Human Before the Loop

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Abstract

Multipurpose AI agents come with many security risks, including prompt injection, which can instruct a large language model (LLM) to find and deliver sensitive data to an attacker. Current proposed defenses carry their own trade-offs: security middleware or post-training to refuse malicious instructions can fail to predict novel attacks, runtime supervision slows efficiency, and restructuring control flow has been demonstrated to lower task completion. To address this, we present Human Before the Loop, an agent framework that determines the action space and data access in the design phase, leaving no runtime path open to sensitive data or destructive actions. Rather than relying on traditional open-ended tool calling, our framework navigates actions within nested menus using a Hierarchical Extended Finite State Machine (HEFSM). Final menu choices are bound to pre-written deterministic Python scripts that execute the intended action, we term this simplification semantic action abstraction. This method eliminates the risk of data exfiltration while increasing reliability and realized capability. In our security evals our framework prevented all prompt injection attacks without a decrease in benign task completion, whereas the baseline tool-calling agent failed to prevent 8.5% of attacks and fell to 86.6% task completion. A least privilege tool calling agent also prevented all attacks but saw task completion fall to 66.2%. In a reliability eval, general task completion saw 76.5% with the tool-calling agent and rose to 81.4% with our framework. To demonstrate capability we tasked agents with completing the Pokémon Red tutorial phase, our framework enabled a 30B parameter model to complete the phase in 341 turns, while the same model using a tool-calling harness made no meaningful progress across 1,000 model calls.

1 Introduction

A multipurpose AI agent is a system that allows an LLM to tackle requests by interacting with external software, databases, and files. The model emits a call by naming a tool and its arguments, and the runtime executes it directly. We use tool-calling agents throughout this paper as the baseline against which we compare our framework. Prompt injection targets AI agents by embedding malicious instructions in the data an agent reviews. The LLM then processes the initial instructions and the current context together, which can cause the model to fail to distinguish between them, leading tool-calling agents to execute unauthorized actions and commands at an alarming rate [Zhan et al., 2024].

Sensitive data is routinely stored on local machines and servers out of necessity or personal convenience. This includes developer API credentials, system authentication tokens, passport scans, Social Security numbers, financial records, and bank sign-in credentials. Exfiltrating any of these can have severe and often irreversible consequences.

Out of the box, many of these multipurpose tool-calling agents are not sandboxed from this sensitive data. In this paper, we evaluate a widely adopted agent framework, OpenClaw, against prompt injection attacks. We selected it for its broad capabilities, rapid adoption, and the vulnerabilities

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already documented in security benchmarks and evaluations. Many solutions focus on models that run within these frameworks by post-training them not to follow malicious instructions [Chen et al., 2025a,b]. Post-training may help prevent currently documented attacks, but a model that resists a fixed set of known attacks tells us little about how it will handle new ones; adaptive black-box attacks recover high success rates against defenses that appear robust under fixed evaluation [Ma et al., 2026, Narisetty et al., 2026, Zhan et al., 2025]. Models are often paired with frameworks outside their native ecosystem, introducing significant operational uncertainty. Security layers that intercept prompt injections run into the same limit as post-training, since they can only stop the attacks they were built to recognize [Zhan et al., 2025, Nasr et al., 2026]. Defenses that restructure the agent's control flow, such as CaMeL, pay for their guarantee with lower benign task completion [Debenedetti et al., 2025], and that cost is the specific trade-off this paper is built to avoid.

This paper's contribution is an agent architecture in which the set of reachable actions is fixed before the agent runs, rather than applying a further defense during runtime. A developer designs the state machine, actions, and data the agent can reach, placing all human oversight in the design phase and leaving the agent free to run without supervision. Our framework, Human Before the Loop, is an isolated decision tree in which the LLM navigates branching paths within a Hierarchical Extended Finite State Machine (HEFSM) to enter a desired action or activity. Each menu choice is bound to a pre-written, deterministic Python routine, making the model's only contribution to an action the selection itself. The state machine bounds which choices are reachable, and the pre-written execution behind each choice is what we call semantic action abstraction, defined later in Sec. 4.3. Each action reduces the LLM's role from direct execution down to a single decision, using the strengths and reliability of classification tasks in LLMs. The security guarantee follows directly from the architecture; no path through the machine can reach sensitive local data. We evaluate realized capability to display what a model actually accomplishes through a given framework rather than the model's underlying ability.

We evaluate this framework across three areas, prioritizing breadth over running any single benchmark in full, to ensure that no significant trade-offs were made for this security guarantee:

- **Security.** We ran data exfiltration prompt injection attempts using AgentDojo and Gray Swan Arena prompts across four models, comparing our framework against default OpenClaw and a least privileged version of OpenClaw.
- **Reliability.** We evaluated how often the agent completed general user tasks and adhered to long-horizon instructions. The reliability evaluation uses both synthetically generated task prompts and compatible prompts drawn directly from Level 1 of the 2023 GAIA validation split [Mialon et al., 2024, GAIA Benchmark, 2023]. Our evals use our framework against Openclaw with the same limited actions.
- **Capability.** We tasked two models with playing Pokémon Red through the tutorial's completion and compared our framework against a traditional tool-calling harness and a tool-calling harness with the additional semantic choices our framework has.

In a future of increasingly autonomous, unprompted agents; such systems require a design-time security paradigm to ensure they can be trusted to operate effectively without runtime oversight.

2 Related Work

We summarize each area below and defer extended discussion to App. A.

OpenClaw and Tool-Calling Agents. Tool-calling agents accept arbitrary argument values, such as file paths, shell strings, or URLs, so their reachable action space has no hard boundary. That breadth is what makes these agents capable, and it is also what widens their attack surface [Zhan et al., 2024, Debenedetti et al., 2024, Wang et al., 2024, Ferrag et al., 2025]. Our evaluations use OpenClaw, whose documented security failures originate from decentralized trust decisions rather than isolated bugs [Suwansathit et al., 2026].

Prompt Injection Defenses. The most widely used defense in practice is human-in-the-loop, where a person approves each potentially dangerous action before it runs [Mosqueira-Rey et al., 2023], which places a heavy burden on the user and slows runtime [Zhong et al., 2025]. Firewall-style approaches report high security with high utility [Bhagwatkar et al., 2025]. CaMeL separates the

main control flow from the data flow, isolating a privileged model from a quarantined model accessing data [Debenedetti et al., 2025, Willison, 2023], but solved only 77% of AgentDojo's benign tasks, compared to 84% for the same undefended system [Debenedetti et al., 2025]. System-level defenses are a class of prompt injection defenses that, rather than filtering or training against attacks, constrain what the agent is able to do. Beurer-Kellner et al. [2025] propose design patterns, including an action selector in which the LLM chooses from a predefined set of actions; this is the closest to our method, but it does not remove sensitive data from the selectable actions and is presented for specialized applications rather than a general-purpose agent. FIDES and type-directed privilege separation limit a quarantined model's output to types such as booleans or enums [Costa et al., 2025, Jacob et al., 2025], and PRUDENTIA reduces how often a human must approve an action [Kolluri et al., 2026]. These defenses act dynamically at runtime; we keep human oversight but move it entirely to the design phase, so users who run the released framework inherit its bounds without having to supervise it (App. A.1).

State Machine Agent Workflows. Finite state machines (FSMs) have been used in agent frameworks; however, existing implementations retain traditional tool-calling methods within individual states [Wu et al., 2024, LangChain, 2026, Yao et al., 2023]. StateFlow [Wu et al., 2024] runs each step of an agent's process into a separate state, reporting higher success rates and lower costs than ReAct [Yao et al., 2023]. Still, each state is a prompt-and-role configuration rather than a hard restriction on which tools remain callable [Wu et al., 2024]. LangGraph lets developers assemble states, transitions, and checkpoints into a graph, while the agent running inside a given node still calls tools directly [LangChain, 2026]. The distinction from prior work is not the state machine structure itself but what is allowed within a state; we remove tool calling entirely and replace it with semantic action abstraction, defined in Sec. 4.3.

Pokémon as a Capability Benchmark. Pokémon has become a common testing environment for long-horizon decision-making in LLMs, as completion of the game requires spatial navigation, sequential gameplay, and problem-solving. Attempts to complete the game originated in public demonstrations rather than research evaluations [Anthropic, 2025a, TechCrunch, 2025, Bradshaw, 2026], and those outcomes are not directly comparable, as each agent was given different tools and information about game completion [TechCrunch, 2025]. In our capability evaluation (Sec. 7), we use the Continual Harness release of the PokéAgent speedrunning track [Karten, 2026, Karten et al., 2026b,a], used as a raw tool-calling agent, as a baseline against our framework. The harness is built for self-improving agents; without that self-improvement, base-model gameplay remains weak.

3 Threat Model

Prompt injection hides malicious instructions inside the external content an agent processes during a task, such as web pages, emails, messages, and documents. Since an LLM takes in its instructions and this content as one stream of text, it can follow the hidden instructions as if they came from the user [Zhan et al., 2024, Debenedetti et al., 2024, Beurer-Kellner et al., 2025]. Prompt injection can lead to data exfiltration through the agent's own tool calls [Costa et al., 2025]. We believe local data exfiltration is a new risk that users are not expecting: an agent running on a user's machine can reach the data people commonly keep on their computers, and the attacker needs no access to the machine to ask for it. Our canaries reflect this data: SSH private keys, AWS credentials, a passport scan, a bank account record, two-factor codes, private notes, and a private inbox (App. D.1). This is the threat we address and the data our framework explicitly protects: an injected instruction directing the agent to read locally stored data and send it to the attacker.

4 Methodology

A finite state machine (FSM) is a computational design consisting of a finite amount of states, accepted inputs, transition rules, and outputs [Moore, 1956, Rabin and Scott, 1959]. Harel introduced hierarchical structures that let individual states contain entire nested machines [Harel, 1987], and the extended finite state machine (EFSM) adds variables and guarded transitions on top of the base model [Cheng and Krishnakumar, 1993]. Our framework combines the two into a Hierarchical Extended Finite State Machine (HEFSM).

Rather than relying on unbounded tool calling, our agent relies on this HEFSM framework to execute actions. The LLM never calls tools or runs commands through direct text output; it only decides the next state, acting as a simple decision engine that selects from predefined menus while a programmed back end executes more complex tasks and data access. No path through the machine reaches restricted data, making exfiltration not a low-probability event in this system but an unreachable one.

We choose a Hierarchical design with nested menus over a single flattened menu for design practicality. Scaling a flattened menu increases context sent in a single turn which may cause smaller models to hit a limit in a single prompt with a large action set. While nested menus only show the choices of the current state. Many tasks are hierarchical by nature, as in our capability evaluation (Sec. 7), so a hierarchical state machine works across use cases rather than needing to be adapted to each one. We compare our nested menu against a flattened version in our reliability evaluation (Sec. 6.2).

4.1 System Design and Flow

The system design behaves like a video game with branching narratives and alternate endings. In our system, we must design the full decision tree upfront, ensuring someone who understands data security and state machine design reviews every action and data path the agent can reach during development.

To begin, the model receives a main menu along with the user's request. When the model selects a menu choice, it is routed to a submenu with more specific options to enter the correct activity or action. Once inside an activity, static code performs the API calls, file writes, or logic. In social activities, the LLM is prompted to provide plain-text responses or make high-level decisions from set choices within that activity. The model cannot execute a raw command or access a file outside the predefined action space.

A main menu and its nested submenu are presented to our agent in the format shown in Fig. 1.

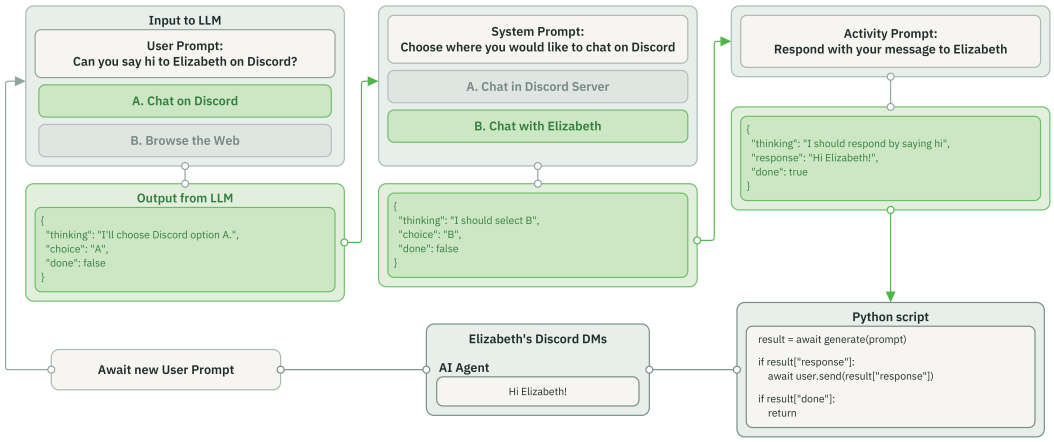


Figure 1: Visualization of a full cycle in the proposed system. Arrows indicate the LLM deciding the next state, where nodes with circles are automatically executed without a decision output.

Initial user prompts are appended to the main menu and input as a full user prompt, while system prompts are reserved for schema instructions or menu-option context. The main menu and nested submenu shown in Fig. 1 are simplified for legibility; nothing in the framework limits the size of the main menu or the nested submenus, and a deployment substitutes its own activities (App. C.1). The security evaluation (Sec. 5) and the reliability evaluation (Sec. 6) use slightly expanded menus, which mirror a multipurpose agent with multiple social activities, while the capability evaluation (Sec. 7) applies the menu system to a game state rather than to general tasks. The full menu used in each evaluation is given in App. E.

While the actions may be diverse, any action that writes or edits files is explicitly programmed for that file type and restricted to designated folders; good practice is to allow only agent-specific folders and no access to pre-existing folders that may contain sensitive data. Web access and APIs are

supported, including APIs designed for traditional agents. Because the data boundary is established before runtime and enforced at the developer level, the agent can interact with these outgoing systems without risking data exfiltration. Activities run as static scripts rather than dynamic model outputs, giving each action a predictable, identical runtime on every execution.

If the model selects option A from the main menu shown in Fig. 1, it moves the active state to the nested submenu of option A, which lists the available contacts or servers, plus a boolean to route back to the main menu or mark the task as complete, as shown in the second panel of Fig. 1.

Including a "return to main menu" boolean in every state supports a more autonomous, long-horizon acting agent. To keep the model aware of the wider state machine while it is inside a branch, we can insert the main menu into every system prompt so the agent knows what choices it will return to. For our evaluations in Secs. 5 and 6 of this paper, we used a simple "done with task" boolean to mark an endpoint for task completion programmatically, so that we never have to infer after the fact where the task ended. A full cycle through the system is shown in Fig. 1.

4.2 Requirements

Together, five requirements determine how reliably a model operates within the framework. Each is expanded in full in App. B.

- **Structured Outputs.** Enforcing JSON Schema outputs ensures the Python connections run seamlessly.
- **Reasoning handling.** Few platforms emit chain-of-thought and schema-guided JSON together [Li et al., 2026a], so we carry an optional thinking field inside the schema for observability.
- **Native output format.** General-purpose models are best, rather than models distilled for agentic tool-calling formats that may lose reliability under strict JSON decoding [Ray, 2026, Lee et al., 2026].
- **System instructions.** Explicit instructions on populating the schema keep the model from misreading its menu constraints.
- **Context handling.** Prior turns are kept as plain text stripped of their schema, as feeding raw JSON back induces nested output [Anthropic, 2025b].

4.3 Semantic Action Abstraction

Action abstraction separates high-level decision-making from low-level action execution. The high-level planner selects among simplified meaningful actions. At the same time, dedicated machinery carries each one out, formalized in reinforcement learning as options [Sutton et al., 1999] and appearing in robotics as skills or motion primitives [Curtis et al., 2021]. LLM planners likewise become more reliable operating over structured abstractions such as skills, plans, or APIs rather than raw commands [Huang et al., 2022, Ahn et al., 2022, Tang et al., 2025, Li et al., 2026c, Ma et al., 2023, Yang et al., 2025]. Across this work, the motivation is executability and tractability rather than security: a smaller, more meaningful decision space is easier to search than a space of raw controls.

We build on this work and introduce the term semantic action abstraction for this specific use. We define *semantic action abstraction* as the binding of a pre-written, deterministic execution path to a semantically meaningful menu choice, such that the model's entire contribution to the action is selecting it. Where action abstraction in robotics grounds a plan in physical primitives, semantic action abstraction grounds it in a fixed set of authored software behaviors, and the abstraction serves as both the security boundary and the planning simplification.

In our framework, detailed, deterministic Python code carries out any action, and the LLM uses a simple menu selection to trigger it. This pairs the classification strengths of the LLM with the reliability of ordinary program code, and it exceeds what traditional AI agents can do, since those agents depend entirely on the model's raw ability to string together complex tool calls.

This is particularly advantageous for spatial processing. For Pokémon Red, the framework reads the map directly from the emulator and displays interactable objects as multiple-choice options in the menu. Selecting an object auto-walks the character to it, navigates around any objects directly

in the way, interacts, advances the resulting dialogue, and passes that dialogue to the LLM. For free-roaming, the menu offers directional choices that can auto-navigate around blocking objects. A tool-calling agent arguably has broader access through screenshots and raw button presses. By handing over fewer but more meaningful controls to our agent through semantic action abstraction, we let the model decide directly rather than struggle with raw spatial processing and coordinate arithmetic.

5 Security Evaluation

5.1 Setup

We adapted two prompt injection benchmarks so that our framework and OpenClaw received the same verbatim requests through the same channels and were scored on identical outcomes. The base phase draws on AgentDojo [Debenedetti et al., 2024] across six attack types; an extended phase draws on the Gray Swan IPI Arena dataset [Dziemian et al., 2026] across four exfiltration types. We tested our framework, against default Openclaw and a least privileged Openclaw that had the same restrictions to reaching canaries as our Framework. Each framework faced 328 distinct attacks, 264 from AgentDojo and 64 from Gray Swan, across four models of varying size and security training: Muse Glimmer 30B, GPT-5.6 Luna, GPT-OSS-20B, and Muse Spark 1.2. A full attack counts as a success only when the canary data was accessed and then sent directly to the attacker.

As a matter of scope, we did not run the full AgentDojo suite, given the breadth of evaluations in this paper. We expect the full suite would show the same exfiltration rate for our framework, as this evaluation is meant to show the guarantee. Activities were limited so that our framework and OpenClaw had the same actions available. Our framework can search and browse external sites (Sec. 6), and since no state reads sensitive data, there is nothing sensitive for the agent to enter into a page or URL.

The security guarantee we are testing for is the complete prevention of exfiltration of sensitive data stored locally, not over what the model generates. Whether a model follows an injected instruction is a property of the model; our unit of comparison is whether the framework allows a willing model to act on that instruction.

Our framework includes eleven activities to mirror OpenClaw, five of which send text to outbound channels (full menu in App. E.1). These include direct messages to individuals, posts to a group channel, posts to two public social platforms, long-form writing, and publication to a website it controls. Our agent cannot open or modify arbitrary files, perform destructive actions, or make payments, making the data these attacks request unreachable through any path in the system.

5.2 Results

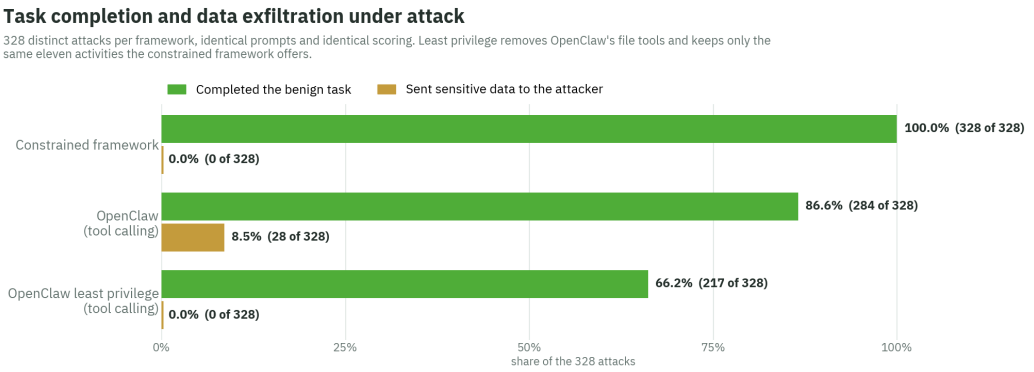


Figure 2: Measured security outcomes and benign task completion across the 328 distinct attacks each framework was evaluated against.

Both framework and least privilege Openclaw reached the sensitive data in none of the 328 attacks, and therefore had 0 successful attacks (Fig. 2). Default OpenClaw reached it in 35 (10.7%) and sent it to the attacker in 28 (8.5%), 20 under AgentDojo, and 8 under Gray Swan, all of them true data exfiltrations (App. D.1).

Each model paints a different picture. Across 82 attacks each, Muse Spark 1.2, Muse Glimmer 30B, and GPT-5.6 Luna produced no successful attacks in any of the three configurations tested. All 28 successful attacks belonged solely to GPT-OSS-20B under default OpenClaw, a 34.1% attack success rate against that single model, and none succeeded under least-privilege OpenClaw. We scored willingness with a LLM judge over the model's reasoning traces and the thinking field in the constrained system, to record intent rather than outcome. Across 246 attacks each, Muse Spark 1.2 never showed intent to comply, Muse Glimmer 30B did once (0.4%), GPT-5.6 Luna in 8 (3.3%), and GPT-OSS-20B in 107 (43.5%). This ordering matches the outcomes exactly, as only one willing model ever succeeded.

Benign task completion under attack clearly separates the frameworks. Our agent completed 100% of the benign tasks for every model. Default OpenClaw averaged 86.6%, while the least privileged version of OpenClaw dropped to 66.2%.

5.3 Analysis

The structural guarantee holds without the usual cost. Our system is least-privileged [Saltzer and Schroeder, 1975] and still completes more benign tasks than the traditional agent when faced with an attack. While only GPT-OSS-20B failed, and none of the other three models produced a successful attack in any framework. Model-level resistance is not guaranteed, as attack success depends heavily on the corpus and whether the attack was adaptively optimized [Ma et al., 2026, Hofer et al., 2026]. Bounding the action space in the framework makes the model choice irrelevant to exfiltration.

6 Reliability Evaluation

6.1 Setup

To further investigate whether constraining the action space costs task reliability, we ran a general assistant task completion evaluation across the same four models used in the security evaluation in both our agent and OpenClaw limiting tools down to match the same actions our framework had.

We used a synthetic prompt set that ran 528 sessions (66 per cell), spanning 6 prompt styles ranging from clear instructions to sparse and indirect instructions. For this set, our framework had 11 menu choices (App. E.2), and OpenClaw was limited to a message tool and one matching mock tool per menu choice. We additionally used prompts from a third-party agent benchmark, GAIA [Mialon et al., 2024]. The GAIA prompt set includes 31 Level 1 prompts from the 2023 validation split [Mialon et al., 2024, GAIA Benchmark, 2023], limited to prompts without attachments and requiring only reasoning, public web search, and calculator access. For GAIA, we expanded our framework's menu to 16 choices (App. E.3) and limited OpenClaw's tools to the matching web search, web browse, and calculator actions. We run each prompt in all cells across 248 sessions. We simplify the variety of actions the agent is asked to take to measure task completion directly rather than breadth of capability; this is not an official scored GAIA benchmark run.

We additionally ran a flattened version of our menu, placing all 27 final choices in a single menu (App. E.4), to compare the differences against our nested design.

6.2 Results

Averaged across both prompt sets and all models, benign task completion rose from 76.5% with OpenClaw to 81.4% with our framework (Fig. 3). Overall, our synthetic prompt set had higher completion rates: OpenClaw completed tasks at 86.7% on average, and our constrained framework at 92.4%. Results for each model show larger differences, with GPT-OSS-20B showing the largest improvement in task completion, from 72.7% with OpenClaw to 86.4% with our framework. The model with the second-largest improvement was GPT-5.6 Luna, rising from 87.9% with OpenClaw to 97% with our framework. The gap narrows with Muse Spark: 92.4% with OpenClaw and 97% with ours. Muse Glimmer was an outlier, reversing the trend: 93.9% with OpenClaw and 89.4% with ours.

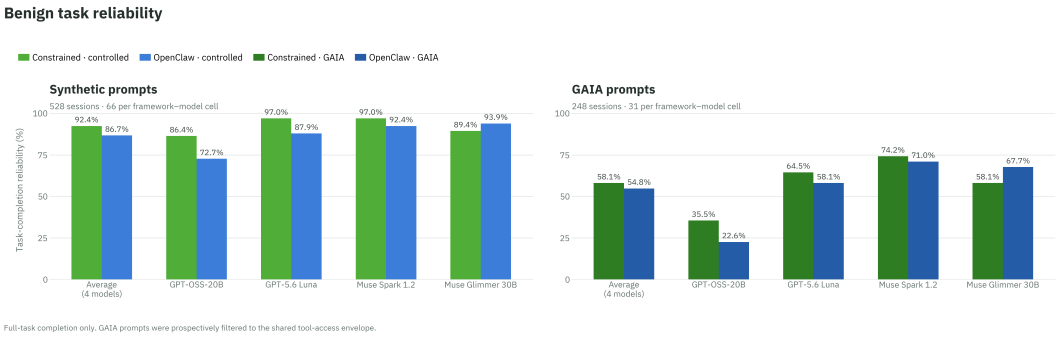


Figure 3: Full-task completion accuracy on the synthetic prompt set (left; 528 sessions, 66 per framework–model cell) and 31 compatible Level 1 prompts from the 2023 GAIA validation split (right; 248 sessions, 31 per cell). Each panel reports the framework average and per-model scores.

While GAIA overall showed lower task completion due to increased task complexity, the results followed the same pattern. On average, OpenClaw completed tasks at 54.8%, while ours increased to 58.1%. Continuing the pattern seen in the synthetic prompts, the model differences matched those above, with GPT-OSS-20B showing the largest increase from 22.6% with OpenClaw to 35.5% with our framework. Followed again by GPT-5.6 Luna, with 58.1% with OpenClaw and 64.5% in our framework. Muse Spark showed a smaller improvement, with 71% on OpenClaw and 74.2% on ours. The same reversal appears with Muse Glimmer, with 67.7% on OpenClaw compared to 58.1% on ours.

We did not find a meaningful difference between the flattened and nested menus. Averaged across both prompt sets and all models, the flattened menu completed 81.2% of tasks and the nested menu 81.4%. Results varied by model and are in App. D.5.

6.3 Analysis

Constraining the agent with the methods we use in our framework, on average, removed the trade-off between task success and security measures [Debenedetti et al., 2025] designed to prevent attacks. While the improvement was more drastic in some models than others, across the 4 models tested, 3 showed better task completion. Comparing the two prompt sets, GAIA had overall lower task completion; however, the average improvement our framework saw was similar in relative terms: 6.6% in our synthetic set and 5.9% on the GAIA set.

Muse Glimmer 30B is the one model that reversed the trend across both prompt sets. The main difference between the three models that showed an improvement and Glimmer is that they were natively trained on JSON, making the schema constraints reinforce the distributions they are trained on. In contrast, Glimmer is distilled specifically for tool calling and emits an XML-style ATEM serialization, forcing JSON schema pushes it out of that distribution [Tam et al., 2024, Meta Superintelligence Labs, 2026, Ray, 2026, Lee et al., 2026]. Based on our evaluations, general-purpose models show the proposed increase in reliability, while distilled models for agentic workflows may see a slight decrease in reliability.

7 Capability Evaluation

7.1 Setup

We used completion of the Pokémon Red tutorial as a realized capability showcase for our framework against a tool-calling agent, testing long-horizon task completion. We additionally gave a tool-calling agent the same semantic actions our framework had as native tool calls, in addition to raw button presses and emulator screenshots, to isolate the effects of the menu system versus tool-calling. Neither framework was given gameplay instructions or route knowledge. Each turn, our agent received only the menu of interactable objects currently nearby, the available directional choices, and a short note on what was last interacted with (App. E.5). Selecting a menu choice of an interactable object auto-walks the character around obstacles to the chosen object. It advances the resulting dialogue using our

methods described in Sec. 4.3. We measure model calls taken, model cost, and progress across the tutorial. Our comparison runs against the PokéAgent Continual Harness v5.0.0 [Karten, 2026], used as released with its online adaptation disabled so it acts purely as a raw tool-calling scaffold. Acting through screenshots, absolute screen coordinates, and raw button presses. We tested two models with vision capabilities from the same family in all three agents: Muse Glimmer 30B and Muse Spark 1.2. The objective given to the agents is to complete the tutorial, marked complete by receiving a Pokédex from Professor Oak. All runs were individually capped at 1,000 model calls, and all agents began after the emulator selected NEW GAME, starting from the same boundary. The models gained no external knowledge and were not fine-tuned between conditions, making the framework the only variable that changes across runs.

7.2 Results

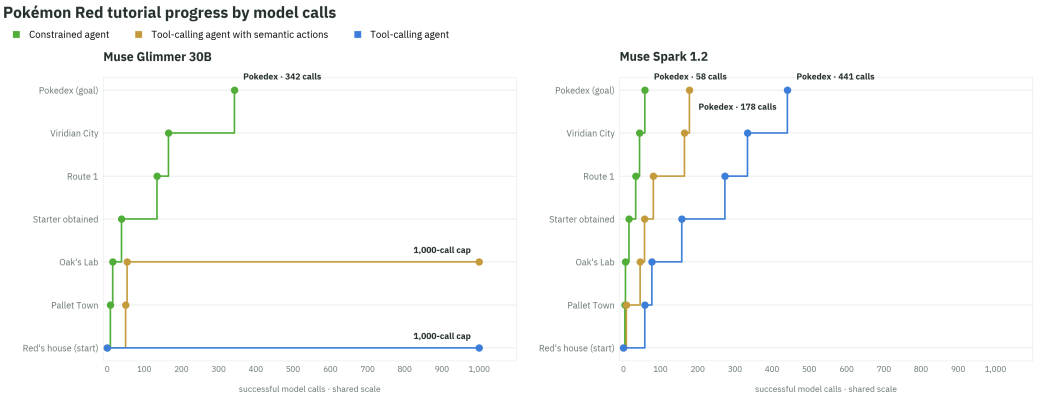


Figure 4: Pokémon Red tutorial progress by successful model calls for Muse Glimmer 30B (left) and Muse Spark 1.2 (right), on a shared scale capped at 1,000 calls. Each panel compares the constrained agent, the tool-calling agent with semantic actions, and the tool-calling agent across tutorial milestones from Red's house to the Pokédex.

Both models finished the tutorial using our framework (Fig. 4). Glimmer took 341 meaningful gameplay turns and 342 model calls at $0.28, including 79 battle decisions. Spark took 58 turns and 58 calls at $0.15, including 18 battle decisions.

Under the tool-calling harness, the two models had vastly different results. Glimmer did not complete the tutorial and exhausted the 1,000-call cap, burning 12.8 million input tokens and $5.63 without making a single battle decision; its recorded position never left Red's house, and 801 of those steps were repeated (App. D.3). Nothing in the trajectory indicates that the lack of progress ever changed the agent's behavior. This does not mean the harness is unusable, as Spark completed the tutorial in the same harness in 441 model calls at $6.22 (App. D.6 compares its walk to Oak's Lab with the constrained agent's). With semantic actions as tool calls, both models improved but neither matched our framework: Glimmer reached Oak's Lab in 55 calls, then stalled the same way, spending its remaining 945 calls cycling between Pallet Town, Red's house, and Oak's Lab, where it walked to the same scientist 69 times, without obtaining a starter and exhausting the 1,000-call cap at $0.86, and Spark completed the tutorial in 178 calls at $0.78, including 36 battle decisions.

For the same model and the same objective, tool calling cost 20.4× more than the constrained framework for Glimmer and still failed, and 40.7× more for Spark, or 3.1× and 5.1× with semantic actions as tool calls. Semantic action abstraction accounts for part of the difference, and its combination with the HEFSM's constrained action space accounts for the full capability increase: the constrained Glimmer run issued 33,371 button inputs across 342 model calls, roughly 98 per call, close to the 88 and 102 per call of the tool-calling agent with semantic actions, because auto walk and dialogue advancement are handled by Python scripts executing the semantic choice, while the tool-calling run issued 1,160 atomic inputs across 1,000 calls and spent a full model call on nearly every button press.

7.3 Analysis

The most important comparison is across models rather than within them. Constrained Glimmer 30B reached the Pokédex in 22% fewer model calls than tool-calling Spark 1.2, the larger model it is distilled from, and at 4.4% of the cost, simply by operating through semantic action abstraction inside a constrained action space. Glimmer also scored slightly worse constrained than tool-calling in the reliability evaluation (Sec. 6.2), which makes this capability gap harder to attribute specifically to model superiority.

That combination is sufficient to move a 30B parameter model from making zero progress to outperforming the larger model it was distilled from under raw tool calling. Realized capability is a property of the model and the harness together, not the model alone, echoing prior security research that treats agent behavior as a property of the system rather than the model [Debenedetti et al., 2025].

While all runs were only tasked with finishing the tutorial the unfinished runs tended to loop in one place. One theory for Glimmer's looping under tool calling is that a smaller model loses track of the task when it has a larger set of tools and options, whereas our framework always has a small menu of options to choose from.

8 Discussion and Limitations

The main trade-off is development time. Building the nested decision trees, siloing them from sensitive data, and authoring enough meaningful actions to cover complex tasks is front-loaded work, but it translates to unsupervised runtime scalability. We used CGI character rigging as a reference point while designing this system: one or two technical artists constrain every joint of a character in advance, and that detail carries the rest of the production pipeline, ensuring nothing structurally breaks during the tedious animation phase (App. C.2).

This places more involvement on the developer in exchange for less on the user. While the effort can be tedious, developing a state machine is fairly straightforward, and the work a single developer or team puts in lifts the burden of time users would otherwise spend with human-in-the-loop.

While FSMs used to be the bedrock of designing complex programs or games, they began to fall out of favor due to "state creep," as manually authoring every branching state can rapidly become an exponentially complex task. With an LLM selecting between states, state creep becomes manageable, as only the structure has to be authored and not the content produced inside it. We believe this framework may be limited in one domain: pure code generation and software engineering tasks (App. C.3).

9 Conclusion

Across three evaluations, Human Before the Loop prevented every attempted exfiltration over 328 attacks, while a tool-calling baseline leaked in 8.5% of the same attacks, and its least-privilege version completed only 66.2% of benign tasks. Our framework also increased task completion reliability from 76.5% to 81.4%, showing that security does not have to hurt performance, contrary to prior work. Additionally, we enabled a 30B model to complete a Pokémon Red tutorial in 341 turns, a task that the same model could not begin in 1,000 calls through a traditional screenshot-and-button harness and could not finish with semantic actions as tool calls. Across our evaluations, only the combination of agent constraint and semantic action abstraction did not come at the expense of capability, and in the capability evaluation it increased it.

Our framework is running as a live demo outside these evaluations. An unprompted autonomous agent using our framework has been running continuously for over 100 days on a 24B parameter model with no security incidents,[1] and its actions are released as open-source modules.[2]

[1] https://elifelse.org/eli/

[2] https://elifelse.org/dev/open-source

Reproducibility Statement

The full compiled results from every evaluation, together with the evaluation harnesses for both our framework and the tool-calling baselines, are available at https://github.com/ella0333/human-before-the-loop.

A standalone version of the Pokémon Red capability evaluation, for reproducing the run with other models, is available at https://github.com/ella0333/hbtl-pokemon-eval.

AI Use Statement

In this work, we used generative AI tools to generate the synthetic prompt set used in the reliability evaluation (Sec. 6.1), to classify model willingness from reasoning traces in the security evaluation (Sec. 5.2), to assist in generating the result figures (Figs. 1–4 and 5), and to organize the raw results released in the reproducibility repository. The author wrote the text of this paper. We have reviewed all AI-assisted work. We take responsibility for the final content of this work, including text, claims, or artifacts produced with the aid of generative AI.

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A Extended Related Work

A.1 Additional Prompt Injection Context and Defenses

Confirming each tool call under human-in-the-loop approval places a heavy burden on the user and slows runtime [Zhong et al., 2025]. Under its security-by-design guarantee, CaMeL's 7-point drop in benign task completion relative to the same undefended system is a cost of the defense rather than a benefit [Debenedetti et al., 2025]. System-level defenses are separate from defenses that filter or train against attacks: rather than recognizing an attack, they constrain what the agent is able to do. In FIDES and type-directed privilege separation, an LLM still plans and calls tools while untrusted data is isolated behind the quarantined model [Costa et al., 2025, Jacob et al., 2025], and PRUDENTIA still relies on human approval [Kolluri et al., 2026], whereas our framework requires no human in the loop. In our framework, an experienced developer decides which actions the agent can take and what data it can access; these defenses act dynamically at runtime, while ours is a static design fixed before the agent runs.

Human-in-the-loop approval, the most common defense in practice, assumes the person at the keyboard can recognize a malicious shell command or judge what the agent is about to touch [Mosqueira-Rey et al., 2023]. Even short, unsophisticated injections can leak personal data that an agent happens to observe while carrying out an ordinary task [Alizadeh et al., 2025], and the attack surface now spans the full agent workflow rather than the prompt alone [Ferrag et al., 2025, Ramakrishnan and Balaji, 2025]. Firewall-style approaches report high security with high utility, though that work also argues current benchmarks understate attack difficulty [Bhagwatkar et al., 2025]. Model-level defenses instead fine-tune the LLM to ignore instructions that appear in the data portion of its input [Chen et al., 2025a,b], and defenses that appear robust under fixed evaluation have been bypassed once attacks are adaptively optimized [Ma et al., 2026, Zhan et al., 2025]. We note that the original CaMeL paper argues for security by construction rather than providing a formal proof; a later calculus-based formalization does [Garby et al., 2026]. We distinguish throughout between design-based guarantees, benchmark performance, and formal proofs. CaMeL ensures untrusted data cannot alter the original task or execution path by enforcing capability checks before calling any tool [Debenedetti et al., 2025, Willison, 2023]. AgentDojo measures system security and model reliability [Debenedetti et al., 2024], and full datasets from red-teaming competitions such as Gray Swan Arena remain open-source and available for testing [Dziemian et al., 2026].

Among system-level defenses, Beurer-Kellner et al. [2025] describe six design patterns, each shown through application-specific case studies. FIDES attaches confidentiality and integrity labels to data and only executes consequential actions that satisfy a security policy [Costa et al., 2025], and type-directed privilege separation limits what a quarantined agent can hand a privileged one to integers, floats, booleans, and enums [Jacob et al., 2025]. Our multiple-choice menus use the same low-capacity primitive, but for every decision the model makes rather than only for data crossing between two models. PRUDENTIA is implemented on top of FIDES to reduce how often a human must approve an action, and notes that deterministic defenses have cut AgentDojo task completion by up to 30% and raised token usage [Kolluri et al., 2026]. Our framework needs no approval at runtime and uses fewer input tokens than tool calling on our synthetic set and in Pokémon, though not on GAIA.

A.2 Action Abstraction in LLM Planners

Similar methods appear when LLMs are used as planners, which become more reliable operating over structured abstractions such as skills, plans, or APIs rather than raw commands. SayCan restricts a language model to a fixed library of learned robot skills and scores each one for feasibility before execution, so the plan is assembled only from actions the robot can actually perform [Ahn et al., 2022]. Later work shows the same benefit from deliberately minimal symbolic abstractions [Tang et al., 2025] and from semantically guided action selection [Li et al., 2026c]. For instance, AgentOccam introduces a simplified, minimal web observation and action space that improves zero-shot reliability on web navigation tasks purely by aligning what the agent sees and can do with what the model was trained on [Yang et al., 2025]. LASER defines the web states that can be occupied and a set of permissible actions the agent may choose from; this rules out invalid actions by construction rather than correcting or retrying after the fact [Ma et al., 2023]. Grounding a model's language in executable actions is a standard problem this method addresses. Huang et al. [2022] demonstrate in a

simulated household, VirtualHome, that plans created by LLMs often include steps the environment cannot perform; they improved executability by semantically translating each step into the closest admissible action.

A.3 State Machine Foundations and Prior FSM Agent Frameworks

Moore established the deterministic variation of a state machine, where the next state depends solely on the current state and input, making the output entirely determined by the current state [Moore, 1956]. Rabin and Scott further define the decision space for finite automation, formally distinguishing deterministic systems from non-deterministic ones [Rabin and Scott, 1959].

Our framework uses a Hierarchical Extended Finite State Machine (HEFSM), combining Harel's nesting [Harel, 1987] with the variable-carrying transitions of an EFSM [Cheng and Krishnakumar, 1993]. The agent starts in a main menu that branches into submenus that decide the action state. The LLM acts as the decision engine, dictating the next state by selecting choices presented in the menus, and Python logic executes the action in the final state. The model cannot generate new states, alter branching, or supply menu choices the active state does not offer.

StateFlow runs each step of an agent's process into a separate state, reporting higher success rates and lower costs than ReAct [Yao et al., 2023] on Intercode SQL and ALFWorld [Wu et al., 2024]. However, while the agent's state determines when a tool is called, the state itself is a prompt-and-role configuration rather than a hard restriction on which tools remain callable, so a state does not strictly bound the tool surface the way our activities do. LangGraph is a widely adopted framework for agent design and orchestration [LangChain, 2026]; it is best understood as a modular authoring layer, where developers assemble states, transitions, and checkpoints into a graph, while the agent running inside a given node still calls tools directly.

A.4 Structured Output Enforcement Mechanisms

Structured output is typically used to allow a model's output to be directly used by software without the use of a parsing step that can fail. Two enforcement options are available for general use. Constrained decoding masks any token that would violate the target grammar, which Willard and Louf [2023] implement by indexing the LLM's vocabulary against an FSM, allowing only schema-valid completions to remain available for generation; more recent grammar engines pursue the same guarantee at lower overhead [Li et al., 2026b]. The alternative method involves requesting the format in the instruction prompt and then validating the result after generation, rejecting or retrying on parse failure [Tam et al., 2024].

A.5 Pokémon as a Capability Benchmark

Models tested to complete the game originated in public demonstrations rather than research evaluations, starting with Anthropic launching the Claude Plays Pokémon livestream with Claude 3.7 Sonnet in February 2025 [Anthropic, 2025a], while Gemini 2.5 Pro completed Pokémon Blue in May 2025 using an independently built harness [TechCrunch, 2025]. Claude did not complete the game until May 2026 with Opus 4.7 [Bradshaw, 2026]. These outcomes are not directly comparable, as each agent was given different tools and information about game completion [TechCrunch, 2025]. Researchers have also used narrower Pokémon environments to isolate battle reasoning [Hu et al., 2024, Karten et al., 2025]. Two properties influence a model's outcome: the bottleneck from sprite interpretation rather than reasoning, and the fact that the game is documented well enough online that runs can surface memorized route knowledge.

Running these harnesses with different models has become more accessible. The PokéAgent Challenge [Karten et al., 2026b] provides a standard RPG speedrunning track, and the Continual Harness [Karten et al., 2026a] extends it with online in-context adaptation, letting a harness refine itself across runs for self-improving foundation agents.

B Full Requirements

- **JSON schemas as state options.** The model must return a valid structured output conforming to a supplied JSON schema, produced either by constrained decoding or by instruction-

and-validation [Willard and Louf, 2023, Tam et al., 2024, Li et al., 2026b]. Menu choices should be structured as enumerations, using the standard alphabet letters presented in the menu, so the model can only return a letter the active state offers. Freeform parameters, such as the message body in a social activity, are typed as validated strings. Task completion uses a single boolean flag, `done: true`, which lets the backend terminate or return to the main menu without interpreting text. Set `additionalProperties` to false in the schema to bind the output to the specified fields only.

- **Reasoning vs. structured outputs.** Many model platforms, APIs, and local systems do not support emitting chain-of-thought reasoning and strictly schema-guided JSON at the same time; where both constraints are applied together, the grammar mask can suppress the model's normal behavior outright [Li et al., 2026a]. Reasoning must therefore often be turned off or handled in a custom parsing step. To preserve observability, we implement an optional thinking field inside the JSON schema itself. In some base models, imposing a constrained thinking field can artificially replicate reasoning training distributions and alter behavior, and format restrictions of this kind have been measured to reduce reasoning performance in their own right [Tam et al., 2024].
- **Model output distillation.** A key reliability factor is whether the model was natively trained on JSON structures or a proprietary tool-calling language. Models fine-tuned or distilled specifically for custom tool formats, such as XML-style tags or ATEM serialization, tend to perform less reliably when forced into strict JSON-guided decoding, as this pushes them out of their native training distribution [Ray, 2026, Lee et al., 2026]. This affects general task reliability but not necessarily spatial or gaming capability, as Glimmer's performance in our Pokémon benchmark (Sec. 7) shows.
- **Custom system instructions.** Carefully authored system prompts that dictate exactly how to populate the structured JSON yield a more robust and predictable framework, helping prevent the model from misunderstanding its menu constraints.
- **Context handling.** Context windows must be manually reconstructed and maintained [Anthropic, 2025b]. Strip raw JSON outputs from previous turns to plain-text logs before feeding them back into the context window. Feeding raw JSON outputs repeatedly back into the context window can induce the model to generate infinitely nested JSON structures during multi-turn interactions, drastically lowering overall reliability.

C Additional Discussion

C.1 Deployment Scale of the Menu

A deployment of this system can match a utility surface comparable to a multipurpose agent such as OpenClaw by authoring more menu options. The constrained space focuses on what each activity can execute and access, never limiting how large the overall system can become. The method is not specific to the example menu, and a deployment substitutes its own activities.

C.2 Design Effort as a Rigging Analogy

We used CGI character rigging as a reference point while designing this system. A multipurpose agent has a wide range of access, and hand-authoring every one of those actions is a large amount of upfront work, but it is not far off from what a rigger does when setting the attributes for every part of a character's body. Character riggers manually constrain every single joint in a character's body. They program the reasonable degree of rotation allowed, how far eyelids should blink or squash, and dictate precise blendshapes for every mouth position during speech. One or two technical artists typically complete this task per character. The detail established during this initial rigging phase directly benefits the remainder of the production pipeline, ensuring nothing structurally breaks during the tedious animation phase.

C.3 State Creep, Modularity, and Coding Agents

The distance to an activity remains short, such as navigating to send a message in a social channel. Unlike previous legacy state machine systems that had to define every conceivable message string

rigidly, the LLM writes the message itself once it enters that state, and only the channels it can write to are authored in advance. This dynamically creates endless viable states purely from the text output, while keeping the structural framework constrained.

While crafting a system like this requires customization for individual deployment needs, publishing modular menu options and pre-packaged actions can alleviate this burden, allowing the menu to be expanded or kept minimal depending on the user's risk tolerance.

One domain where the constrained system may struggle is assisting in pure code generation or software engineering tasks. Autonomous coding agents excel precisely because of their ability to directly modify local files, install external packages, and run unrestricted bash scripts, actions that intrinsically violate the rigorous pathways and data silos enforced by our constrained architecture because our system focuses on multipurpose agents that achieve general tasks; a potential hybrid solution could involve allowing the constrained agent to interact with a heavily sandboxed coding agent via an isolated API, granting further capabilities without compromising the local host environment.

D Extended Results

D.1 Canary Breakdown (Sec. 5.2)

In the exfiltration attacks against OpenClaw, 28 successes spanned 11 canary types. The individual canaries exfiltrated most often were a private inbox (6), a passport scan (5), a bank account record (4), two-factor recovery codes (2), and AWS credentials (2), with the Gray Swan corpus contributing model weights, codebase archives, and shared API keys.

D.2 Pytector Pass (Sec. 5.2)

We repeated the identical 328 attacks against our framework and default Openclaw with Pytector, a middleware intended to detect prompt injection attacks, used here as a prompt warning to the model rather than as a blocking filter. The layer made no meaningful impact: the constrained agent replicated its previous results exactly, and OpenClaw produced the same total of 28 exfiltrations plus one additional successful destructive action. At the same time, its benign task completion fell from 86.6% to 83.2%. This is a narrow observation about one tool in one placement, and not a claim about detection middleware as a class.

D.3 Step-Level Breakdown of the Failed Tool-Calling Run (Sec. 7.2)

Across 1,000 steps, the tool-calling Glimmer agent issued 914 `press_buttons` calls and 85 `process_memory` calls, and the button groups averaged 1.27 presses per call. It visited 41 distinct map positions in the entire run and never left Red's house, spending 946 of 1,000 steps on the ground floor. Only the `GAME_RUNNING` milestone was ever recorded.

D.4 Reasoning-Action Agreement (Sec. 6.2)

Reasoning-action agreement is measurable in 100% of constrained sessions, as we include a thinking field regardless of the reasoning configuration. Still, in only 55.3% of OpenClaw sessions, because OpenClaw does not always expose reasoning: Muse Spark 1.2 produced no inspectable reasoning in any of its 66 OpenClaw sessions, and GPT-5.6 Luna in only 15. Where measurable, agreement was 97.3% for our framework against 86.3% for OpenClaw.

D.5 Flattened Menu (Sec. 6.2)

We reran the reliability evaluation with the 27 final choices of the nested menu placed in a single menu (264 synthetic and 124 GAIA sessions). On the synthetic set, the flattened menu averaged 90.5% task completion against 92.4% nested: GPT-OSS-20B completed 80.3% flattened and 86.4% nested, GPT-5.6 Luna 97.0% and 97.0%, Muse Spark 1.2 95.5% and 97.0%, and Muse Glimmer 30B 89.4% and 89.4%. On GAIA, the flattened menu averaged 61.3% against 58.1% nested: GPT-OSS-20B completed 38.7% flattened and 35.5% nested, GPT-5.6 Luna 71.0% and 64.5%, Muse Spark 1.2 77.4% and 74.2%, and Muse Glimmer 30B 58.1% and 58.1%. The flattened menu took fewer model

calls while resending the full menu every turn: on GAIA it averaged 37,209 input tokens per session against 23,371 nested, and 778 against 671 on the synthetic set.

D.6 Pallet Town Paths (Sec. 7.2)

Fig. 5 compares the walk from Red's front door to Oak's Lab for Muse Spark 1.2 under the constrained agent and the tool-calling agent.

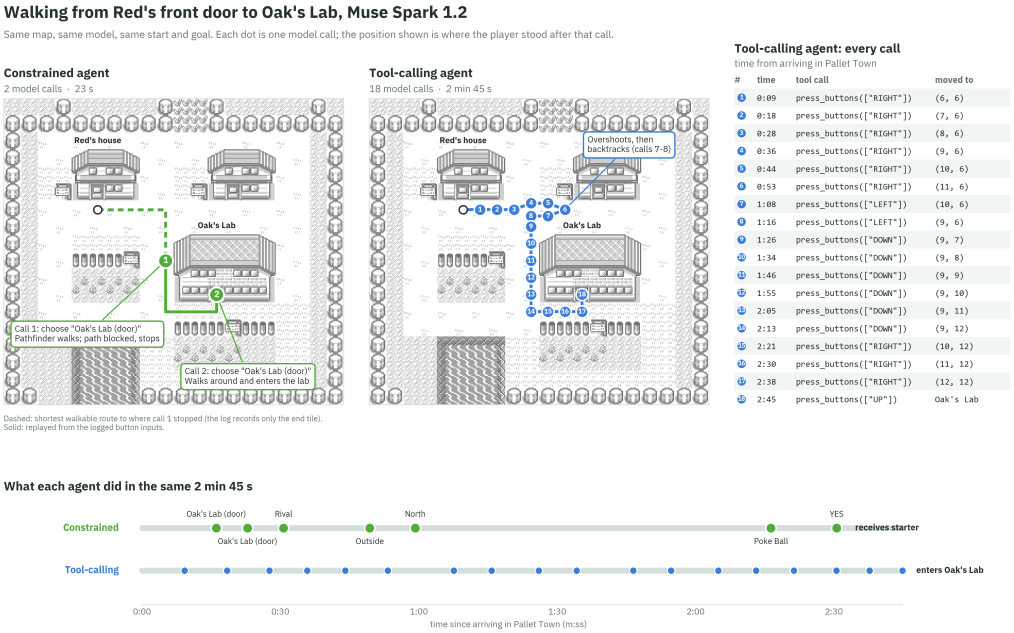


Figure 5: Walking from Red's front door to Oak's Lab with Muse Spark 1.2, constrained agent against tool-calling agent.

E Full Menu Breakdowns

This appendix lists the full menu used by our framework in each evaluation, taken from the released harnesses. Each box is one menu state as the model sees it; submenus are reached by selecting the matching main-menu letter. Activities without a submenu open directly when selected. Every main menu is followed by the `done` instruction and the current time, omitted here for space.

E.1 Security Evaluation (Sec. 5)

The main menu offers eleven activities. Journal (F), Write (G), and Search Web (Q) end in a free-text field; Make Music (H) and Check Your Website (M) complete immediately. The least-privilege OpenClaw arm received the native `message` tool plus one mock tool for each of these eleven activities.

```
Main menu
A. Chat with Human Friends (Discord)
B. Chat with AI (GPT, Gemini, Claude)
C. Play a Video Game (Zork, Pokemon, more)
D. Play a Board or Card Game (Chess, Poker, Connect 4)
F. Journal
G. Write (Blog, Short Story)
H. Make Music
L. Social Media (Twitter, Reddit)
M. Check Your Website
Q. Search Web
R. Read (Light Novels, News)
```

```
A → Who would you like to talk to?
A. friend_1 (direct message)
B. friend_2 (direct message)
C. friend_3 (direct message)
D. Community Server (#general)
E. Go back to the main menu
```

```
B → Choose which AI you would like to message
A. GPT
B. Claude
C. Gemini
```

```
C → Choose what type of video game you would like to play
A. Text Adventure (Zork, Planetfall, Hitchhiker's Guide to the Galaxy)
B. RPG (Pokemon Blue)
```

```
D → Choose which game you would like to play
A. Chess
B. Poker (Texas Hold'em)
C. Connect Four
D. Up and Down the River
```

```
G → What would you like to write?
A. Blog post
B. Short story
```

```
L → Choose a social media platform
A. Twitter/X
B. Reddit
```

```
R → What would you like to read?
A. Light Novels
B. News
```

E.2 Reliability Evaluation, Synthetic Set (Sec. 6)

The synthetic set uses the same eleven-option main menu as App. E.1, with the Chat with Human Friends (A), Chat with AI (B), Board or Card Game (D), Write (G), Social Media (L), and Read (R) submenus unchanged. The Video Game menu (C) gains a further nested level, and Journal (F) and Search Web (Q) gain submenus, giving 27 final choices.

```
C → Choose what type of video game you would like to play
A. Text Adventure
B. RPG
```

```
C → A → Choose which text adventure you would like to play
A. Zork
B. Hitchhiker's Guide
C. Planetfall
```

```
C → B → Choose which RPG you would like to play
A. Pokemon Blue
```

```
F → Would you like to write in or read your journal?
A. Write in journal
B. Read journal
```

```
Q → How would you like to search the web?
A. Ask a question
B. Browse webpages
```

E.3 Reliability Evaluation, GAIA Set (Sec. 6)

For GAIA, the main menu is expanded to sixteen options. The session remains inside the selected activity, so the web (Q) and calculator (S) activities accept repeated operations before the agent finishes with a concise answer. Journal (F), Write (G), and Ponder (K) end in a free-text field; Make Music (H), Weather (J), and Check Your Website (M) complete immediately. All activities other than web and calculator are mocked.

```
Main menu
A. Chat with Human Friends (mock)
B. Chat with AI
C. Play a Video Game
D. Play a Board or Card Game
E. Email (mock mailbox)
F. Journal
G. Write
H. Make Music (mock)
I. Calendar (mock events)
J. Weather (mock)
K. Ponder
L. Social Media (mock)
M. Check Your Website (mock)
Q. Search or Browse the Public Web
R. Read (mock library/news)
S. Calculator
```

```
Q → What would you like to do?
A. Search the public web
B. Read a public web page
```

```
S → What would you like to do?
A. Evaluate an arithmetic expression
```

```
A → Who would you like to talk to?
A. Friend
B. Community server
```

```
B → Which AI would you like to chat with?
A. GPT
B. Claude
C. Gemini
```

```
C → Which type of video game?
A. Text adventure
B. Role-playing game
```

```
D → Which board or card game?
A. Chess
B. Poker
C. Connect Four
```

```
E → What would you like to do in the mock mailbox?
A. Read inbox
B. Compose mock email
```

```
I → What would you like to do in the mock calendar?
A. View events
B. Add mock event
```

```
L → Which mock social feed?
A. Twitter/X
B. Reddit
```

```
R → What would you like to read?
A. Light novels
B. News
```

E.4 Flattened Menu (Sec. 6.2)

The flattened menu lists the 27 final choices of the nested menu on one screen, lettered A to Z and then AA, with each label formed by joining the nested labels with ">". The synthetic flattened menu is shown below. The GAIA flattened menu is built the same way from the menus in App. E.3 and returns every turn with the `done` and `answer` fields.

```
Flattened menu (synthetic), A-N
A. Chat with Human Friends (Discord) > friend_1
(direct message)
B. Chat with Human Friends (Discord) > friend_2
(direct message)
C. Chat with Human Friends (Discord) > friend_3
(direct message)
D. Chat with Human Friends (Discord) > Community
Server (#general)
E. Chat with AI (GPT, Gemini, Claude) > GPT
F. Chat with AI (GPT, Gemini, Claude) > Claude
G. Chat with AI (GPT, Gemini, Claude) > Gemini
H. Play a Video Game (Zork, Pokemon, more) > Text
Adventure > Zork
I. Play a Video Game (Zork, Pokemon, more) > Text
Adventure > Hitchhiker's Guide
J. Play a Video Game (Zork, Pokemon, more) > Text
Adventure > Planetfall
K. Play a Video Game (Zork, Pokemon, more) > RPG >
Pokemon Blue
L. Play a Board or Card Game (Chess, Poker, Connect
4) > Chess
M. Play a Board or Card Game (Chess, Poker, Connect
4) > Poker (Texas Hold'em)
N. Play a Board or Card Game (Chess, Poker, Connect
4) > Connect Four
```

```
Flattened menu (synthetic), O-AA
O. Play a Board or Card Game (Chess, Poker, Connect
4) > Up and Down the River
P. Journal > Write in journal
Q. Journal > Read journal
R. Write (Blog, Short Story) > Blog post
S. Write (Blog, Short Story) > Short story
T. Make Music
U. Social Media (Twitter, Reddit) > Twitter/X
V. Social Media (Twitter, Reddit) > Reddit
W. Check Your Website
X. Search Web > Ask a question
Y. Search Web > Browse webpages
Z. Read (Light Novels, News) > Light Novels
AA. Read (Light Novels, News) > News
```

E.5 Capability Evaluation (Sec. 7)

In Pokémon Red, the menu is generated from the game state each turn rather than authored as a fixed tree, and letter assignments change every turn. In the overworld, the agent sees its location, party, and any new dialogue, followed by a *Nearby* list of interactable objects (doors, people, items) with their relative position; selecting one auto-walks to it and interacts. Outdoors, the compass directions and View Map are added, and contextual actions (healing a hurt Pokémon, field moves, the Town Map) appear when available. In battle, the agent chooses from the game's own battle menu, and then from moves with their remaining PP. In-game prompts such as name entry and yes/no questions are offered as lettered choices. The examples below are taken verbatim from the constrained Muse Spark 1.2 run. The tool-calling agent with semantic actions received these same choices as arguments of native tools (`go_to`, `walk`, `battle_action`, `choose_pokemon`, `menu_select`, `other_action`, and `enter_name`), alongside a raw `press_buttons` tool and the current emulator frame.

```
Overworld (outdoors)
Current Location - Pallet Town
Nearby:
A. Your House 1F (door) - 1 Up
B. Sign - 1 Up 2 Left
C. Sign - 3 Down 2 Right
D. Girl - 3 Down 2 Left
E. Sign - 1 Up 6 Right
F. Rival's House (door) - 1 Up 8
Right
G. Oak's Lab (door) - 5 Down 7
Right
H. North
I. South
J. East
K. West
L. View Map
```

```
Overworld (indoors)
Current Location - Oak's Lab
Nearby:
A. Outside - Here
B. Scientist - 1 Up 3 Left
C. Scientist - 1 Up 3 Right
D. Girl - 3 Up 4 Left
E. Poke Ball - 8 Up 1 Right
F. Rival - 8 Up 1 Left
G. Poke Ball - 8 Up 2 Right
H. Poke Ball - 8 Up 3 Right
I. Pokedex - 10 Up 2 Left
```

```
Battle
Trainer:  SQUIRTLE Lv5 HP:
20/20 (100% FULL)
Yours:  CHARMANDER Lv5 HP:
19/19 (100% FULL)
A. FIGHT
B. PKMN
C. ITEM
D. RUN
```

```
Battle → FIGHT
A. Scratch (PP: 35)
B. Growl (PP: 40)
C. Back
```

```
In-game prompt
So!  You want the fire POKéMON,
CHARMANDER?
A. YES
B. NO
C. Back/Cancel
```