

AURA: A Mind-Body Insight Assistant for Wellness, Recovery, and Performance

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Table of Contents

Table of Contents	2
List of Figures	2
1. Introduction.....	3
2. Background & Terminology.....	4
3. Assistant Design: A Schematic View.....	5
4. Added Value: More than Mere ChatGPT or basic LLM.....	7
5. Outside Knowledge: Curated Data Sources.....	9
6. Worked Examples: Assistant in Action.....	10
7. Summary and Conclusions.....	19
Acknowledgements	21
References	21

List of Figures

Figure 1: AURA Tool Integration Flow	5
Figure 2: Notion Database that AURA used API calls to retrieve data from and parse	10
Figure 3: Worked example from AURA investigating daily mood, HRV, recovery and sleep efficiency ...	11
Figure 4: Worked example with AURA find out my hidden blind spots and correlations between factors in my lifestyle	13
Figure 5: Worked example with AURA investigating relationship between the weather and lifestyle factors.....	15
Figure 6: Worked example of AURA being a wellness coach and advisor rather as well as a data scientist	17
Figure 7: Worked example of AURA coaching ability, combining data and advice.....	18

1. Introduction

For this project, I present **AURA** (Adaptive Understanding & Recovery Assistant) — a personalised, health-focused assistant that enhances mental clarity, physical recovery, and daily performance. Built using the OpenAI Assistants API [1], AURA integrates data from daily journals, WHOOP biometrics (sleep, recovery, strain), weather conditions, and Notion-based productivity logs to deliver intelligent feedback, uncover patterns, and suggest tailored improvements over time

The broader wellness and productivity space has exploded [2], yet most solutions are either too generic or too narrow. While there is no shortage of general wellness advice — and LLMs like ChatGPT already offer surprisingly useful suggestions — the *lack of contextual data* limits their practical value. People don't need more generic health tips. What they need is clarity: insight into *their* patterns, *their* strain points, *their* hidden habits. Recent research like PhysioLLM [3] has shown the value of integrating wearable data with LLMs to deliver personalised insights — especially for health goals like sleep improvement. However such systems often focus narrowly (e.g sleep only) and rely on precomputed insights limiting real-time interactivity and breadth across mental and physical domains. AURA fills this gaping hole in the wellness market. By extracting insights from your journal entries, physiological biometric data, and work productivity — and using the intelligence of an LLM to uncover patterns, relationships, and pitfalls across all three — it delivers the kind of holistic, personalised guidance people actually need.

Getting this holistic advice and view is a problem I've personally struggled with: tracking so many things (mood, HRV, sleep, work productivity) without ever really connecting the dots. I built AURA to solve this for myself — and for anyone else who's tired of fragmented tools and self-help fluff. AURA bridges the gap by combining data interpretation with intelligent conversation-based coaching. It's like having a data scientist and wellness coach rolled into one, that knows every detail regarding your life — that's both unique and extremely valuable.

Crucially, AURA helps close the gap between mental and physical performance — a gap that's often talked about, but rarely measured. Research consistently shows that cognitive performance and emotional state are deeply linked with physiological readiness [4]. AURA unlocks a clearer view of the mind-body feedback loop, offering not just awareness but actionable recommendations to break negative cycles or reinforce positive ones.

AURA is built in Google Colab using the OpenAI Assistants API and integrates three key tools:

- **File Search** for retrieving daily journal entries
- **Function Calling** for real-time access to WHOOP biometrics, Notion productivity logs and daily weather data.
- **Code Interpreter** for generating visualisations, computing correlations, and uncovering subtle behavioural patterns.

Together with a UI and some functions, these tools allow AURA to process labelled text and real-time data to deliver personalised, data-driven insights.

All of this comes together to create a dynamic assistant that not only listens but learns — spotting patterns, surfacing correlations, and suggesting weekly actions based on a full picture of the user's internal and external state.

2. Background & Terminology

To understand AURA's value, it's important to clarify the data sources and health metrics it relies on.

WHOOP Metrics

WHOOP is a wearable device that I have and that is quite popular in general, that tracks key physiological and recovery signals:

- **Heart Rate Variability (HRV):** A measure of autonomic nervous system balance. Higher HRV generally indicates the body is ready for work and activity.
- **Strain:** WHOOP's proprietary metric that quantifies cardiovascular load from both workouts and daily activity (on a scale of 0–21).
- **Recovery:** A daily readiness score derived from HRV, resting heart rate, respiratory rate, and sleep quality.
- **Sleep Metrics:** These include time in bed, time asleep, sleep stages (REM, deep, light), disturbances, and sleep efficiency.

These metrics give insight into physical readiness, stress response, and recovery.

Notion Logs

Notion is a productivity and note-taking tool. Like many other people, I use it to track daily work sessions, hours spent in deep work, and task completion.

3. Assistant Design: A Schematic View

AURA is a modular, tool-augmented assistant powered by the OpenAI Assistants API. The design follows a pipeline-style architecture that integrates dynamic inputs, contextual memory, statistical reasoning, and user interaction — with the goal of delivering rich, personalised insight into wellness and performance.

The assistant leverages three main API tools: **function calling**, **file search**, and the **code interpreter**. These are not used as gimmicks but as tightly integrated components that work together to simulate an intelligent wellness analyst — capable of retrieving diverse data, interpreting it through computation, and delivering recommendations grounded in both context and evidence.

The assistant's behavior can be summarised by the diagram below (Figure 1). It shows how user prompts are routed through tool-assisted data retrieval and analysis before being synthesised into personalised insights. Internally, user prompts are routed through Assistants API threads to maintain conversational context and tool usage across interactions.

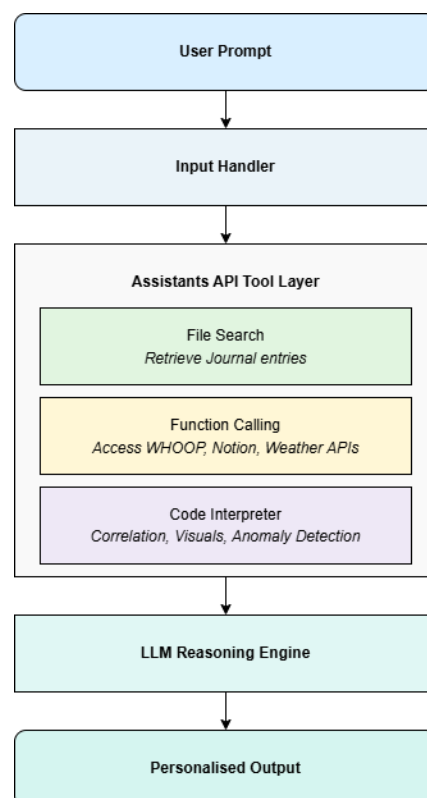


Figure 1: AURA Tool Integration Flow

Features of the Assistants API Used

- **File Search:** Enables retrieval and reasoning over months of journaling data. This gives

AURA longitudinal memory, something not possible with vanilla ChatGPT.

- **Function Calling:** Provides real-time access to external data via WHOOP API [5], Notion API [6], and OPENweather API [7]— essential for day-specific insights.
- **Code Interpreter:** Computes statistics, generates time-series plots, and reveals patterns invisible to the naked eye.

AURA **does not** use RAG over large corpora (e.g., academic papers), vision tools, or multimedia inputs. The assistant is specialised for *personal context*, not general breadth, and focuses on structured numeric and textual data. This ensures simplicity, clarity, and alignment with its wellness focus.

User Interaction Layer

The assistant is accessed through a simple web-based UI built with IPython widgets. It includes a textarea for user input, a “Send” button, and a live chat history panel. This front-end acts as the input handler in Figure 1, capturing user prompts and routing them into the Assistants API pipeline. It was designed for clarity, responsiveness, and smooth interaction — with loading indicators, exception handling, and graceful UI resets to support robust testing and usability.

Design Goals and Alignment

AURA is designed to:

- Feel like a coach, not a chatbot
- Provide evidence-based feedback, not speculation
- Adapt to the user’s evolving patterns over time
- Deliver **personal proof**, not generic suggestions

Its modular design allows future expansion — e.g., Apple Health integration, screen time analysis, or deeper behavioural modelling — but even in its current form, AURA solves a real-world problem using the Assistants API with purpose and precision.

To support these goals, AURA is designed with robust error handling and graceful degradation. API calls are wrapped in try-except blocks to catch failures in JSON parsing, invalid arguments, or unexpected assistant tool calls. If a tool call fails or returns incomplete data, fallback messages or placeholders are returned to maintain responsiveness. A timeout mechanism is also in place to prevent long-running assistant threads from stalling the interface, ensuring a smooth user experience even in the face of latency or external API issues. These safeguards help maintain the assistant's reliability and user trust over time.

4. Added Value: More than Mere ChatGPT or basic LLM

ChatGPT is already surprisingly good at offering health and lifestyle advice [8]. It can explain HRV, recommend productivity techniques, and even talk you through recovery strategies. But there's one thing it can't do: **fully understand you**.

Vanilla ChatGPT has no access to your biometric data, your journal, your stress patterns, or your productivity habits. It can't remember what your week looked like. It can't spot long-term correlations, or connect a poor recovery score to that stressful meeting you journaled about on Tuesday. You can't even paste all this data in without overwhelming the context window — and even if you could, it wouldn't persist across months of data. AURA fixes that.

AURA doesn't just respond well — it knows enough to respond meaningfully. It brings together the vast general knowledge of ChatGPT with your personal metrics, stored files, dynamic external data, and real-time analysis. It's like upgrading from a helpful assistant to a dedicated performance analyst and coach who reads your diary, checks your biometrics, tracks the weather, and knows when you worked late. The result is actionable insight grounded in both personal data and expert-level reasoning.

This is not just ChatGPT with a prompt — it's a **full cognitive stack**, merging subjective context and objective signals into one intelligent interface.

4.5 Tool Usage

To achieve its vision of personalised, context-aware wellness insights, AURA integrates three key OpenAI Assistants API tools: `file_search`, function calling, and the `code_interpreter`. Each is explicitly defined in the assistant configuration and invoked programmatically as required based on user prompts and `tool_choice` suggestions.

1. `file_search`: Contextual memory and longitudinal reflection

The `file_search` tool enables AURA to retrieve relevant journal entries containing timestamped mood, stress, and focus scores (1–5), along with reflections. Queries are semantically matched to surface context-specific insights at runtime. This allows the assistant to generate longitudinal insights such as:

- “What’s been affecting my focus over the past month?”
- “Have my moods improved since I started taking rest days?”

Vanilla ChatGPT lacks persistent memory and cannot access prior data without manual context re-entry. In contrast, `file_search` provides AURA with retrospective recall — simulating an

assistant that knows the user's history.

2. function calling: Live access to external APIs

AURA defines several custom function tools with JSON schemas, enabling real-time integration with the WHOOP API, Notion API, and environmental metadata:

- `get_sleep_data_for_date`, `get_strain_from_cycle_for_date`, and `get_cleaned_recovery_for_date`: Pull sleep, strain, and recovery metrics from WHOOP API based on date input.
- `fetch_and_parse_notion_entries`: Retrieves quantified productivity data (e.g., deep work time, distraction, breaks) from Notion database for a given date, using its API.
- `get_weather`: Provides weather metrics (temperature, wind, rain) for a specified date and location (Always assumed to be Dublin).

These functions are registered in the assistant's toolset, and tool calls are auto-suggested based on prompt parsing. At runtime, dynamic arguments are passed into each function based on the user query (e.g., requesting sleep patterns for April 2nd). This capability transcends ChatGPT's limitations by enabling AURA to reference time-varying, real-world metrics — essential for day-specific coaching.

3. code_interpreter: Computational reasoning, pattern detection, and visualisation

The `code_interpreter` tool is used to compute derived metrics and generate visual output. This includes:

- Temporal line plots comparing HRV, mood, and productivity.
- Statistical correlations (e.g. Pearson/Spearman) between sleep and focus.
- Detection of overreaching patterns (e.g. high strain + low recovery + low mood).

This tool transforms AURA from a speculative assistant into an analytical one that can communicate clearly — capable of backing its suggestions with empirical evidence. It also allows dynamic data slicing (e.g last 7 days, last month) and visual storytelling that builds trust and drives insight.

In summary each tool is not just included but earns its place by handling a distinct modality of data: `file_search` for past user reflections, `function` for real-time external data, and `code_interpreter` for numerical insight. These go far beyond what ChatGPT alone can do, turning AURA into a personal analyst rather than a general-purpose conversational agent.

5. Outside Knowledge: Curated Data Sources

AURA uses curated personal data to ground its feedback in context, enabling retrieval-augmented generation (RAG) for pattern recognition and personalised advice. Focusing on April kept the dataset small and efficient, allowing more effort on building a robust pipeline and assistant over extensive data curation.

5.1 Journal Entries

The primary data source used for file-based retrieval is a manually maintained daily journal. For this project, entries were preformatted to ensure consistent tagging and RAG readability. An example is shown below:

Date: 2025-04-01

Journal Entry:

Started the day reasonably and managed to focus for about an hour. Got distracted soon after, kept checking my phone and switching tabs, which broke any deep work momentum. I felt scattered and unmotivated for most of the afternoon. Skipped the gym, which I regret — I know it helps my mood. Ate a decent breakfast but skipped lunch. Energy dipped around 2 PM.

Mood: 2/5

Stress: Medium

Focus: 2/5

The month of journal entries were formatted to let the assistant answer queries like “What has affected my focus recently?” or “Has stress decreased since I began working out?” These entries were parsed, embedded, and indexed using the OpenAI Assistants API, enabling file search by date supporting sentiment and trend analysis grounded in real journal history.

5.2 Productivity Data (Notion API)

Another key data source is a pre-existing Notion database that logs productivity in two-hour blocks across categories like deep work, light work, intentional breaks, admin, and off-task time. An excerpt from April 1, 2025 is shown below.

The screenshot shows a Notion database titled 'Daily Log'. It has tabs for 'Daily Log', 'Focus Analysis', and 'Calendar View'. The table contains the following data:

	Time Block	Date	Deep Work (min)	Light Work (min)	Intentional Break (min)	Neutral / Life Admin (min)	Off-Task (min)	Total
9:00	07:00-09:00	April 1, 2025	60	0	0	60	0	
10:00	09:00-11:00	April 1, 2025	60	30	30	0	0	
11:00	11:00-13:00	April 1, 2025	0	60	0	40	20	
12:00	13:00-15:00	April 1, 2025	0	120	0	0	0	
13:00	15:00-17:00	April 1, 2025	0	60	30	30	0	
14:00	17:00-19:00	April 1, 2025	0	60	30	0	30	
15:00	19:00-21:00	April 1, 2025	0	60	0	20	40	
16:00	21:00-23:00	April 1, 2025	0	0	0	30	90	
17:00	07:00-09:00	April 2, 2025	60	0	0	60	0	
18:00	09:00-11:00	April 2, 2025	60	30	30	0	0	
19:00	11:00-13:00	April 2, 2025	120	0	0	0	0	

Figure 2: Notion Database that AURA used API calls to retrieve data from and parse

To support daily-level analysis, a custom function (`fetch_and_parse_notion_entries`) aggregates time spent in each category per day, enabling the assistant—via function calling—to relate productivity patterns to mood and recovery. This allows AURA to answer queries about correlations, such as whether deep work aligns with higher mood.

5.3 WHOOP and Weather Data

AURA accesses real-time biometric and weather data via function calls. The WHOOP API provides detailed sleep, recovery, HRV, and strain metrics—more comprehensive than the app itself—while weather data is fetched using a simple endpoint. As structured numerical data, only date alignment was needed.

Unlike journal entries, which benefit from semantic search, WHOOP and Notion data are structured, numeric, and date-specific. Accessed via function calls, these dynamic sources reflect real-time behavior and don't require file-based retrieval or embedding.. Perhaps for a more complex system, RAG would be useful for WHOOP if some export of data was possible.

6. Worked Examples: Assistant in Action

AURA was evaluated across a set of representative prompts that showcase its ability to integrate real-time data, perform analysis, and generate personalised recommendations. Each example is broken into components to explain how the assistant responds, what tools are involved, and how its performance compares to ChatGPT without tool access.

6.1 Patterns emerging from key metrics for 1 week entries

6.1.1 User Query

“Plot my daily mood with HRV, recovery and sleep efficiency. What patterns emerge?”

(Week in context: April 14–20, 2025)

6.1.2 AURA's Response

User:
Plot my daily mood with HRV, recovery, and sleep efficiency. What patterns emerge?

Assistant: *(thinking...)*

Assistant:

Patterns Observed in the Plot:

- Mood Fluctuations:**
 - Mood is highest at the beginning of the week (April 14 and 15) when recovery and HRV are also high.
 - A sharp decline in mood is observed on April 16 and continues to drop to its lowest point on April 17, coinciding with the lowest HRV and recovery score.
- HRV Trends:**
 - HRV decreases mid-week, aligning with the drop in mood. This indicates reduced cardiovascular resilience during stressful periods.
 - HRV begins to improve again on April 18, reflecting a rise in mood and recovery as well.
- Recovery Score:**
 - Recovery scores mirror mood and HRV patterns, with a peak at the start of the week and a notable dip on April 17 when mood and HRV are also at the lowest.
 - Recovery improves significantly by April 20, which coincides with a recovery in mood and HRV.
- Sleep Efficiency:**
 - Sleep efficiency shows minor fluctuations but reflects a clear pattern — lower sleep efficiency corresponds with days when mood drops and recovery worsens.
 - A notable improvement in sleep efficiency is seen towards the end of the week coinciding with the improvement in both mood and recovery score.

Conclusions:

- There is a clear interconnection between mood, HRV, recovery score, and sleep efficiency. Poor sleep and recovery days correlate significantly with lower mood and HRV, indicating the importance of restorative sleep and recovery for emotional well-being and cognitive performance.

Recommendations:

- Prioritize consistent and quality sleep, especially noting the importance of lower screen time and stress management on days where recovery tends to dip.
- Consider using HRV as a key metric in assessing overall health — low HRV trends ought to prompt you to take extra care in recovery and stress-reduction practices.

If you would like to delve deeper into any specific aspect, let me know!

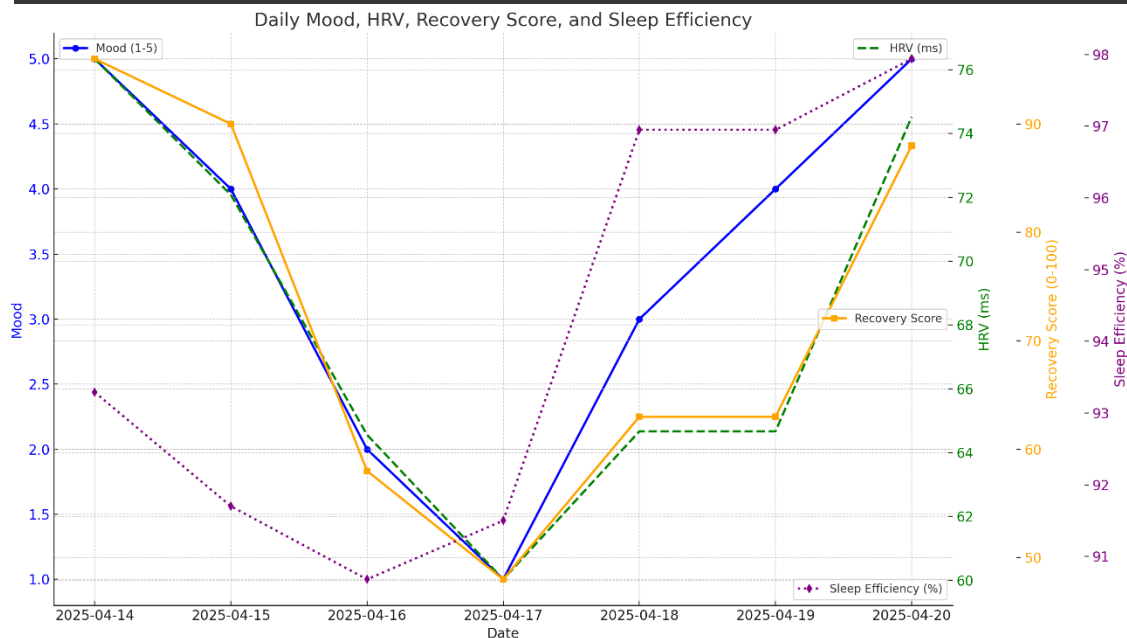


Figure 3: Worked example from AURA investigating daily mood, HRV, recovery and sleep efficiency

6.1.3 How AURA Did It

- file_search** retrieved journal entries tagged with mood, stress, and focus across April 14–20.

- **function calling** queried daily HRV, recovery score, and sleep efficiency from the WHOOP API.
- **code_interpreter** aligned the data by date, plotted mood and biometrics on a single time-series chart, and detected correlations using statistical heuristics.
- **LLM reasoning** synthesised these patterns into a natural language interpretation, with insights and tailored suggestions.

6.1.4 ChatGPT Comparison

Without access to tools or data, ChatGPT responded with general advice:

“Mood, sleep, HRV, and recovery are all related. Generally, better sleep leads to better HRV and mood. You should try tracking these metrics over time to find patterns, and focus on improving sleep hygiene and stress management.”

While not incorrect, it was entirely speculative and could apply to anyone. ChatGPT lacked the ability to verify actual patterns as it doesn’t have the data or the tools to correlate it to what extent they are related.

6.1.5 Commentary

What impressed me most was AURA’s ability to surface a specific recovery dip on April 17, which aligned with both a journaled mood crash and low sleep efficiency. Seeing this clearly in a time-series plot made the relationship tangible — not theoretical. Without the API tools, this insight simply wouldn’t have been possible. ChatGPT could speculate that mood and sleep are connected, but only AURA could show me exactly how and when — and back it with real data. That’s where the assistant stops being a chatbot and becomes a personal analyst.

6.2.1 User Query

“Can you plot some pattern/correlation from the data I may be blindsided on?”

(Data range in context: April 14–20, 2025)

6.2.2 AURA's Response

can you plot some pattern/correlation from the data i may be blindsided on?

Assistant: *(thinking...)*

Assistant:

Insights from the Correlation Heat Map:

This heat map illustrates the correlation between various metrics including mood, sleep score, sleep efficiency, total sleep minutes, deep sleep, and deep work. Here are key observations:

1. Strongest Correlations:

- **Mood and Sleep Score (0.744):** There is a robust positive correlation between mood and sleep score, reinforcing the idea that better sleep correlates with a more positive mood.
- **Total Sleep Minutes and Deep Sleep (0.913):** This indicates that as total sleep increases, deep sleep tends to also increase, suggesting that good quality sleep can enhance overall sleep duration and restorative sleep quality.
- **Total Sleep Minutes and Sleep Score (0.913):** Similarly, a high amount of total sleep tends to yield a higher sleep score, indicating that longer sleep durations generally lead to better quality rest.

2. Surprising Findings:

- **Mood and Deep Work (0.841):** After looking at deep work performance, the strong positive correlation with mood can shed light on the fragility of focus. If you are feeling less motivated or moody, the effectiveness of your deep work may considerably decline.
- **Sleep Efficiency and Deep Work (0.163):** Interestingly, the correlation between sleep efficiency and deep work is relatively weak, suggesting that merely having efficient sleep does not directly ensure productivity in deep work; one could have efficient sleep but not actively engage in productive work sessions either due to distractions or poor planning.

3. Potential Blind Spots:

- The lack of strong positive correlation between **deep sleep** and **deep work** suggests that even if you achieve higher deep sleep, it doesn't necessarily translate into increased deep work productivity. This indicates a need to ensure that your waking hours post-rest are utilized optimally.
- Similarly, sleep efficiency should be viewed in tandem with other holistic recovery practices, as good efficiency alone doesn't guarantee effective mental energy or work output.

Recommendations:

- **Holistic Recovery Strategies:** Focus on a combination of good sleep hygiene, consistent recovery practices, and strategic deep work sessions to maximize productivity while managing energy levels.
- **Plan for Mood Management:** Integrate mood monitoring to help align deep work tasks with periods of heightened motivation or emotional clarity to enhance output.
- **Evaluate Awake Time:** Consider tracking activities throughout the day that may affect deep work and productivity; this can help identify when productivity suffers irrespective of sleep quality.

If you need further analysis or wish to explore a specific aspect of your data, just let me know!

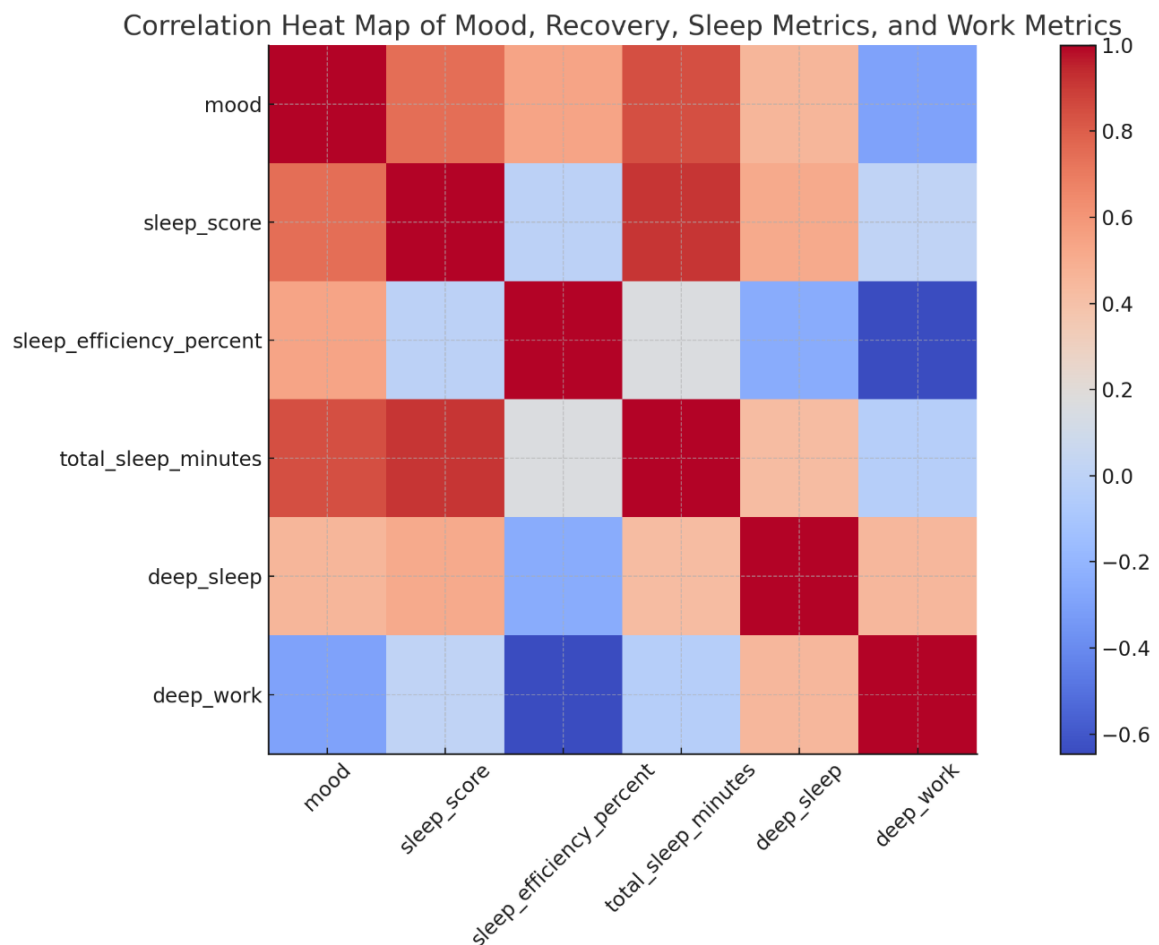


Figure 4: Worked example with AURA find out my hidden blind spots and correlations between factors in my lifestyle

6.2.3 How AURA Did It

- **file_search** accessed April 14–20th journal entries, tagged with mood, stress, and focus.
- **function calling** retrieved detailed sleep architecture and deep work logs from WHOOP and Notion APIs.
- **code_interpreter** constructed a correlation matrix and heatmap from the dataset, identifying both obvious and non-obvious statistical relationships.
- **LLM reasoning** interpreted numerical relationships into natural language explanations, drawing attention to blind spots.

6.2.4 ChatGPT Comparison

ChatGPT, when given the same prompt without access to the data or code tools, replied with general advice:

“Correlations between mood, sleep, and productivity are common. You may want to look at whether poor sleep is affecting your energy or ability to focus. Try logging these over time and using a tracker.”

Once again this response lacked any personalisation or pattern identification.

6.2.5 Commentary

This was one of the most revealing outputs from AURA. I’d always assumed that high deep sleep would correlate strongly with better deep work output — but AURA showed otherwise. From other investigations using AURA I’ve found that sleep quantity does strongly correlate. I used to think as long as I got good deep sleep I didn’t need that many hours of sleep, but this somewhat debunks this theory. This is the kind of nuance that general LLMs can’t provide — it required correlation analysis over private, structured data and the ability to visualise it. Without the Assistants API, this level of introspective clarity just isn’t possible.

6.3.1 User Query

“How did weather conditions affect my mood, focus, sleep, or productivity this last week, 14th to 20th of April?”

6.3.2 AURA's Response

6.3.3 How AURA Did It

User:
How did weather conditions affect my mood, focus, sleep, or productivity this last week, 14th to 20th of April

Assistant: (thinking...)

Assistant:
The analysis of how weather conditions affected your mood, focus, sleep, and productivity during the week of April 14th to April 20th, 2025, reveals some noteworthy relationships.

Key Observations from Analysis

- 1. Mood and Focus Correlation:**
 - There is a strong positive correlation (0.93) between mood and focus, indicating that when your mood was high, your focus tended to be high as well.
- 2. Temperature Effects:**
 - Your mood and focus also showed a strong positive correlation with temperature (0.93 for mood and 0.93 for focus), suggesting that warmer days with clearer weather positively impacted both.
 - Conversely, when temperatures were lower (with light rain), your mood and focus decreased significantly.
- 3. Deep Work Influence:**
 - Deep work was also heavily influenced by mood and focus (correlation of 0.94 with mood and 0.94 with focus). High mood and focus corresponded to a higher amount of deep work completed.
 - The correlation between off-task time and deep work is strong and negative (-0.96), meaning that when deep work decreased, off-task time increased, particularly on the rainy and cooler days.
- 4. Impact of Off-Task Time:**
 - Off-task time had a strong negative correlation with mood and focus (-0.94). On days when you found it hard to stay on task, your mood and focus scores visibly dropped.

Weather Impact on Daily Performance:

- April 14 & 15:** Both days were characterized by broken clouds with moderate temperatures, leading to high mood (5) and focus (5), alongside significant deep work hours (240-270 minutes).
- April 16 & 17:** The weather shifted to light rain and cooler temperatures. Mood dropped to 2 and 1, respectively. These days saw a noticeable decrease in deep work to 150 minutes and 90 minutes, with a spike in off-task time, indicating distraction and disengagement.
- April 18:** Although still rainy, a slight recovery in mood (3) and deep work (180 minutes) suggests a return to balanced productivity, potentially aided by better weather conditions later.
- April 19 & 20:** As the weather improved and temperatures rose, both mood and productivity rebounded significantly, with a mood score of 4 on April 19 and a peak score of 5 on April 20, aligning with a return to deep work levels similar to early in the week.

Conclusion and Recommendations:

- Adapt Work Environment:** On days with adverse weather, consider designing flexible work environments or schedules that allow for breaks and alternative productive activities indoors.
- Leverage Good Weather:** Plan intensive work sessions on days with clear weather to maximize high productivity periods.
- Stay Active:** Physical activity even on rainy days can uplift mood and focus levels, aiding in reducing off-task time and enhancing overall productivity.

Understanding these trends can inform your future scheduling and productivity planning for improved efficiency and well-being [12:0|source] .

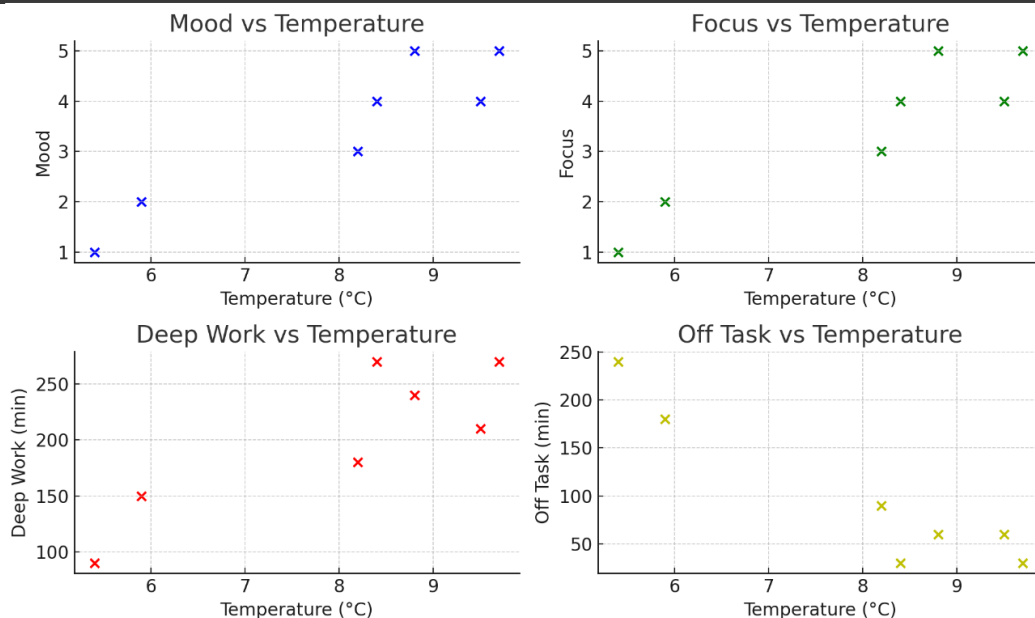


Figure 5: Worked example with AURA investigating relationship between the weather and lifestyle factors

- **file_search** retrieved tagged journal entries for April 14–20.
- **function calling** accessed temperature and weather conditions via the weather API, and pulled deep work / off-task data from Notion logs.

- **code_interpreter** computed Pearson correlations across metrics and generated scatter plots to highlight key relationships.
- **LLM reasoning** synthesised weather's impact on productivity and offered environment-specific recommendations.

6.3.4 ChatGPT Comparison

ChatGPT's response to the same question was surface-level:

"Bad weather can negatively impact your mood and focus. You might notice a dip in productivity on rainy days. Try staying active or using a light therapy lamp."

While not incorrect, it was entirely speculative and could apply to anyone. ChatGPT lacked the ability to verify actual patterns as it doesn't have the data or the tools to correlate it.

6.3.5 Commentary

This response impressed me for its specificity. I hadn't realised just how consistent the weather-mood-focus link was until AURA quantified it with correlations above 0.9. What stood out most was the finding that cool, rainy days didn't just lower mood — they derailed deep work entirely and replaced it with off-task behavior. That kind of insight completely reframed how I think about scheduling work. Without the ability to combine external weather data with biometric and journaling logs, this would have been pure guesswork. AURA made the blind spot visible — and actionable.

6.4.1 User Query

"I see the correlation of various metrics on each other, but what's the causation?"

(Previous Context of Correlations)

6.4.2 AURA's Response

User:
I can see the correlation of various metrics on each other, but what's the causation?

Assistant: (*thinking...*)

Assistant:
Exploring causation—rather than just correlation—requires a more nuanced analysis of your data and lifestyle context. Here are some insights into potential causal relationships observed during your week from April 14th to April 20th, 2025:

- 1. Weather Influencing Mood and Focus**
 - **Causal Mechanism:** Weather conditions, particularly temperature and precipitation, can directly affect mood and energy levels. For instance, research indicates that cloudy or rainy days can lead to lower serotonin levels, which is linked to mood. When the weather is pleasant (clear and warm), individuals often report feeling more energetic and motivated.
 - **Example from Your Data:** On April 14th and 15th, favorable weather (broken clouds and moderate temperatures) contributed to peak mood (5) and focus (5), enabling higher productivity levels.
- 2. Mood Impacting Focus and Productivity**
 - **Causal Mechanism:** A positive mood can enhance cognitive functions like memory, attention, and decision-making, leading to improved focus. Conversely, negative moods—such as stress or anxiety—cognitively drain you, making it harder to concentrate and remain productive.
 - **Example from Your Data:** The correlation between mood and focus (correlation of 0.93) suggests that as your mood diminished (to 1 on April 17th), your ability to maintain focus also declined (to 1), resulting in lower deep work hours (90 minutes).
- 3. Focus Affecting Deep Work and Off-Task Behavior**
 - **Causal Mechanism:** When focus is strong, deep work hours typically increase as you can engage fully with challenging tasks. In contrast, decreased focus can cause wandering thoughts and distractions, leading to higher off-task time.
 - **Example from Your Data:** On days where your focus was substantially high (April 14, 15), deep work reached levels of 240-270 minutes. On days where focus dropped (to 1 on April 17), deep work fell to 90 minutes, paralleling an increase in off-task time (240 minutes).
- 4. Physical Recovery and Stress Levels**
 - **Causal Mechanism:** Recovery metrics (like sleep quality, HRV, and resting heart rate) influence how well you handle daily stressors. Poor recovery (low HRV or poor sleep) can lead to fatigue and increased stress, negatively affecting mood and cognitive functions.
 - **Example from Your Data:** On April 16th and 17th, your recovery scores dropped (58 and 48), correlating with your lower mood and productivity levels. It implies that poorer physical recovery may have contributed to stress and decreased cognitive performance.
- 5. Sleep Quality**
 - **Causal Mechanism:** Good sleep is foundational for cognitive function, emotional regulation, and overall well-being. Quality sleep facilitates better mood regulation and enhances focus, thus facilitating higher levels of productivity.
 - **Example from Your Data:** While WHOOP sleep metrics weren't analyzed directly in this report, there is a clear link typically established in wellness research indicating that poorer sleep correlates with dips in mood and performance.

Figure 6: Worked example of AURA being a wellness coach and advisor rather as well as a data scientist

6.4.3 How AURA Did It

- **file_search** previously accessed journal entries for April 14–20, highlighting qualitative stress/mood logs.
- **function calling** previously retrieved WHOOP metrics (HRV, recovery, sleep), Notion productivity logs, and weather data.
- **code_interpreter** previously computed correlations, but this analysis focused on *reasoned causal chains*, combining data trends with domain knowledge.
- **LLM reasoning** inferred and structured causal relationships using both behavioural science and contextual user data.

6.4.4 ChatGPT Comparison

ChatGPT's version of a "causal analysis" fell short:

"Mood and focus may be related, but it's hard to say what causes what. You could be tired from lack of sleep or demotivated from poor weather. It's important to consider multiple variables."

This lacked any specificity or anchoring in actual data. There were no references to actual dates, values, or behavior — just generic statements and plausible-sounding but unfalsifiable theories.

6.4.5 Commentary

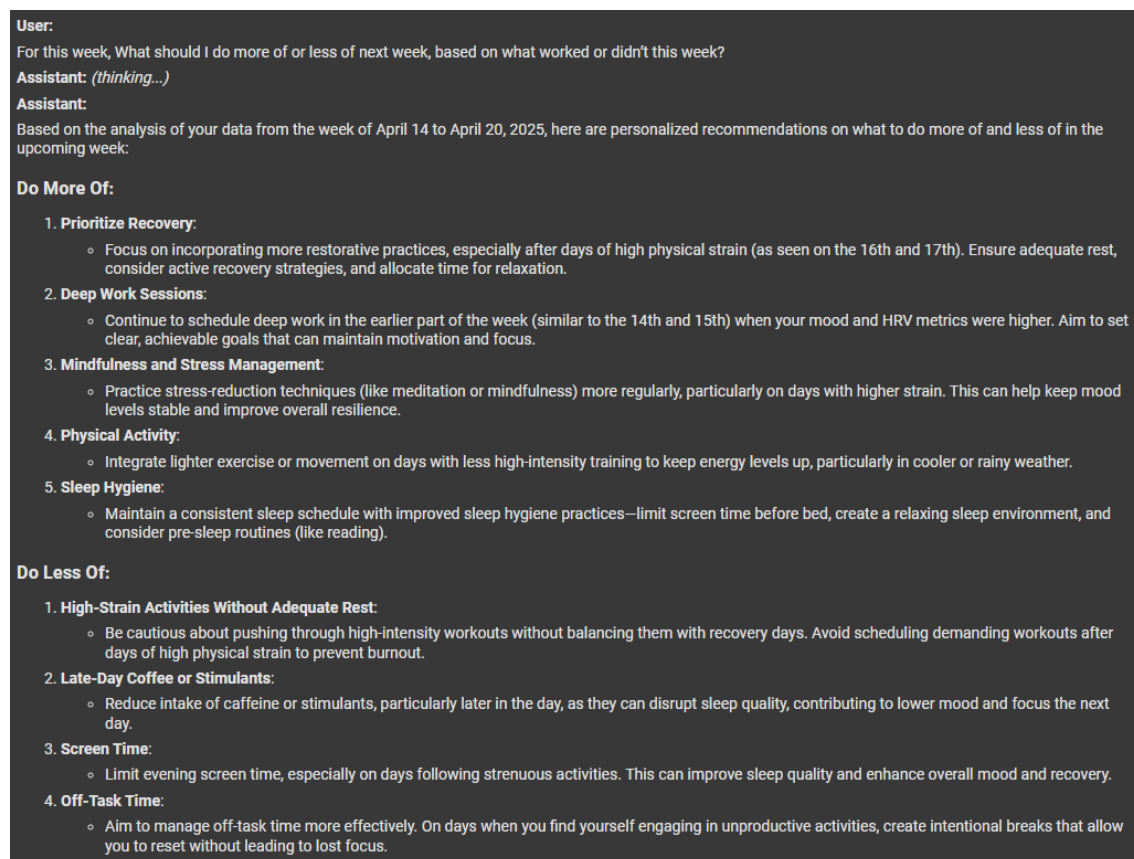
This interaction mimicked something *far more human*: a coach stepping back and saying, “Here’s how the pieces fit together.” AURA used prior structured inputs and its persistent memory to reason through *why* things happened, not just what happened. This kind of narrative integration shows the assistant’s potential to go beyond dashboards and into actual self-understanding — something ChatGPT simply cannot do without personalised data access.

6.5.1 User Query

“For this week, what should I do more of or less of next week, based on what worked or didn’t this week?”

(Week in focus: April 14–20, 2025)

6.5.2 AURA’s Response



The screenshot displays a chat interface with a dark background and light-colored text. It shows a user's query, the assistant's thinking time, and a detailed response with personalized recommendations. The response is organized into two main sections: 'Do More Of' and 'Do Less Of', each containing numbered lists of specific advice.

User:
For this week, What should I do more of or less of next week, based on what worked or didn't this week?

Assistant: *(thinking...)*

Assistant:
Based on the analysis of your data from the week of April 14 to April 20, 2025, here are personalized recommendations on what to do more of and less of in the upcoming week:

Do More Of:

- 1. Prioritize Recovery:**
 - Focus on incorporating more restorative practices, especially after days of high physical strain (as seen on the 16th and 17th). Ensure adequate rest, consider active recovery strategies, and allocate time for relaxation.
- 2. Deep Work Sessions:**
 - Continue to schedule deep work in the earlier part of the week (similar to the 14th and 15th) when your mood and HRV metrics were higher. Aim to set clear, achievable goals that can maintain motivation and focus.
- 3. Mindfulness and Stress Management:**
 - Practice stress-reduction techniques (like meditation or mindfulness) more regularly, particularly on days with higher strain. This can help keep mood levels stable and improve overall resilience.
- 4. Physical Activity:**
 - Integrate lighter exercise or movement on days with less high-intensity training to keep energy levels up, particularly in cooler or rainy weather.
- 5. Sleep Hygiene:**
 - Maintain a consistent sleep schedule with improved sleep hygiene practices—limit screen time before bed, create a relaxing sleep environment, and consider pre-sleep routines (like reading).

Do Less Of:

- 1. High-Strain Activities Without Adequate Rest:**
 - Be cautious about pushing through high-intensity workouts without balancing them with recovery days. Avoid scheduling demanding workouts after days of high physical strain to prevent burnout.
- 2. Late-Day Coffee or Stimulants:**
 - Reduce intake of caffeine or stimulants, particularly later in the day, as they can disrupt sleep quality, contributing to lower mood and focus the next day.
- 3. Screen Time:**
 - Limit evening screen time, especially on days following strenuous activities. This can improve sleep quality and enhance overall mood and recovery.
- 4. Off-Task Time:**
 - Aim to manage off-task time more effectively. On days when you find yourself engaging in unproductive activities, create intentional breaks that allow you to reset without leading to lost focus.

Figure 7: Worked example of AURA coaching ability, combining data and advice

6.5.3 How AURA Did It

- **file_search** reviewed the full week's journal entries to track mood, focus, and self-reported distractions.
- **function calling** pulled WHOOP data for strain, recovery, and sleep patterns.
- **code_interpreter** analysed correlations and daily sequences to identify which activities coincided with dips or improvements.
- **LLM reasoning** generated clear behavioural recommendations tailored to personal patterns, not generic advice.

6.5.4 ChatGPT Comparison

ChatGPT responded with general wellness tips:

"You should aim for better sleep, stay hydrated, avoid too much screen time, and get exercise. Try to reflect on what helped you feel best."

While well-intentioned, this response was vague and impersonal in comparison.

6.5.5 Commentary

This was one of the most useful, **actionable** outputs AURA generated. Unlike the correlation or visual analysis examples, this one felt like a personalised strategy coach. AURA reviewed an entire week's data, spotted what helped or hurt performance, and translated that into simple "do more / do less" rules. This isn't just helpful — it's behavioral feedback in its most usable form. No single tool could've done this alone; it took AURA's ability to reason across context, structure, and memory to make it happen.

7. Summary and Conclusions

This project introduced AURA, a personalised mind-body insight assistant built using the OpenAI Assistants API. By integrating WHOOP biometrics, daily journal entries, productivity logs, and weather data, AURA provides a novel, context-rich interface for wellness and performance reflection. Unlike generic assistants such as ChatGPT, AURA delivers specific, data-driven recommendations grounded in the user's real history.

Three core tools — file search, function calling, and the code interpreter — were leveraged in tandem to enable this assistant to retrieve personal context, integrate dynamic real-world inputs, and analyse patterns through code-based computation. This multi-tool integration

transforms the assistant from a conversational model into a personal analyst and coach.

While the current version already identifies behavioral patterns and suggests tailored actions, there is strong potential to further evolve AURA by reducing friction, improving intelligence, and expanding reach. Key next steps include:

- **Conversational Memory, Goal Tracking, and Long-Term Insight**

Equip AURA with memory of past conversations, insights, and user-defined goals — enabling it to follow up over time (e.g. “Did avoiding late-night screens help your recovery this week?”).

- **Multi-Wearable Support**

Expand integration beyond WHOOP to include popular platforms like Apple Health, Garmin, and Fitbit — making AURA accessible to more users with different tracking devices.

- **Passive Productivity Tracking**

Replace manual Notion logs with automated tools (e.g., screen time APIs, RescueTime) to passively track digital focus and off-task time — removing the need for user input.

- **Smart Journal Integration**

Connect AURA with users’ preferred journaling platforms (such as Notion, Apple Notes, or Day One) and extract mood, stress, and focus indicators using an API.

Ultimately, AURA serves as a blueprint for how LLM-based assistants can support more intentional living by combining subjective experience with objective data. The assistant’s strength lies not in novelty of tools used, but in how they are orchestrated to offer clarity, self-understanding, and personalised behavior change. Future iterations may extend this foundation — but even in its current form, AURA represents a compelling case for LLMs as intelligent wellness partners

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