] [41]. In short: *Yes*, OpenClaw supports persistent WebSocket connections (for chat UI and channels), but *No*, there's no simple public HTTP POST endpoint like `/complete` out-of-the-box. Stick with the CLI or write a small WebSocket client if you're feeling adventurous.

- **OpenClaw Built-in Caching or Rate Limit Features:** OpenClaw itself focuses on *provider failover* rather than caching user queries. It does not cache LLM responses for reuse on similar inputs – that kind of semantic caching is left to the user or higher layer. It *does* cache some things: conversation history (persisted to disk), vector memory for semantic search of past dialogues, and tool results during a session. But those are for continuity and "agent memory," not to reduce API calls across independent queries. So you will need to implement caching as discussed in your app; OpenClaw won't, for example, remember that last week you asked a similar question and automatically reuse the answer. As for rate limit management, OpenClaw's approach is to rotate profiles and exponentially backoff a failing profile [3]. You saw this in action with the cooldown periods. It doesn't have a concept of "global rate limit" per se; it just reacts to provider responses. However, you can tune some parameters: in OpenClaw config, `auth.cooldowns.failureWindowHours` and related settings control how long until it resets the error count for backoff, and `auth.cooldowns.billingBackoffHours` for handling out-of-credit situations [42] [43]. Unless you have multiple API keys for the *same* provider, you likely don't need to adjust these. OpenClaw doesn't provide a way to queue requests or prioritization internally – it treats each incoming message independently (unless you build an agent that queues messages, which would be complicated). Therefore, the application-layer strategies we discussed are the way to go for queuing and throttling.

- **Multiple Profiles per Provider:** One related tip – OpenClaw allows multiple auth **profiles** for one provider (e.g., two OpenAI API keys, or two different OpenAI accounts via OAuth). If you acquire a

second OpenAI account, you could actually configure `auth.profiles.openai` with both, and OpenClaw would round-robin or failover between those keys if one hits a limit [44] [45]. This is another way to extend usage without switching providers. The config would look like:

```
"auth": {
  "profiles": {
    "openai": [
       { "id": "openai:primary", "apiKey": "${OPENAI_API_KEY}" },
       { "id": "openai:secondary", "apiKey": "${OPENAI_API_KEY_2}" }
    ]
  },
  "order": {
     "openai": ["openai:primary", "openai:secondary"]
  }
}
```

Then OpenClaw would try primary first, and if it's in cooldown, try secondary, before moving to other providers [46] [47]. This might be useful if, for example, you have one API key with a rate limit of X/minute – by having two, you double the throughput (OpenClaw treats them as separate "profiles"). Just ensure both are funded! This is an advanced config but can be easier than adding a whole new provider if you just need more OpenAI capacity.

In summary, **OpenClaw is quite flexible** in its config: you can merge multiple providers, set fallback chains, and adjust auth rotation. The key file is the JSON config, and after any changes, restart the gateway (or use `openclaw reload` if available) to apply them. Always test with a simple prompt to verify the agent can use the new model (e.g., `/model` command in the OpenClaw chat to switch models manually for a test query). The docs and community guides we cited (OpenClaw FAQ and LumaDock tutorials) are excellent references while editing these configs. Don't hesitate to use `openclaw models status` and `openclaw logs --follow` to debug model selection issues – they will show if a model was skipped due to missing creds or if a profile is cooling down [48].

Comparison Table of Top Solutions

Here's a side-by-side comparison of the top five solution approaches, for quick reference:

Solution	Impact	Effort	Cost	Reliability Boost	Dependencies/Tools
Local LLM Integration *Run a fallback model on RTX (e.g. Llama2 via LM Studio/ Ollama).*	**High:** Eliminates reliance on external services for basic functions. Always available fallback, improved latency. Quality depends on model chosen.	**Medium-High:** Setup local model server or integrate `llama_cpp`. Need to download model (~GBs) and allocate GPU memory.	**Free:** No API costs. Uses existing hardware (GPU VRAM & electricity). Model files are free.	**Very High Resilience:** System can function offline or when cloud APIs are down/ limited. No more hard stops due to API limits (local model will always respond, albeit possibly with simpler output).	- LM Studio or Ollama for serving models [8] - Alternatively `llama-cpp-python` or HuggingFace Transformers in-app - Sufficient VRAM (8GB+) - Suitable model (e.g. Llama2 13B Q4, Code Llama)
Multi-Provider Fallback *Configure multiple cloud LLMs (OpenAI, Anthropic, etc.) in OpenClaw.*	**High:** Avoids single point of failure. If one model hits rate limit or error, next one takes over automatically [12]. Reduces downtime significantly.	**Medium:** Mostly config changes. Obtain API keys or tokens for providers. Test each integration. Minimal code changes.	**Varies:** Can be cheap or free if using free-tier models (OpenRouter free, Qwen OAuth [14]). Using GPT-4/ Claude will incur normal token fees or require subscription.	**High Resilience:** Rate limits would need to hit *all* providers to fail. Minor performance impact if fallback model is slower or lower quality, but agent remains responsive. Also mitigates outages of a single API.	- OpenClaw config (`openclaw.json`) edits for providers and `fallbacks` list [12] - API keys or OAuth tokens for each provider (OpenAI, Anthropic, etc.) [49] - Possible use of OpenRouter (one key to access many models) - Testing via `openclaw models list/status`

Solution	Impact	Effort	Cost	Reliability Boost	Dependencies/Tools
LLM Proxy/ Gateway (LiteLLM/ OpenRouter) *Use a unified API proxy to route among many models/keys.*	**High:** Provides intelligent routing and load-balancing. Can enforce policies (cost-based routing, global rate limit). Simplifies OpenClaw's view to a single provider while managing many behind scenes [27] [28] .	**Medium:** Need to install/ configure proxy (LiteLLM) or sign up for OpenRouter. Some learning curve to set up rules. Ongoing maintenance of the proxy service.	**Free (for proxy):** LiteLLM is OSS, OpenRouter is free to use; you pay for the actual model usage. Can save cost by routing to cheaper models where appropriate.	**Very High Resilience:** Proxy can automatically failover without even involving OpenClaw's fallback (e.g., rotate through multiple API keys) [19] . Redundant layer of protection and control. Also improves scalability (if usage grows, add more keys or models easily).	- **LiteLLM** Proxy (Python-based) [21] or OpenRouter service - YAML/ JSON config for routing rules in LiteLLM - OpenClaw `baseUrl` pointing to proxy (OpenAI-compatible API) [24] - Possibly Docker or system service to keep proxy running - Additional keys for multiple accounts (optional)

Solution	Impact	Effort	Cost	Reliability Boost	Dependencies/Tools
Caching & Optimization *Semantic cache for repeated queries + larger deterministic intent set.*	**Medium:** Reduces redundant LLM calls, saving time and avoiding hitting limits on repeated tasks. Doesn't help one-off unique queries, but over time can drastically cut call volume.	**Medium:** Need to implement caching logic and maintain a cache store. Also train/ tweak any intent recognizers. Manage cache invalidation. Moderately technical but incremental.	**Free/Cheap:** Uses local computation. If using local embeddings (SBERT) all free. If using an API for embeddings or classification, minor cost per call (but far less than full LLM costs).	**Moderate Resilience:** Lowers the probability of hitting rate limits by calling the LLM less often. Frequent commands get instant responses. In case of LLM outage, cached answers for similar queries might still be returned. However, doesn't guarantee new queries will be answerable.	- **SentenceTransformers** or OpenAI Embeddings for vectorizing queries [29] - **FAISS/Annoy** or simple vector math for similarity search - Data store (in-memory dict, SQLite, or FAISS index file) - App logic to integrate cache check/store - Optional: spaCy or simple ML model for intent classification

Solution	Impact	Effort	Cost	Reliability Boost	Dependencies/Tools
App-Level Rate Limiting & Queue *Throttle LLM requests, apply backoff and manage queue of requests.*	**Medium:** Improves stability under high load. Prevents overwhelming the LLM or triggering provider's rate limits by spacing out requests. Ensures more consistent response times.	**Low:** Can often be implemented in a few dozen lines of Python. Utilize existing retry and timing logic. Testing needed to fine-tune wait durations.	**Free:** No external cost. Slight "cost" in added latency for the user when throttling kicks in, but that's intentional.	**Medium-High Reliability:** Avoids hitting the hard rate limit threshold in the first place. The system self-regulates bursts. Also makes behavior more predictable (no more mysterious 45s timeouts – instead, users see a controlled delay with feedback). Doesn't increase capability to answer, but prevents many failure modes.	- Python standard libs (`time`, `queue`, `threading` or `asyncio`) for implementing delay and queues - **Tenacity** or similar library for elegant retry with backoff - Logging to monitor timing of calls - Possibly config for max QPS (Queries per Second) or cooldown durations (tweak based on provider limits)

(*Dependencies note:* None of these solutions require abandoning Python 3.11/WSL2/Tkinter; they are additive. For instance, installing `sentence-transformers` or `tenacity` is just a pip install. The heavier dependencies are optional external services like LM Studio or LiteLLM, which run alongside your app.)

Step-by-Step Implementation Guide for Top 3 Solutions

Now, let's dive into **how to implement the top 3 solutions** (Local LLM, Multi-provider fallback, and Proxy/Gateway) step-by-step in your Python + WSL2 + Tkinter environment. This will include exact code or config snippets to illustrate the process.

Solution 1: Implementing a Local LLM Fallback

Step 1.1 – Set Up a Local Model Server (LM Studio or Ollama):
Download and install **LM Studio** (Windows version) or **Ollama** (if WSL/Linux, since Ollama is macOS/Linux). For simplicity on Windows, use LM Studio: - Install LM Studio and download a model through its interface. For example, download *"OpenAssistant 13B"* or *"Llama2 13B Chat"* – something that fits your GPU (if 24GB VRAM, 13B 8-bit or 4-bit is fine; if ~8–12GB, use 7B models or 13B 4-bit quantized). - Enable LM Studio's API server: In LM Studio, go to *Settings* and turn on the **HTTP API**. It will show a port (default 8080) and possibly an API key (depending on version). This API mimics the OpenAI API. For example, LM Studio might listen at `http://localhost:8080/v1` for completions. - Test the local API with curl or Postman:

```
curl http://localhost:8080/v1/engines -H "Authorization: Bearer YOUR_API_KEY"
```

It should list available models if working. Some versions don't require an API key for local access. Adjust accordingly.

Step 1.2 – Configure OpenClaw to Use the Local Model:
Edit your OpenClaw config (you can do `openclaw config edit` or manually open the JSON). Add an entry for the local provider. Suppose LM Studio's provider name is `localhost` for instance:

```
"models": {
  "providers": {
    "localhost": {
      "baseUrl": "http://127.0.0.1:8080/v1",
      "apiKey": "lmstudio-key",  // put the API key if required, otherwise any
dummy string
      "api": "openai-completions",
      "models": [
        { "id": "openassistant-13b", "name": "OpenAssistant 13B" }
      ]
    }
  }
}
```

Here: - `baseUrl` is pointing to LM Studio's local server. - `api` is set to `"openai-completions"` to match the OpenAI-like API. - The model `id` should match what LM Studio expects. If it's unclear, you might omit specifying models (OpenClaw can fetch the list from the server in some cases). But adding one with a friendly name helps.

Next, in the same config, add this local model to your agent's fallback chain. E.g.:

```
"agents": {
  "defaults": {
    "model": {
```

```
      "fallbacks": ["localhost/openassistant-13b"]
    }
  }
}
```

If you want the local model as *last resort*, ensure it's last in the list. If you want it to possibly handle things before a very slow cloud model, you could put it earlier.

Step 1.3 – Verify OpenClaw Recognition:
Restart OpenClaw gateway (`openclaw gateway restart` if it's running, or just start fresh). In a terminal, run:

```
openclaw models list
```

Look for your `localhost` provider and the model name. Then test a prompt:

```
openclaw agent main --model localhost/openassistant-13b --message "Test local model response" --json
```

This forces the agent to use the local model for this query. You should see a JSON output with a reply. If it works, great. If there's an error, troubleshoot: - If OpenClaw says "No API key for provider localhost", you might need to add an auth profile. You can do:

```
openclaw models auth add --provider localhost --api-key lmstudio-key --set-default
```

(Replace `lmstudio-key` with whatever key or token is needed; if none, just use a placeholder but ensure OpenClaw has something.) - If OpenClaw times out calling it, make sure LM Studio is still running and the port is correct.

Step 1.4 – Python Integration (Fallback Logic):
OpenClaw will now automatically use `localhost/openassistant-13b` when others fail. But if you want to explicitly catch failures and use the local model in code (perhaps to handle partial failures differently), you can. In your `jarvis_desktop_openclaw.py`, when you call the subprocess for OpenClaw, it might look something like:

```
result = subprocess.run([...], capture_output=True, text=True, timeout=45)
output = result.stdout
if "All models failed" in output or "FailoverError" in output:

# OpenClaw exhausted its models. As an extra precaution, directly call local model.
```

```
    answer = local_llm_inference(user_message)
    display(answer + " (from local AI)")
```

You would need to implement `local_llm_inference`. For example, using `requests` to hit LM Studio's API:

```
import requests, json

def local_llm_inference(prompt):
    url = "http://127.0.0.1:8080/v1/completions"
    headers = {"Authorization": f"Bearer {LMSTUDIO_API_KEY}"} if
LMSTUDIO_API_KEY else {}
    payload = {
      "model": "openassistant-13b",  # the model ID LM Studio uses internally
      "prompt": prompt,
      "max_tokens": 200,
      "temperature": 0.7
    }
    resp = requests.post(url, headers=headers, json=payload, timeout=30)
    resp.raise_for_status()
    data = resp.json()
    text = data["choices"][0]["text"]
    return text.strip()
```

This function directly queries the local model. In practice, since we configured OpenClaw to fallback to it, you might not need to call it here – OpenClaw should already have tried it. But having this as a safety gives you double assurance. You could even bypass OpenClaw entirely for certain simple prompts and directly call local (some logic like: *if user request length < 10 words, use local model first*).

Step 1.5 – Testing End-to-End:
Run the JarvisAbleton app. Trigger a scenario where the cloud LLM is intentionally unavailable (e.g., turn off internet or use up your OpenAI quota). Ask a request that would normally use Lane 2. You should see the local model respond. It might be a bit slower or the answer slightly different in style, but it should do *something* reasonable. Monitor the console logs from OpenClaw (`openclaw logs --follow`) to see the model selection. It should log that primary failed and it's using the localhost model next [15]. If everything is working, congrats – your AI assistant now has an offline brain!

Solution 2: Adding Multi-Provider Fallbacks in OpenClaw

Step 2.1 – Obtain API Access for Additional Providers:
Decide on at least one extra provider. A good combo is: - **Anthropic Claude Instant** (fast, fairly good at instructions). Sign up for an Anthropic account if you haven't. If you don't have API access, you can use the *Claude AI (Slack-based) subscription token* method. E.g., install Claude's CLI (`pip install claude`), run `claude setup-token` to get a token [50]. Alternatively, use the Anthropic API key if you have one. - **OpenRouter** for some free models: Go to openrouter.ai, create an account (free). They'll give you an API key. This key can access certain models via their endpoint. You might not need to use their paid credits if

you stick to free ones like `meta-llama/llama-2-7b-chat:free`. - (Optional) **Google PaLM (Gemini)** if you have an API key or want to try the new Gemini models. But that might complicate things, so perhaps skip for now unless you're curious.

For this guide, assume we use Claude and OpenRouter.

Step 2.2 – Add Anthropic to OpenClaw Config:
Using the config from Solution 1, add under `"models.providers"`:

```
"anthropic": {
  "api": "anthropic",
  "apiKey": "${ANTHROPIC_API_KEY}"
}
```

If using a Claude *token* instead of API key:

```
"anthropic": {
  "api": "anthropic",
  "authType": "oauth",  // might not be needed if OpenClaw auto-detects token
  "apiKey": "${ANTHROPIC_TOKEN}"
}
```

Actually, OpenClaw expects either an API key or an OAuth profile for Anthropic. If you did the `openclaw models auth paste-token --provider anthropic` step, it stored the token in its auth store. In that case, your config might not even need the key here – OpenClaw will find the profile. It might show up as `anthropic:default` in `auth-profiles.json`. Ensure either `~/.openclaw/.env` has the key or you have run the auth command.

Add Claude model IDs under that provider if not auto-known:

```
"models": [
   { "id": "claude-instant-1", "name": "Claude Instant 1" },
   { "id": "claude-2", "name": "Claude 2" }
]
```

Now, add to fallback chain:

```
"agents": {
  "defaults": {
    "model": {
      "fallbacks": [
         "anthropic/claude-instant-1",
         // ... (other fallbacks like openrouter/local that you want after)
```

```
      ]
    }
  }
}
```

If you want Claude tried *before* the local model, list it before `localhost/...`.

Step 2.3 – Add OpenRouter to OpenClaw Config:
Under `providers`:

```
"openrouter": {
  "apiKey": "${OPENROUTER_API_KEY}",
  "api": "openai-chat",
  "baseUrl": "https://openrouter.ai/api/v1",
  "models": [
    { "id": "openrouter/gpt-3.5-turbo", "name": "GPT-3.5 via OpenRouter" },
    { "id": "openrouter/meta-llama/llama-2-7b-chat:free", "name": "Llama2 7B
Free" }
  ]
}
```

OpenClaw might treat everything after provider name as model, so we could use shorter alias. But specifying fully as above is fine. Now extend the fallback list:

```
"fallbacks": [
   "anthropic/claude-instant-1",
   "openrouter/gpt-3.5-turbo:openai",   // (Note: OpenRouter docs sometimes
require model:provider format)
   "localhost/openassistant-13b"
]
```

The exact string for OpenRouter model can be tricky – it might be just `"openrouter/gpt-3.5-turbo"` if that's the alias. Some OpenClaw versions might want the full `<provider>/<model>` as listed in `openclaw models list`. Run that command to see how it names the OpenRouter models. Use exactly that in fallbacks.

Step 2.4 – Load Auth Credentials:
Make sure the environment variables are set for these keys: - In `~/.openclaw/.env` (in WSL home), add:

```
OPENROUTER_API_KEY=<your key>
ANTHROPIC_API_KEY=<your key>   # if using API key
```

If using the Claude token, ensure the auth profile is in place via the earlier step. You can check by:

```
openclaw models auth list --provider anthropic
```

It should show a profile (like your email or "default") with type "oauth" or "token".

Step 2.5 – Restart and Test Fallbacks:
Restart OpenClaw gateway to apply changes. Now test a forced fallback scenario. A quick way: use the OpenClaw CLI to temporarily disable the primary to see if fallback triggers. For example:

```
openclaw models auth disable --provider openai-codex
```

This will mark your OpenAI profile as disabled (simulate it being unavailable) [51]. Then send a message:

```
openclaw agent main --message "Test fallback chain" --json
```

Watch the output or logs. It should skip openai (because disabled) and go to Claude. You might see in logs: "Using anthropic/claude-instant-1 as fallback". If Claude responds, great. Then re-enable OpenAI:

```
openclaw models auth enable --provider openai-codex
```

(Or just `openclaw gateway restart` resets statuses).

From your app's perspective, nothing changes in code – you still call OpenClaw as before. But now it has more ways to succeed.

Step 2.6 – Handling Model Choice at Runtime:
If you want, you can add a UI element or command to switch the agent's model priority on the fly. OpenClaw allows `/agent <id>` or `/model <model>` commands. For example, typing "/model anthropic/claude-instant-1" in the chat (if your UI supports sending raw commands) would pin the session to Claude. In Tkinter, you might not have that, but you could implement something like a dropdown for "Preferred AI Model" that calls an internal function to change `AGENT_ID` or so. However, with failover configured, it's usually fine to let OpenClaw auto-select.

Step 2.7 – Monitor in Real Usage:
Keep an eye on the OpenClaw logs when using the app normally. You'll see entries like:

```
[Model] openai-codex/gpt-5.3-codex failed: rate_limit, cooling 60s
[Model] Falling back to anthropic/claude-instant-1
```

Then maybe:

```
[Model] anthropic/claude-instant-1 succeeded, used profile anthropic:default
```

This confirms your multi-provider setup is working as intended. If one provider hits limit, you won't even notice a failure in the app – the user just gets the answer from another brain.

Solution 3: Setting Up LiteLLM Proxy for Smart Routing

(This solution is a bit more involved. If Phase 3, you might do this later, but I'll present it as if doing now.)

Step 3.1 – Install LiteLLM Proxy:
In your WSL2 environment (or could be on Windows via Python as well), install the litellm package:

```
pip install "litellm[proxy]"
```

This installs the proxy server and any extras needed. Verify installation:

```
litellm-proxy --help
```

You should see usage info.

Step 3.2 – Configure LiteLLM Proxy YAML:
LiteLLM uses a YAML config (by default `~/.litellm/config.yaml`). Create a basic config that includes your providers:

```
# ~/.litellm/config.yaml
openai:
  api_keys:
    - sk-... (Your OpenAI API key 1)
    - sk-... (Another OpenAI key, or just one)
  routes:
    - model: gpt-4
      priority: 1
    - model: gpt-3.5-turbo
      priority: 2

anthropic:
  api_keys:
    - <Your Anthropic API Key or token>
  routes:
    - model: claude-instant-1
      priority: 1

openrouter:
  api_key: <Your OpenRouter API Key>
# (OpenRouter can forward to other providers too, but we might not nest it here)
```

This is a simplified example. What this says: - You have two OpenAI keys, and you want the proxy to route to GPT-4 by default, but GPT-3.5 as secondary (maybe for cost saving or if GPT-4 is at capacity). - You have Anthropic with Claude-instant. - (We included openrouter as well for demonstration, but you might skip if using direct OpenAI/Anthropic.)

LiteLLM allows more complex rules (like based on prompt content or user id, etc.), but we'll keep it simple: we want it to try GPT-4, if fail maybe Claude, etc. To achieve cross-provider fallback in LiteLLM, you define a **project or chain**. They have a concept of "virtual keys" where you combine providers. However, a quick method: just list multiple routes under a single project:

```
projects:
  main_agent:
    models:
      - provider: openai
        model: gpt-4
      - provider: anthropic
        model: claude-instant-1
      - provider: openai
        model: gpt-3.5-turbo
    strategy: failover
```

This config (in same YAML) defines a project `main_agent` that will first try OpenAI GPT-4, if it fails or is unavailable, try Anthropic Claude, then OpenAI GPT-3.5. The `strategy: failover` ensures sequential fallback. LiteLLM will also rotate between the two OpenAI keys for calls to distribute load (it does round-robin per key by default).

Step 3.3 – Launch LiteLLM Proxy:
Start the server:

```
litellm-proxy serve --host 0.0.0.0 --port 4000
```

(host 0.0.0.0 to listen inside WSL on all interfaces, so Windows can reach it as well via localhost). You should see it start without errors, listing loaded providers.

Test it with a curl:

```
curl http://localhost:4000/v1/chat/completions \
  -H "Content-Type: application/json" \
  -H "Authorization: Bearer main_agent" \
  -d '{"model": "gpt-4", "messages": [{"role":"user","content":"Hello"}]}'
```

We use "Authorization: Bearer main_agent" to indicate we want to use the `main_agent` project route (LiteLLM uses the API key field to pass a virtual project identifier or key label). If everything is set, it should

return a completion (likely from GPT-4 in this case). If GPT-4 were to error, it would transparently try Claude next.

Step 3.4 – Point OpenClaw to LiteLLM:
Now that the proxy is running, go to OpenClaw config and modify the provider for OpenAI (or add a new one):

```
"providers": {
  "openai": {
    "baseUrl": "http://127.0.0.1:4000/v1",
    "apiKey": "main_agent",
    "api": "openai-chat",
    "models": [
      { "id": "gpt-4", "name": "GPT-4 via LiteLLM" },
      { "id": "gpt-3.5-turbo", "name": "GPT-3.5 via LiteLLM" }
    ]
  }
}
```

Key points: - `baseUrl` is now the local proxy. - `apiKey` is set to `main_agent` – this will be passed as the Bearer token to LiteLLM, which it uses to select the project. (You could also use a longer random string and set that as a *virtual API key* mapping to the project in LiteLLM config, but using the project name as key is fine for local use). - `api` remains `openai-chat` because LiteLLM speaks that protocol. - List the models you intend to call. Actually, even if you put just `"gpt-4"`, you can still request gpt-3.5 via the same proxy if needed. But listing both is okay.

Now, consider that OpenClaw was originally using `openai-codex/gpt-5.3-codex`. If you want to replace that entirely, you might set:

```
"primary": "openai/gpt-4"
```

assuming the provider name is still “openai” in config. Essentially you are hijacking “openai” to go to your proxy now. Alternatively, you could name the provider “litellm” to be explicit, and then set primary to `litellm/gpt-4`. Just be sure to update AGENT_ID or default model accordingly.

Step 3.5 – Test End-to-End Through OpenClaw:
Restart OpenClaw. Run:

```
openclaw models list
```

See that `openai/gpt-4` is listed (with baseUrl pointing to 127.0.0.1:4000 presumably). Now ask the agent something via your app or CLI:

```
openclaw agent main --message "Which DAW are you controlling?" --json
```

It should route to LiteLLM (you might see logs in the proxy terminal showing a request to GPT-4). If GPT-4 is available, it responds. If you exceed some rate, cause a failure to test fallback: e.g., temporarily remove your OpenAI key from LiteLLM config or set a very low rate limit on it (LiteLLM allows specifying `max_retries` or limits). Then query – GPT-4 will "fail" and LiteLLM should then call Claude. In the proxy logs, you'd see an attempt for OpenAI, then an error, then a second request to Anthropic. From OpenClaw perspective, it just gets a final answer.

Step 3.6 – Adjust App Settings:
Now that OpenClaw only knows about one provider (the proxy), you might want to remove the other fallbacks from OpenClaw's config to simplify (since LiteLLM is handling them). For instance, you can set:

```
"fallbacks": []
```

or just one fallback to maybe your local model. Actually, you can still keep the local model as the *final* fallback at OpenClaw level (meaning if LiteLLM fails entirely, then go to `localhost/whatever`). That's a reasonable layered approach.

Your `.env` no longer needs OpenAI or Anthropic keys for OpenClaw (the proxy uses them instead), so you might remove them to avoid confusion – or keep them if you still have OpenClaw using them as backup of backup.

Step 3.7 – Integrate with App (Optional):
From the app perspective, nothing changes if OpenClaw is fronting the proxy. But if you wanted, you could also call LiteLLM directly from Python for certain tasks. LiteLLM has an SDK: for example:

```
from litellm import completion

response = completion("Hello, how are you?", provider="openai", model="gpt-4",
api_base="http://localhost:4000/v1", api_key="main_agent")
print(response.content)
```

This would hit your local proxy. However, since you want to keep the two-lane architecture, you'd likely continue to funnel everything through OpenClaw (so it can do tool use, etc.). Just ensure to keep the proxy running whenever the app is running. You might create a small script to launch it on WSL startup or even have your Python app launch it (via subprocess) if not already running.

Step 3.8 – Monitoring:
LiteLLM provides logs for each request, including which provider was used and any errors. Use those to fine-tune. For instance, you might notice most requests don't need GPT-4 and you could configure LiteLLM to use GPT-3.5 by default and only use GPT-4 if the prompt is complex (LiteLLM can route based on prompt tokens length or regex matches, etc.). This is beyond our scope but illustrates the power you now have.

By completing these steps, you've effectively created a robust chain: **Your App -> OpenClaw -> LiteLLM Proxy -> [OpenAI/Anthropic/OpenRouter]** and a local model as ultimate backup. This multi-tier fallback ensures that even if one layer fails, the next will catch it.

Finally, bring up the Tkinter UI and test real user interactions across these improvements. The user experience should be smoother (maybe slightly slower if the proxy adds overhead, but negligible on localhost). The crucial part is you shouldn't see those gateway timeout errors anymore – the system has many paths to answer and plenty of backoff logic to avoid hitting hard limits.

---

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