

---

# KS Assistant: A Simple General-Purpose AI Agent for Software Engineering

---

Anonymous Author(s)

Affiliation

Address

email

## Abstract

1 Large language models can generate code and call tools with remarkable fluency,  
2 yet deploying them as practical software engineering assistants still exposes stub-  
3 born gaps: finite context windows, a single mistake that can derail entire sessions,  
4 agents that get stuck in dead ends, AI slop, and generated changes that are difficult  
5 to review or revert.

6 We present **KS Assistant**, a general-purpose assistant and integrated development  
7 environment (IDE) built on top of the **KS Agent Framework**, a simple AI agent  
8 framework of roughly 1,900 lines of code for the core agents. The framework ad-  
9 dresses these gaps through a robust system prompt and a five-layer agent hierarchy  
10 in which each layer adds exactly one concern: budget-tracked ReAct execution,  
11 automatic continuation across sub-sessions via summarization, coding and browser  
12 tools with parallel sub-agents, persistent multi-turn chat with history recall, and git  
13 worktree isolation so every task runs on its own branch. Both KS Assistant and the  
14 KS Agent Framework are grounded in disciplined software engineering practice;  
15 these principles are encoded directly into the agent’s system prompt, enabling KS  
16 Assistant to write code that is simple, elegant, maintainable, and bug-free.

17 We implemented KS Assistant as a free, open-source Visual Studio Code exten-  
18 sion that runs locally, is effective for long-horizon tasks, and supports browser  
19 automation, multimodal input, and Docker containers. We deliberately prioritize  
20 output quality over speed: giving a frontier model adequate time to validate its  
21 own output—running linters, type checkers, and tests—dramatically reduces the  
22 low-quality code that plagues faster but less thorough agents. The entire system  
23 was built using itself over four months, providing a continuous stress test in which  
24 any bug was patched immediately after its manifestation. On Terminal-Bench 2.0,  
25 KS Assistant achieves a 62.2% overall pass rate with Claude Opus 4.6 [Anthropic,  
26 2026a], comparing favorably to Claude Code (58%) and Cursor Composer 2  
27 (61.7%). These results are achieved without benchmark-specific prompt tuning or  
28 model fine-tuning.

## 1 Introduction

29 Modern large language models (LLMs), such as Claude Opus 4.7 [Anthropic, 2026b], GPT 5.5 [Ope-  
30 nAI, 2026], and Gemini 3.1 [Google DeepMind, 2026], have demonstrated a remarkable ability to  
31 generate code, reason about software architecture, and use developer tools [Chen et al., 2021, Rozière  
32 et al., 2023]. A growing body of work has explored how to harness these capabilities for autonomous  
33 software engineering, from single-session agents that resolve GitHub issues [Yang et al., 2024,  
34 Wang et al., 2024] to industrial products marketed as AI software and general assistants [GitHub,  
35 2021, Cursor, 2024, Cognition Labs, 2024, Anthropic, 2025, OpenAI, 2025a, OpenClaw AI, 2025].  
36 Yet using an LLM as a practical software engineering assistant still exposes several stubborn gaps:  
37 context windows are finite, a single mistake can derail an entire session, agents get stuck in dead  
38

ends, models generate AI slop, and generated changes are difficult to review or revert once applied to a live codebase.

We propose the *KS Agent Framework*, a simple AI agent framework containing around 1,900 lines of code for the core agent implementation. The name “KS” reflects the *Keep Simple* design philosophy: each layer is small, each concern is isolated, and the overall system avoids unnecessary abstraction. We address the above-mentioned gaps through a robust system prompt (Section 4 and Appendix A) and a five-layer agent hierarchy in which each layer solves exactly one concern:

1. **KS Agent** — budget-tracked ReAct [Yao et al., 2023b] loop with native function calling.
2. **Relentless Agent** — automatic summarization and continuation across sub-sessions.
3. **Tool Agent** — coding tools, browser automation, and parallel sub-agent execution.
4. **Chat Agent** — persistent multi-turn chat sessions with history recall.
5. **Worktree Agent** — git worktree isolation so every task runs on its own branch.

To demonstrate the power of the KS Agent Framework, we implemented KS Assistant as a Visual Studio Code extension that runs locally. It has full browser support (using open-source Chromium and Playwright), multimodal support, Docker container support, and a mobile/web app. KS Assistant is completely free and open-source; all one needs is a model API key from a major LLM provider. The open-source repository link is withheld to respect double-blind review.

KS Assistant has been built using itself. The entire codebase—the KS Agent framework, the agent layers, the VS Code extension, and the system prompt—was developed by KS Assistant operating on its own repository. This self-hosting discipline provides a continuous-integration-style stress test: if the agent introduces a bug that impairs its ability to function, the developers immediately ask the agent to fix it by analyzing the trajectory and code. The simplicity of the framework enabled the agent to implement features confidently without bugs and AI slop. The five core agent classes are remarkably compact: the KS Agent comprises 413 lines, the Relentless Agent 321 lines, the Tool Agent 322 lines, the Chat Agent 125 lines, and the Worktree Agent 704 lines—a total of roughly 1,885 lines of code (excluding empty lines and comments).

We deliberately prioritize output quality over speed. Using a weaker or cheaper model often forces the developer to discard the agent’s work and retry, ultimately increasing the total cost. Conversely, giving a frontier model adequate time to validate its own output—running linters, type checkers, and tests before declaring success—dramatically reduces slop. We expect token costs and inference latencies to continue to fall [Gao et al., 2025], making this quality-first posture increasingly practical.

We evaluate on Terminal-Bench 2.0 and achieve a 62.2% overall pass rate using Claude Opus 4.6 [Anthropic, 2026a], comparing favorably to Claude Code (58%) and Cursor Composer 2 (61.7%) [Cursor Research, 2026] on the same benchmark (Section 3). These results are achieved without benchmark-specific prompt tuning or model fine-tuning. We show that a simple agent framework, without sophisticated agent technologies such as trajectory compaction and asynchronous multi-agent orchestration, is sufficient to build a competitive software engineering assistant. By building KS Assistant using itself and matching or beating both the Cursor and Claude Code agents, we demonstrate that time-tested software engineering principles and techniques are invaluable for building reliable, practical agent systems.

**Outline.** Section 2 presents the five-layer agent architecture. Section 3 reports evaluation results on Terminal-Bench 2.0. Section 4 describes the two most distinctive aspects of the system prompt: the execution mindset and the web research protocol (the full prompt is detailed in Appendix A). Section 5 covers unique features of the VS Code extension. Section 6 demonstrates a “painless” natural-language development workflow drawn from the project’s own history. Section 7 discusses related work, and Section 8 concludes.

## 2 Agent Architecture

The KS Agent Framework was originally built to rapidly prototype and experiment with prompt optimization techniques [Agrawal et al., 2026] and evolutionary algorithms for algorithmic optimization [Novikov et al., 2025, Algorithmic Superintelligence, 2025]. The emphasis on simplicity enabled coding agents to write simple, bug-free code. Eventually, no prompt optimization techniques were used when creating the system prompt for KS Assistant; it was hand-tuned based on long-term experience with the agent and its behavior. The framework uses five agent layers combining composition and inheritance. Each layer delegates upward for concerns it does not own.

## 93 2.1 KS Agent

94 The KS Agent is the innermost execution unit implementing a standard ReAct loop [Yao et al.,  
95 2023b].

```
96 from ks.core.ks_agent import KSAgent
97
98 def calculate(expression: str) -> str:
99     """Evaluate a math expression."""
100     return str(eval(expression))
101
102 agent = KSAgent(name="Math Buddy")
103 result = agent.run(
104     model_name="gemini-2.5-flash",
105     prompt_template="Calculate: {question}",
106     arguments={"question": "What is 15% of 847?"},
107     tools=[calculate]
108 )
109 print(result) # 127.05
110
```

Listing 1: A complete KS agent with a single tool.

112 **Native function calling.** Tools are registered as ordinary Python callables. The agent builds an  
113 OpenAI-compatible tool schema once at setup time and caches it. A special `finish` tool signals task  
114 completion and returns the result. Using a model’s native calling API avoids the mistakes that models  
115 make on custom function calling conventions.

116 **Step, token, and budget tracking.** At every step, the agent extracts input and output token counts  
117 from the API response, computes dollar cost using a per-model pricing table, and updates both local  
118 and global budget counters protected by a class-level lock. Three limits are checked before each step:  
119 per-agent budget, global budget, and maximum step count.

120 **Error resilience.** The agent retries transient API errors (rate limits, server errors) up to a configurable  
121 threshold. Non-retryable errors (authentication failures, permission denials) are raised immediately.

122 **Non-agentic mode.** When tools are not needed, the agent runs a single generation without the ReAct  
123 loop, useful for summarization sub-tasks.

124 Listing 1 shows a complete, working agent in under ten lines of code. The developer defines an  
125 ordinary Python function (`calculate`), instantiates a `KSAgent`, and calls its `run` method with a  
126 model name, a prompt template, template arguments, and a list of tools. The framework automatically  
127 handles tool-schema generation, the ReAct loop, and budget tracking.

128 The KS Agent is stateless across runs: each call resets the conversation, token counters, and tool  
129 registry, making it safe to reuse a single instance for multiple sequential tasks.

## 130 2.2 Relentless Agent

131 The Relentless Agent wraps a KS Agent in a continuation loop. Its core contribution is executing  
132 tasks that exceed a single context window by breaking them into sub-sessions.

133 Rather than investing in context-compaction techniques, we adopt a simple continuation protocol:  
134 when a sub-session exhausts its context window or step budget, the agent produces a *structured*  
135 *summary* of every action taken so far—chronologically ordered, with explanations and relevant  
136 code snippets—and a fresh sub-session resumes from that summary. This approach is related to  
137 Reflexion [Shinn et al., 2023], which feeds verbal self-critiques back into subsequent trials, but  
138 uses a Reflexion-like technique to *continue* a task rather than retry it. We found that a naïve  
139 instruction to “summarize the current context” produced poor continuations; requiring a *step-by-step*  
140 *chronological account with code snippets* dramatically improved coherence across sub-sessions. A  
141 potential limitation is that summaries may grow unwieldy for multi-day tasks; in practice, we have  
142 not encountered this problem even for tasks spanning several hours, but a thorough evaluation of  
143 summary scaling remains future work.

144 **Continuation protocol.** The `finish` tool accepts three fields: a success flag, a continue flag, and  
145 a summary. When `is_continue=True`, the Relentless Agent starts a new sub-session with a fresh  
146 context window. The prompt for the new session includes a chronologically ordered list of all prior  
147 attempt summaries, instructs the agent not to redo completed work, and advises it to step back and  
148 rethink the strategy from scratch if it has been retrying the same approach without progress.

149 **Forced continuation on failure.** If a sub-session raises an exception (e.g., the step limit is hit before  
150 calling `finish`), the Relentless Agent saves the full trajectory to a temporary file, spawns a separate  
151 summarizer agent to produce a concise summary, and uses that summary as the progress text for the  
152 next sub-session. This ensures that even crashed sessions contribute useful context. The summarizer  
153 is instructed to read the (potentially large) trajectory file and return a precise, chronologically-ordered  
154 list of things the agent did, with the reason for each action and relevant code snippets.

155 **Pre-emptive continuation.** To force the agent to self-continue before exhausting its step budget, the  
156 system prompt is augmented with a step-threshold instruction that requires the agent, at a designated  
157 step or whenever the task is at risk of running out of steps or context length, to call `finish` with  
158 `success=False`, `is_continue=True`, and a precise chronologically-ordered summary of work  
159 done so far. This instruction is injected near the end of the budget window. Without it, the agent  
160 exhibits a “rush to finish” behavior when steps are running low—skipping verification, making hasty  
161 edits, and calling `finish` with an incomplete result. The explicit step threshold redirects that urgency  
162 into the continuation protocol, ensuring that a clean handoff to a new sub-session produces better  
163 results than a frantic attempt to squeeze everything into the remaining steps.

## 164 2.3 Tool Agent

165 The Tool Agent adds the tools that make the system useful for software development and general-  
166 purpose automation.

167 **Coding tools.** Four core tools: a shell command executor with streaming output, a file reader, a  
168 precise string-based file editor, and a file writer. The shell executor supports configurable timeouts,  
169 streams output in real time, and respects a stop event for user cancellation.

170 **Browser automation.** A web-use tool provides programmatic browser control: navigating to URLs,  
171 reading page accessibility trees, clicking elements, typing text, pressing keys, scrolling, and taking  
172 screenshots. It uses the open-source Chromium browser via the Playwright library.

173 **Parallel sub-agents.** An optional parallel execution tool spawns independent Tool Agent instances  
174 in a thread pool. Each sub-agent gets its own LLM context and tool set, useful for embarrassingly  
175 parallel tasks such as summarizing multiple files or researching independent topics. Results are  
176 collected and returned in input order. This tool is not activated by default because the IDE cannot  
177 stream multiple agent outputs coherently in the chat window.

178 **User interaction.** An ask-user-question tool pauses execution and requests clarification from the  
179 user.

180 **Docker isolation.** When a Docker image is specified, coding tools are replaced with Docker-aware  
181 variants that execute commands inside a container.

## 182 2.4 Chat Agent

183 The Chat Agent adds multi-turn conversation persistence.

184 **Chat sessions.** Each task is assigned to a chat session identified by a stable chat ID. Tasks and results  
185 are persisted to a local database. New tasks within the same session include prior tasks and results as  
186 numbered context entries, allowing the LLM to reference earlier work.

187 **Bounded chat context.** The agent caps in-context history entries at  $K = 10$ . When the cap is  
188 exceeded, it preserves the first two entries (which establish the user’s intent) and the most recent  
189 entries, dropping the middle entries least likely to be referenced.

190 **Session management.** Three operations are supported: starting a new chat, resuming by task  
191 description, and resuming by explicit chat ID.

192 **Frequent task tracking.** Each time a task is executed, the agent records the task description in  
193 a frequency table. The IDE sidebar surfaces the most frequent tasks so users can re-issue them  
194 with one click, turning recurring requests (“run the test suite,” “regenerate the changelog”) into a  
195 click-to-replay experience.

196 **Metadata persistence.** After each task, the agent records metadata including the model used,  
197 working directory, software version, token counts, cost, and whether the task used parallel execution  
198 or worktree isolation. This audit trail supports cost analysis and debugging.

## 2.5 Worktree Agent

The Worktree Agent is the outermost layer. Its defining feature is git-worktree isolation.

**Branch-per-task.** When a task starts, the agent creates a new git branch and corresponding worktree directory. All agent modifications happen inside the worktree; the user’s main working tree remains untouched.

**Dirty-state preservation.** Uncommitted changes in the main working tree are copied into the worktree with a baseline commit. During merge, cherry-pick from the baseline replays only the agent’s changes.

**Concurrency safety.** A per-repository file lock serializes checkout, stash, merge, and pop operations. Thread-local storage isolates per-task state.

**Crash recovery.** All worktree state is stored in git itself (branch names, git config entries) rather than sidecar files. On process restart, the agent queries git and reconstructs instance attributes, enabling seamless recovery.

**Graceful fallback.** If the working directory is not inside a git repository, has no commits, or has a detached HEAD, the agent falls back to direct execution without worktree isolation.

## 3 Evaluation on Terminal-Bench 2.0

We evaluate on Terminal-Bench 2.0,<sup>1</sup> a benchmark comprising 89 diverse terminal-based programming tasks, ranging from building legacy compilers and configuring servers to solving cryptanalysis challenges and training machine-learning models. Each task runs in an isolated Docker container; a separate verifier automatically judges the result. We use the Harbor<sup>2</sup> framework to orchestrate execution and Claude Opus 4.6 [Anthropic, 2026a] as the underlying LLM. We do not modify the general system prompt or inject benchmark-specific instructions. Evaluation was carried out on a 2025 MacBook Air 15” with an M4 processor and 24 GB RAM.

### 3.1 Setup

We run 5 independent trials per task. The agent is a thin Harbor adapter that installs and invokes the KS Assistant CLI inside each container. We hard-skip 9 tasks verified to be infeasible for Opus 4.6 across 6+ prior attempts (e.g., CompCert compilation, Windows 3.11 GUI installation, video OCR) to save time and token cost. Skipped tasks still count as failures.

### 3.2 Aggregate Results

Table 1 summarizes the aggregate statistics.

Table 1: Terminal-Bench 2.0 aggregate results (89 tasks, 5 trials each, Claude Opus 4.6).

Metric	Value
Total tasks	89
Overall pass rate	62.2% (277/445)
pass@any (at least 1/5 passes)	78.7% (70/89)
pass@all (all 5 pass)	43.8% (39/89)
Always-fail tasks	19
Always-pass tasks	39
Mixed-result tasks	31
Median cost per trial	\$0.45
Mean cost per trial	\$0.90
Median duration per trial	202 s
Mean duration per trial	446 s

The 62.2% overall pass rate compares favorably to other agents using the same underlying model: at the time of writing, Claude Code (also Opus 4.6) scores approximately 58% on the Terminal-

<sup>1</sup><https://www.tbench.ai/>

<sup>2</sup><https://github.com/harbor-framework/harbor>

231 Bench 2.0 leaderboard, and Cursor’s Composer 2—a custom fine-tuned model trained with large-scale  
232 reinforcement learning [Cursor Research, 2026]—achieves 61.7%. Our result suggests that the layered  
233 architecture and the structured system prompt contribute meaningfully beyond what the base model  
234 provides.

### 235 3.3 Task-Level Breakdown

236 **Consistently solved tasks (39 of 89).** These include cryptanalysis (FEAL differential), game-playing  
237 (chess best move), git operations (leak recovery), server configuration (gRPC key-value store, PyPI  
238 server, NGINX logging), data processing (resharding), formal verification (Coq plus\_comm), ML  
239 inference (HuggingFace model serving, LLM batching scheduler), and system emulation (QEMU  
240 startup). The breadth of this set demonstrates that the agent’s generality is not limited to a single  
241 domain.

242 **Consistently failed tasks (19 of 89).** The failures cluster into three categories: (1) tasks requiring  
243 graphical or multimedia capabilities unavailable in the container (video processing, Windows 3.11  
244 GUI installation, MTEB leaderboard scraping), (2) tasks demanding very long or resource-intensive  
245 builds that exceed time or memory limits (CompCert compilation, Doom for MIPS, Caffe CIFAR-  
246 10, training fastText on Yelp data), and (3) tasks with niche domain-specific requirements that the  
247 model struggles to satisfy (DNA insertion, OCaml GC patching, polyglot C/Python binaries, protein  
248 assembly, cell segmentation).

249 **Mixed-result tasks (31 of 89).** Tasks such as write-compressor (3/5), crack-7z-hash (4/5),  
250 and feal-linear-cryptanalysis (4/5) succeed in most trials but occasionally fail due to non-  
251 determinism in the model’s reasoning or timing-sensitive environment interactions. Conversely,  
252 cancel-async-tasks (1/5) and dna-assembly (1/5) succeed rarely, suggesting they are at the  
253 boundary of the model’s capability.

254 **Leaderboard context.** KS Assistant does not score as high as some coding agents on the Terminal-  
255 Bench 2.0 leaderboard, but we believe that our results are significant because we didn’t tune our  
256 prompts or any model specifically for the Terminal Bench 2.0. We simply used the general system  
257 prompt and the Claude Opus 4.6 model. Regarding low score compared to other coding agents,  
258 we wanted to note that recent analysis has found widespread cheating on popular agent bench-  
259 marks, including Terminal-Bench 2.0: the top three submissions commit harness-level cheating (e.g.,  
260 leaking verifier code or answer keys into the agent’s environment), and task-level cheating (e.g.,  
261 Googling answers, mining git history, hardcoding test outputs) affects 28+ submissions across 9  
262 benchmarks [Stein et al., 2026a,b]. Separately, an automated benchmark audit found 45 confirmed  
263 hacking solutions across 13 widely used benchmarks exhibiting process-isolation failures, answer  
264 leakage, and weak test assertions that allow perfect scores without solving a single problem [Wang  
265 et al., 2026].

## 266 4 The System Prompt

267 The system prompt is a structured document that governs the agent’s behavior across all tasks. It is  
268 not a generic instruction to “be helpful” but rather a precise specification of engineering discipline.  
269 We present the two most distinctive aspects here; the complete prompt is detailed in Appendix A.

### 270 4.1 Execution Mindset

271 The prompt opens with two directives that set the tone for the entire session:

272 # FOCUS ON THE GIVEN TASK. ITS COMPLETION IS YOUR SOLE GOAL.  
273 # BE RELENTLESS. BE CALM. BE RIGOROUS. BE ACCURATE. CHECK FACTS. NO AI SLOP.  
274

276 Each directive addresses a specific failure mode observed in LLM-based agents:

277 **“FOCUS ON THE GIVEN TASK. ITS COMPLETION IS YOUR SOLE GOAL.”** LLMs have a  
278 tendency to drift: they comment on the difficulty of a problem, explore tangential concerns, or ask  
279 clarifying questions that the user has already answered. This directive anchors the model on the task  
280 at hand and discourages meta-commentary that consumes tokens without making progress.

281 **“BE RELENTLESS.”** When an agent encounters an error—a failing test, a type violation, a command  
282 that returns unexpected output—the default LLM behavior is to apologize, summarize the failure,

283 and ask the user what to do next. This directive instructs the model to treat errors as obstacles to  
284 overcome, not as reasons to stop.

285 **“BE CALM.”** The complement of relentlessness. An overly aggressive agent may thrash between  
286 approaches without deliberation. This directive encourages the model to analyze errors methodically  
287 before reacting.

288 **“BE RIGOROUS.”** This instructs the model to follow the verification and testing disciplines encoded  
289 later in the prompt, rather than taking shortcuts when a solution *looks* right.

290 **“BE ACCURATE.”** LLMs frequently generate plausible-but-wrong code, file paths, or command-line  
291 flags. This directive raises the model’s threshold for asserting facts, encouraging it to verify claims  
292 against the actual file system or documentation rather than relying on parametric memory.

293 **“CHECK FACTS.”** A more specific version of “be accurate,” targeting information the agent collects  
294 via web tools.

295 **“NO AI SLOP”** “AI slop” refers to the low-quality, generic, hedging text that LLMs produce when  
296 they lack confidence: filler phrases like “certainly!”, unnecessary caveats, and boilerplate explanations.  
297 This directive encourages the model to be concise and substantive.

298 These two sentences occupy only two lines, yet they establish a behavioral contract that permeates  
299 every subsequent interaction. We observe empirically that removing any single directive degrades the  
300 agent’s behavior along the corresponding dimension (e.g., removing “BE RELENTLESS” causes the  
301 agent to give up after the first error more frequently).

## 302 4.2 Web Research Protocol

303 When the agent needs external knowledge, the prompt prescribes a structured research workflow  
304 rather than allowing ad-hoc browsing:

```
305 ## Web Research (MANDATORY)
306
307 - **Visit >=30 websites every search. Hard requirement---don't stop before 30 or rationalize fewer.**
308 - Procedure:
309   1. Create PWD/tmp/information- $\{unique\_id\}$ .md: '# Web Research --- Websites visited: 0/30'
310   1. Per site, append: '## [N/30] URL' + extracted info. Update header counter each visit.
311   1. **Don't proceed until counter >=30.**
312   1. If results dry up, try different queries, synonyms, official docs, GitHub repos/issues, Stack Overflow
313     , blogs, Reddit, papers, API refs.
314   1. After 30, review and think deeply.
315 - Ask user for login help when needed.
316
```

318 The rationale is a two-phase separation between *collection* and *synthesis*. LLMs tend to anchor on  
319 the first few results they encounter, biasing their solutions toward a narrow slice of the design space.  
320 By forcing the agent to accumulate a broad set of information into a file *before* reasoning about it, the  
321 protocol counteracts anchoring bias and encourages the model to consider diverse approaches.

322 The “visit  $\geq 30$  websites” threshold is deliberately aggressive: it ensures the agent does not shortcut  
323 the research phase after two or three hits, and the resulting information file serves as an auditable  
324 artifact of what the agent considered. The structured procedure with a counter header and per-site  
325 entries addresses an empirically observed failure mode in which the model claims to have “visited  
326 many sites” after only a handful of fetches; a concrete counter forces the model to verify the actual  
327 number visited before declaring the collection phase complete. The instruction to try “different  
328 queries, synonyms, official docs” when results dry up prevents the agent from giving up prematurely  
329 on a narrow set of search terms.

330 This two-phase collect-then-synthesize discipline is also applied to local file browsing (Appendix A.9):  
331 the agent writes a structured summary of each file’s relevant information into a temporary markdown  
332 file, externalizing its understanding into a compact artifact that persists across context boundaries.  
333 The instruction to collect “without overthinking” is deliberate: during the collection phase, the agent  
334 extracts and records facts rather than analyzes. Analysis happens in the second phase, when the agent  
335 reads its own summary and reasons about the collected information as a whole.

## 5 VS Code Extension: Unique Features

We release our system as a VS Code extension and a web app. While the underlying agent architecture already differs from existing AI coding assistants, the extension introduces several features that, to our knowledge, are not present in competing assistants—including GitHub Copilot [GitHub, 2021], Cursor [Cursor, 2024], Windsurf [Codeium, 2024], Devin [Cognition Labs, 2024], and Aider [Gauthier, 2023].

**Cross-session self-improvement.** The extension maintains a `USER_PREFS.md` file that the agent reads at the start of each task and *updates* at the end. When the agent discovers a new preference or project invariant during task execution, it writes it to the file. The agent also resolves conflicts: if a new preference contradicts an existing one, the old entry is removed. Over time, the file accumulates a curated set of project-specific knowledge, making the agent progressively more effective without any manual configuration. This mechanism is detailed in Appendix A.7.

**Real-time budget accountability.** The extension displays real-time cost tracking in the sidebar: input tokens, output tokens, cache hits, dollar cost, and elapsed time are updated at every agent step. Both per-task and global budget ceilings are enforced.

**Integrated browser automation.** The extension includes a browser automation tool that allows the agent to navigate URLs, read accessibility trees, click elements, type text, press keys, scroll, and take screenshots—all controlled programmatically from within a VS Code task.

## 6 Painless Software Engineering with KS Assistant

A central claim of our system is that natural-language interaction can replace manual code inspection and ad hoc scripting for understanding and evolving nontrivial subsystems. While developing KS Assistant, we found a particular workflow to be particularly useful. In the workflow, we first ask KS Assistant to generate a detailed, step-by-step description of a workflow or algorithm we found buggy, and then we ask KS Assistant to revise some of the buggy steps in natural language. We illustrate this with a real development session drawn from the project’s own history, in which the worktree merge workflow (Section 2.5) was first understood and then redesigned entirely through conversational prompts. The session comprises four consecutive tasks; we reproduce the prompts verbatim and summarize the agent’s responses.

**Step 1: Understanding the existing workflow.** The developer begins by asking the agent to explain the current post-task git lifecycle:

```
Can you tell me what happens, step by step, with git in worktree_sorcar_agent.py when a task finishes?
```

The agent reads the source code and returns a structured summary of the four-phase lifecycle: (1) during `run()`, a new branch and worktree are created and the task executes inside the worktree; when the task completes, *nothing is committed or merged*—the result is returned with merge instructions appended and the worktree stays pending; (2) `merge()` calls `_finalize_worktree()`, which stages all changes, generates a commit message via the LLM, commits, removes the worktree, checks out the original branch, and runs `git merge`; (3) `discard()` removes the worktree, prunes, checks out the original branch, and deletes the task branch; (4) in CLI mode an interactive prompt forces the user to choose `[c]ommit` and `merge` or `[d]iscard` before exiting. The agent also notes a key design invariant: nothing auto-merges; auto-commit occurs only at merge/finalize time; all steps are idempotent; and state can be recovered from git on restart.

**Step 2: Simplifying the workflow via natural language.** Armed with the workflow description, the developer decides the three-way choice (auto-merge, manual merge, discard) is unnecessarily complex and issues a redesign request:

```
Can you change worktree_sorcar_agent.py and the extension so that after the agent finishes its task, it simply asks "Commit and Merge" or "Discard". When "Commit and Merge" is clicked by the user, the agent must commit the changes with a generated commit message, merge the branch with the original branch, and delete the worktree and the branch associated with the worktree. If the user clicks "discard", it must delete the worktree and the branch, and checkout the original branch.
```



391 The agent modifies six files across Python and TypeScript: it updates `discard()` to check out the  
392 original branch before deleting the task branch, removes the `manual_merge()` method entirely,  
393 simplifies `merge_instructions()` to show only two options, updates the webview UI to replace  
394 the three-button toolbar with a two-button “Commit and Merge or Discard?” bar, removes the `manual`  
395 action type from the TypeScript type definitions, and removes the corresponding handler from the  
396 Python backend. Three tests for the deleted manual-merge path have been removed, and one routing  
397 test has been updated. All 28 worktree tests pass after the change.

398 **Step 3: Investigating unexpected post-merge state.** After testing the simplified flow, the developer  
399 notices that files appear in the Source Control panel of VS Code on the original branch after pressing  
400 “Commit and Merge” and asks:

401 After the user presses "Commit and Merge", why do the modified files show up as  
402 committed in the original branch?  
403

405 The agent traces the exact execution path through `squash_merge_branch()` and discovers that  
406 the implementation deliberately *unstages* the squash-merged changes via `git reset HEAD` so they  
407 appear as uncommitted working-tree modifications in VS Code’s Source Control panel. The design  
408 intention was to let the user review the diff before committing manually. The agent reports this  
409 finding along with the relevant code snippet and a verified end state showing no new commits on the  
410 branch.

411 **Step 4: Directing a design change in one sentence.** The developer realizes that code review  
412 already happened while the worktree was active and decides the unstage step is unnecessary:

413 The review is already happening in the worktree branch. You don’t need the user  
414 to review the modified and new files in the original branch. Fix it.  
415

417 The agent replaces the `git reset HEAD` call in `squash_merge_branch()` with a conditional `git`  
418 `commit -no-edit` that uses the auto-generated squash message. It adds a `git diff -cached`  
419 `-quiet` guard for the edge case where the merge produces no changes. One existing test  
420 (`test_merge_leaves_changes_uncommitted`) is renamed to `test_merge_commits_changes`  
421 and its assertions are updated to verify a clean working tree. All 104 worktree tests pass.

422 **Discussion.** The four-step session illustrates the “painless” development loop that our system enables.  
423 The developer never opens a source file, never writes a line of code, and never runs a test manually.  
424 Instead, the entire cycle—understand the workflow, redesign it, investigate an anomaly, direct a  
425 fix—happens through natural-language prompts, with the agent handling code reading, multi-file  
426 editing, test updates, and verification. This style of development becomes possible because of the  
427 agent hierarchy described in Section 2: the Worktree Agent isolates changes on a branch, the Chat  
428 Agent preserves conversational context across tasks, and the Relentless Agent automatically continues  
429 when the context window is exhausted.

## 430 7 Related Work

431 **Code-specialized language models.** Code Llama [Rozière et al., 2023] fine-tunes Llama 2 for code  
432 generation. StarCoder [Li et al., 2023] trains on permissively licensed code. DeepSeek-Coder [Guo  
433 et al., 2024] trains on a 2-trillion-token corpus. Frontier models such as Claude Opus 4.7 [Anthropic,  
434 2026b], GPT 5.5 [OpenAI, 2026], Kimi K2.5 [Kimi Team, 2026], and GLM-5.1 [Z.ai, 2026] target  
435 agentic software engineering. Our system is model-agnostic and benefits from advances in code-  
436 specialized pre-training without architectural changes.

437 **Code generation agents.** SWE-Agent [Yang et al., 2024] and OpenHands [Wang et al., 2024] provide  
438 LLM-based agents for resolving software engineering tasks. Agentless [Xia et al., 2024] shows that  
439 a two-phase localize-then-repair pipeline can achieve competitive results. Devin [Cognition Labs,  
440 2024], Claude Code [Anthropic, 2025], Codex [OpenAI, 2025a], and Aider [Gauthier, 2023] offer  
441 various approaches to autonomous coding. Cursor released Composer 2 [Cursor Research, 2026],  
442 a fine-tuned coding model trained with large-scale reinforcement learning. Our Relentless Agent  
443 layer addresses the single-session limitation common to most of these systems, while our worktree  
444 isolation provides stronger safety guarantees.

**ReAct, reasoning, and planning.** ReAct [Yao et al., 2023b] interleaves reasoning and action. Chain-of-thought prompting [Wei et al., 2022] elicits step-by-step reasoning. Tree of Thoughts [Yao et al., 2023a] generalizes to search over reasoning paths. Reflexion [Shinn et al., 2023] introduces verbal reinforcement learning. Our continuation protocol is conceptually related to Reflexion, but uses summaries to continue tasks rather than retry them.

**Multi-agent systems.** ChatDev [Qian et al., 2024] and MetaGPT [Hong et al., 2024] model software development as conversations between role-playing agents. AutoGen [Wu et al., 2023] provides a general multi-agent framework. We use a single agent with broad tool access and optional parallel sub-agents, prioritizing practical utility over role-playing fidelity.

**Agent frameworks.** LangChain [LangChain, 2022], DSPy [Khattab et al., 2024], CrewAI [CrewAI, Inc., 2024], smolagents [Roucher et al., 2025], the OpenAI Agents SDK [OpenAI, 2025b], and Google’s ADK [Google, 2025] provide general-purpose agent infrastructure. Our architecture is purpose-built for software engineering, with each layer addressing a specific practical concern.

**Benchmarks and evaluation.** SWE-bench [Jimenez et al., 2024], HumanEval [Chen et al., 2021], LiveCodeBench [Jain et al., 2024], and SWE-bench Pro [Deng et al., 2025] evaluate coding agents at various scales. Prathifkumar et al. [2025] raises concerns about benchmark contamination. We evaluate on Terminal-Bench 2.0, which tests diverse terminal-based tasks in isolated Docker containers.

**Agentic software engineering.** Hassan et al. [2025] articulate the foundational pillars of agentic software engineering. Li et al. [2025] surveys the landscape of autonomous coding agents. Wang et al. [2025] surveys AI agentic programming techniques. Chatlatanagulchai et al. [2025] studies agent context files. Mohsenimofidi et al. [2025] investigates context engineering for AI agents. Our system prompt and per-repository override mechanisms are instances of the context-engineering patterns these works advocate.

**Self-improvement and community prompts.** Robeyns et al. [2025] demonstrates a self-improving coding agent. Our self-improvement loop captures a lighter-weight form of this idea via accumulated preferences. Gao et al. [2025] applies test-time compute scaling to software engineering. Get Shit Done (GSD) [TÂCHES, 2025] is a meta-prompting system for coding agents that addresses context rot through phased planning documents. Parts of our system prompt were inspired by this work.

## 8 Conclusion

We have shown that a simple layered, single-concern architecture can address the practical challenges of deploying LLM agents for real-world software development. On Terminal-Bench 2.0, a benchmark of 89 diverse terminal-based tasks evaluated across 5 trials each, our system achieves a 62.2% overall pass rate (277/445)—outperforming Claude Code (58%) and Cursor Composer 2 (61.7%) on the same benchmark with the same underlying model (Claude Opus 4.6 [Anthropic, 2026a]). These results are achieved without benchmark-specific optimizations, fine-tuning, or reinforcement learning.

We complement the architecture with a system prompt that encodes engineering discipline directly into the agent’s behavior: read before writing, test before fixing, plan before executing, verify before finishing. These are not novel insights—they are the practices of careful software engineering, translated into instructions that an LLM can follow. The evaluation suggests that giving a frontier model the time and tools to validate its own output matters more than model-level customization.

In summary, we showed that a simple agent framework, without sophisticated agent technologies such as trajectory compaction and asynchronous multi-agent orchestration, was sufficient to build KS Assistant. By building KS Assistant using itself and beating both the Cursor and Claude Code agents, we demonstrated that time-tested software engineering techniques and principles are invaluable for building reliable, practical agent systems.

**Limitations.** Our evaluation uses a single frontier model and benchmark; broader evaluation across open-weight models and benchmarks such as SWE-bench Pro is future work. The continuation protocol’s summaries may lose fidelity over many sub-sessions, and the quality-over-speed posture may not suit latency-sensitive workflows.

## References

- Lakshya A. Agrawal, Shangyin Tan, Dilara Soylu, Noah Ziemis, Rishi Khare, Krista Opsahl-Ong, Arnav Singhvi, Herumb Shandilya, Michael J. Ryan, Meng Jiang, Christopher Potts, Koushik Sen, Alexandros G. Dimakis, Ion Stoica, Dan Klein, Matei Zaharia, and Omar Khattab. GEPA: Reflective prompt evolution can outperform reinforcement learning. In *International Conference on Learning Representations (ICLR)*, 2026. Oral. arXiv preprint arXiv:2507.19457.
- Algorithmic Superintelligence. OpenEvolve: Open-source implementation of AlphaEvolve. <https://github.com/algorithmicsuperintelligence/openevolve>, 2025.
- Anthropic. Claude Code: Anthropic’s agentic coding system. <https://www.anthropic.com/product/claude-code>, 2025.
- Anthropic. Introducing Claude Opus 4.6. <https://www.anthropic.com/news/claude-opus-4-6>, 2026a.
- Anthropic. Introducing Claude Opus 4.7. <https://www.anthropic.com/news/claude-opus-4-7>, 2026b.
- Worawalan Chatlatanagulchai, Hao Li, Yutaro Kashiwa, Brittany Reid, Kundjanasith Thonglek, Pattara Lee-laprute, Arnon Rungsawang, Bundit Manaskasemsak, Bram Adams, Ahmed E. Hassan, and Hajimu Iida. Agent READMEs: An empirical study of context files for agentic coding. *arXiv preprint arXiv:2511.12884*, 2025.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Pondé Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.
- Codeium. Windsurf: The AI-powered IDE. <https://windsurf.com>, 2024.
- Cognition Labs. Devin: The first AI software engineer. <https://devin.ai>, 2024.
- CrewAI, Inc. CrewAI: Framework for orchestrating role-playing, autonomous AI agents. <https://github.com/crewAIInc/crewAI>, 2024.
- Cursor. Cursor: The AI-first code editor. <https://cursor.sh>, 2024.
- Cursor Research. Composer 2 technical report. *arXiv preprint arXiv:2603.24477*, 2026.
- Xiang Deng, Jeff Da, Edwin Pan, Yannis Yiming He, Charles Ide, Kanak Garg, Niklas Lauffer, Andrew Park, Nitin Pasari, Chetan Rane, et al. SWE-Bench Pro: Can AI agents solve long-horizon software engineering tasks? *arXiv preprint arXiv:2509.16941*, 2025.
- Pengfei Gao, Zhao Tian, Xiangxin Meng, and Trae Research Team. Trae agent: An LLM-based agent for software engineering with test-time scaling. *arXiv preprint arXiv:2507.23370*, 2025.
- Paul Gauthier. Aider: AI pair programming in your terminal. <https://github.com/paul-gauthier/aider>, 2023.
- GitHub. GitHub Copilot: Your AI pair programmer. <https://github.com/features/copilot>, 2021.
- Google. Agent Development Kit (ADK): An open-source framework for building AI agents. <https://google.github.io/adk-docs/>, 2025.
- Google DeepMind. Gemini 3.1 Pro. <https://deepmind.google/models/gemini/pro/>, 2026.
- Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y. Wu, Y. K. Li, Fuli Luo, Yun Xiong, and Wenfeng Liang. DeepSeek-Coder: When the large language model meets programming — the rise of code intelligence. *arXiv preprint arXiv:2401.14196*, 2024.
- Ahmed E. Hassan, Hao Li, Dayi Lin, Bram Adams, Tse-Hsun Chen, Yutaro Kashiwa, and Dong Qiu. Agentic software engineering: Foundational pillars and a research roadmap. *arXiv preprint arXiv:2509.06216*, 2025.
- Sirui Hong, Mingchen Zhuge, Jonathan Chen, Xiwu Zheng, Yuheng Cheng, Ceyao Zhang, Jinlin Wang, Zili Wang, Steven Ka Shing Yau, Zijuan Lin, Liyang Zhou, Chenyu Ran, Lingfeng Xiao, Chenglin Wu, and Jürgen Schmidhuber. MetaGPT: Meta programming for a multi-agent collaborative framework. In *International Conference on Learning Representations (ICLR)*, 2024.
- Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. LiveCodeBench: Holistic and contamination free evaluation of large language models for code. *arXiv preprint arXiv:2403.07974*, 2024.

542 Carlos E. Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik Narasimhan.  
543 SWE-bench: Can language models resolve real-world GitHub issues? In *International Conference on*  
544 *Learning Representations (ICLR)*, 2024.

545 Omar Khattab, Arnav Singhvi, Paridhi Maheshwari, Zhiyuan Zhang, Keshav Santhanam, Sri Vardhamanan,  
546 Saiful Haq, Ashutosh Sharma, Thomas T. Joshi, Hanna Moazam, Heather Miller, Matei Zaharia, and  
547 Christopher Potts. DSPy: Compiling declarative language model calls into self-improving pipelines. In *The*  
548 *Twelfth International Conference on Learning Representations*, 2024.

549 Kimi Team. Kimi K2.5: Visual agentic intelligence. *arXiv preprint arXiv:2602.02276*, 2026.

550 LangChain. LangChain: Build context-aware reasoning applications. [https://github.com/langchain-ai/](https://github.com/langchain-ai/langchain)  
551 [langchain](https://github.com/langchain-ai/langchain), 2022.

552 Hao Li, Haoxiang Zhang, and Ahmed E. Hassan. The rise of AI teammates in software engineering (SE 3.0):  
553 How autonomous coding agents are reshaping software engineering. *arXiv preprint arXiv:2507.15003*, 2025.

554 Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc  
555 Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. StarCoder: May the source be with you! *Transactions*  
556 *on Machine Learning Research (TMLR)*, 2023.

557 Seyedmoein Mohsenimofidi, Matthias Galster, Christoph Treude, and Sebastian Baltes. Context engineering for  
558 AI agents in open-source software. *arXiv preprint arXiv:2510.21413*, 2025.

559 Alexander Novikov, Ngân Vũ, Marvin Eisenberger, Emilien Dupont, Po-Sen Huang, Adam Zsolt Wagner, Sergey  
560 Shirobokov, Borislav Kozlovskii, Francisco J. R. Ruiz, Abbas Mehrabian, M. Pawan Kumar, Abigail See,  
561 Swarat Chaudhuri, George Holland, Alex Davies, Sebastian Nowozin, Pushmeet Kohli, and Matej Balog.  
562 AlphaEvolve: A coding agent for scientific and algorithmic discovery. *arXiv preprint arXiv:2506.13131*,  
563 2025.

564 OpenAI. Introducing Codex: A cloud-based software engineering agent. [https://openai.com/index/](https://openai.com/index/introducing-codex/)  
565 [introducing-codex/](https://openai.com/index/introducing-codex/), 2025a.

566 OpenAI. OpenAI Agents SDK: A lightweight, powerful framework for multi-agent workflows. [https://](https://github.com/openai/openai-agents-python)  
567 [github.com/openai/openai-agents-python](https://github.com/openai/openai-agents-python), 2025b.

568 OpenAI. Introducing GPT-5.5. <https://openai.com/index/introducing-gpt-5-5/>, 2026.

569 OpenClaw AI. OpenClaw: Personal AI assistant. <https://openclaw.ai>, 2025.

570 Thanosan Prathifkumar, Noble Saji Mathews, and Meiyappan Nagappan. Does SWE-Bench-Verified test agent  
571 ability or model memory? *arXiv preprint arXiv:2512.10218*, 2025.

572 Chen Qian, Wei Liu, Hongzhang Liu, Nuo Chen, Yufan Dang, Jiahao Li, Cheng Yang, Weize Chen, Yusheng  
573 Su, Xin Cong, Juyuan Xu, Dahai Li, Zhiyuan Liu, and Maosong Sun. ChatDev: Communicative agents for  
574 software development. In *Proceedings of the 62nd Annual Meeting of the Association for Computational*  
575 *Linguistics (ACL)*, 2024.

576 Maxime Robeyns, Martin Szummer, and Laurence Aitchison. A self-improving coding agent. *arXiv preprint*  
577 *arXiv:2504.15228*, 2025.

578 Aymeric Roucher, Albert Villanova del Moral, Thomas Wolf, Leandro von Werra, and Erik Kaunismäki. smola-  
579 gents: A smol library to build great agentic systems. <https://github.com/huggingface/smolagents>,  
580 2025.

581 Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu  
582 Liu, Tal Remez, Jérémy Rapin, et al. Code Llama: Open foundation models for code. *arXiv preprint*  
583 *arXiv:2308.12950*, 2023.

584 Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language  
585 agents with verbal reinforcement learning. In *Advances in Neural Information Processing Systems (NeurIPS)*,  
586 2023.

587 Adam Stein, Davis Brown, Hamed Hassani, Mayur Naik, and Eric Wong. Finding widespread cheating on  
588 popular agent benchmarks. Blog post, <https://debugml.github.io/cheating-agents/>, 2026a.

589 Adam Stein, Davis Brown, Hamed Hassani, Mayur Naik, and Eric Wong. Detecting safety violations across  
590 many agent traces. *arXiv preprint arXiv:2604.11806*, 2026b.

591 TÂCHES. Get Shit Done: A light-weight meta-prompting, context engineering and spec-driven development  
592 system for AI coding agents. <https://github.com/gsd-build/get-shit-done>, 2025. Initial commit  
593 December 2025.

594 Hao Wang, Qiuyang Mang, Alvin Cheung, Koushik Sen, and Dawn Song. We scored 100% on AI bench-  
595 marks without solving a single problem. Blog post, [https://moogician.github.io/blog/2026/](https://moogician.github.io/blog/2026/trustworthy-benchmarks/)  
596 [trustworthy-benchmarks/](https://moogician.github.io/blog/2026/trustworthy-benchmarks/), 2026.

597 Huanting Wang, Jingzhi Gong, Huawei Zhang, Jie Xu, and Zheng Wang. AI agentic programming: A survey of  
598 techniques, challenges, and opportunities. *arXiv preprint arXiv:2508.11126*, 2025.

599 Xingyao Wang, Yangyi Chen, Lifan Yuan, Yizhe Zhang, Yunzhi Li, Hao Peng, and Heng Ji. OpenHands: An  
600 open platform for AI software developers as generalist agents. *arXiv preprint arXiv:2407.16741*, 2024.

601 Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and  
602 Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural*  
603 *Information Processing Systems (NeurIPS)*, 2022.

604 Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun  
605 Zhang, Jiale Liu, Ahmed Hassan Awadallah, Ryen W. White, Doug Burger, and Chi Wang. AutoGen:  
606 Enabling next-gen LLM applications via multi-agent conversation. *arXiv preprint arXiv:2308.08155*, 2023.

607 Chunqiu Steven Xia, Yinlin Deng, Soren Dunn, and Lingming Zhang. Agentless: Demystifying LLM-based  
608 software engineering agents. *arXiv preprint arXiv:2407.01489*, 2024.

609 John Yang, Carlos E. Jimenez, Alexander Wettig, Kilian Liber, Karthik Narasimhan, and Ofir Press. SWE-agent:  
610 Agent-computer interfaces enable automated software engineering. *arXiv preprint arXiv:2405.15793*, 2024.

611 Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L. Griffiths, Yuan Cao, and Karthik Narasimhan.  
612 Tree of thoughts: Deliberate problem solving with large language models. In *Advances in Neural Information*  
613 *Processing Systems (NeurIPS)*, 2023a.

614 Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. ReAct: Syner-  
615 gizing reasoning and acting in language models. In *International Conference on Learning Representations*  
616 *(ICLR)*, 2023b.

617 Z.ai. GLM-5.1: Towards long-horizon tasks. Technical blog, <https://z.ai/blog/glm-5.1>, 2026.

## A Full System Prompt Details

This appendix presents the remaining sections of the system prompt not discussed in the main body. The execution mindset and web research protocol are covered in Sections 4.1 and 4.2, respectively.

### A.1 Tool Rules

Tool usage rules are explicit and mechanical:

```
# Rules
- PWD = current working directory. Write() for new files; Edit() for small changes.
- Run Bash synchronously with 'timeout_seconds' (default 300s). Retry with higher timeout on timeout. For
  >10 min commands, run in background, redirect output to file, poll periodically.
- Use go_to_url() for browser. Search the internet extensively.
- **User only sees the finish() summary. Include full details/results/outputs. Never include meta-
  descriptions like "Answered the user's question about X" or "Fixed the bug in Y".**
- Read large files in chunks. Temp files in PWD/tmp; clean up after.
- Use ULTRA thinking ALWAYS.
- **If running out of context/steps, don't rush---call finish(is_continue=true).**
```

Each rule addresses a specific failure mode:

**“Write() for new files; Edit() for small changes.”** Without this distinction, the model may use Write() to overwrite an existing file with a slightly modified version, losing content it forgot to include.

**Bash timeout guidance.** LLMs frequently launch shell commands without considering their runtime. The instruction to use 300 seconds as the default, retry with higher timeouts, and run long-running commands in the background provides a mechanical protocol that handles common cases.

**“Use go\_to\_url() for browser. Search the internet extensively.”** The first clause specifies which tool to use for browser-based interactions. The second encourages the agent to proactively search the web when it encounters unfamiliar APIs or error messages, rather than relying on parametric memory.

**“User only sees the finish() summary.”** This forces the model to put all user-facing information into the finish summary, preventing situations where the model “tells” the user something in an intermediate message and then assumes it was seen. The companion clause about meta-descriptions prevents vague summaries, requiring concrete details and outputs.

**“Read large files in chunks. Temp files in PWD/tmp; clean up after.”** Reading a 10,000-line file in a single tool call consumes a large fraction of the context window. Chunked reading preserves capacity for the rest of the task. Centralizing temporary files in a known directory makes cleanup predictable and prevents project-tree pollution.

**“Use ULTRA thinking ALWAYS.”** This activates the model’s extended reasoning mode, which is particularly valuable for complex, multi-step tasks.

**“If running out of context/steps, don’t rush—call finish(is\_continue=true).”** When the context window is nearly full, LLMs exhibit a “rush to finish” behavior, skipping verification steps. This instruction redirects that urgency into the continuation protocol (Section 2.2).

### A.2 Pre-flight Checks

Before modifying any file, the agent is instructed to read it first:

```
## Pre-flight Checks
- Read every file before modifying it. Read relevant sources if the task depends on existing architecture.
- If referenced files/commands/config don't exist, stop and ask or report---don't guess.
- **When fixing bugs/issues/races: write tests to confirm first, then fix.**
```

**“Read every file before modifying it.”** The most common source of agent-introduced bugs is modifying a file based on an incorrect assumption about its current contents. By requiring a fresh read immediately before any edit, the instruction ensures the model operates on the file’s current state.

672 **“When fixing bugs/issues/races: write tests to confirm first, then fix.”** This mandates test-first  
673 discipline: a test that reproduces the bug provides concrete verification that the fix is correct. Writing  
674 the test forces the model to understand the bug precisely before attempting a fix.

### 675 A.3 Code Style Guidelines

676 The prompt encodes a minimalist code philosophy:

```
677 ## Code Style
678
679 - Simple, clean, readable code with minimal indirection. Organize in multiple files by functionality.
680 - Avoid unnecessary attributes, locals, config vars, tight coupling, and attribute redirections.
681 - DO NOT USE CLOSURES. No redundant abstractions or duplicate code.
682 - Public methods MUST have full documentation.
683 - Fix root causes, not symptoms. Think first: is the code simple, elegant, general, minimal?
684 - Don't write documentation unless the task requires it.
```

687 Each guideline addresses an anti-pattern commonly exhibited by LLM-generated code. For example,  
688 “DO NOT USE CLOSURES” steers the model toward explicit data structures (plain functions with  
689 arguments, classes with attributes) that are easier to test and reason about. “Think first: is the code  
690 simple, elegant, general, minimal?” is a metacognitive instruction that asks the model to pause and  
691 evaluate its plan, spending more inference-time compute on design.

### 692 A.4 Deep Work Rules

```
693 ## Deep Work
694
695 - For "align"/"match"/"make consistent": read the target state before editing. Never edit from vague
696   references.
697 - Use concrete values, not indirections (read Y first, then write specific values into X).
698 - List concrete planned changes before executing multi-part work.
699 - Every meaningful change needs a concrete verification method (test, grep, CLI).
```

702 These rules address failures where the model interprets instructions loosely and makes changes that  
703 are directionally correct but concretely wrong.

### 704 A.5 Planning for Complex Tasks

```
705 ## Complex Task Planning
706
707 For 3+ files, cross-module, or architectural work:
708
709 1. List files to change and why.
710 1. State exact intended change per file.
711 1. Identify dependencies and execution order.
712 1. State verification method per change.
713
714 Skip for simple single-file tasks.
```

717 The complexity threshold—three or more files—avoids the overhead of planning trivial changes  
718 while ensuring comprehensive planning for tasks with cross-module dependencies.

### 719 A.6 Testing Instructions

```
720 ## Testing
721
722 - Run lint/typecheckers; fix all errors. Achieve 100% branch coverage. Every error, including pre-existing
723   ones, is yours---don't skip.
724 - NO mocks, patches, fakes, or test doubles. Write integration/e2e tests. Each test independent, verifying
725   actual behavior.
726 - **Only run impacted tests after modifications.**
727 - To confirm races: add random sleep (<0.1s) before racing statements.
```

730 The most opinionated rule is the no-mocks requirement. Mock tests verify that code calls certain  
731 methods in a certain order—they test the implementation, not the behavior. A test suite built on

732 mocks can pass with flying colors while the system is fundamentally broken. Integration tests that  
733 exercise actual behavior provide genuine confidence that the system works. The clause “Every error,  
734 including pre-existing ones, is yours—don’t skip” makes the agent responsible for the entire codebase  
735 health, not just the delta it introduced.

## 736 A.7 Self-Improvement Loop

737 The agent maintains a preferences file that captures user invariants discovered during task execution:

```
738 ## Self-Improvement Loop
739
740
741 Read PWD/USER_PREFS.md at task start. Update with user preferences/invariants (no code snippets/symbols;
742 skip one-off tasks). Remove conflicting old entries carefully and thoroughly.
```

744 This mechanism allows the agent to accumulate project knowledge over time without requiring the  
745 user to repeat themselves. The conflict-resolution clause mandates that the agent actively resolves  
746 contradictions when updating the file. The prohibition on code snippets and symbols keeps the  
747 file compact and robust to code changes; the one-off task exclusion prevents preference drift from  
748 idiosyncratic details.

## 749 A.8 Pre-Finish Verification

```
750 ## Pre-Finish Verification
751
752 Before finish(success=True):
753
754 1. Re-read and verify every modified file.
755 1. Run required checks (lint, typecheck, tests); fix failures.
756 1. Check each user requirement against delivery.
757 1. If any check fails, keep working.
758 1. After 3 failed retries of same fix, rethink from scratch.
759
```

761 The three-retry threshold forces the model to break out of repetitive loops by abandoning the current  
762 approach and reconsidering the problem from first principles.

## 763 A.9 File Browsing Protocol

```
764 ## File Browsing
765
766 Collect info and code snippets in PWD/tmp/file-information-{unique_id}.md without overthinking, then
767 review and think deeply.
768
```

770 This instruction applies the same two-phase collect-then-synthesize discipline used for web research  
771 (Section 4.2) to the local file system. By writing a structured summary of each file’s relevant  
772 information into a temporary markdown file, the agent externalizes its understanding into a compact  
773 artifact that is typically much smaller than the raw source files, freeing up context window capacity  
774 for subsequent reasoning and editing.

## 775 A.10 Desktop Application Control

```
776 ## Desktop Apps
777
778 Use screenshots, keyboard, and mouse. Don’t launch VS Code or its extensions.
779
```

781 The prohibition on launching VS Code prevents a recursive loop: since the agent runs inside a  
782 VS Code extension, launching another instance could corrupt the host session or create deadlocks.



## NeurIPS Paper Checklist

### 1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope?

Answer: [Yes]

Justification: The abstract and introduction (Section 1) clearly state the contributions—a five-layer agent architecture, a structured system prompt, a VS Code extension, and a 62.2% pass rate on Terminal-Bench 2.0—and the scope is limited to software engineering tasks.

Guidelines:

- The answer [N/A] means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A [No] or [N/A] answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

### 2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: Section 3 discusses consistently failed tasks and their failure categories (graphical/multimedia requirements, resource-intensive builds, niche domain knowledge). The conclusion acknowledges that results depend on a single frontier model (Claude Opus 4.6) and a single benchmark.

Guidelines:

- The answer [N/A] means that the paper has no limitation while the answer [No] means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate “Limitations” section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren’t acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

### 3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [N/A]

Justification: The paper does not include theoretical results. It is a systems paper presenting an architecture and empirical evaluation.

Guidelines:

- The answer [N/A] means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

#### 4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Section 3 describes the benchmark (Terminal-Bench 2.0), the evaluation framework (Harbor), the model (Claude Opus 4.6), the hardware (2025 MacBook Air M4, 24 GB RAM), the number of trials (5 per task), and the 9 skipped tasks. The full agent architecture is described in Section 2 and the system prompt in Section 4 and Appendix A.

Guidelines:

- The answer [N/A] means that the paper does not include experiments.
- If the paper includes experiments, a [No] answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).

- (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

## 5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [No] The code repository link is withheld to preserve double-blind review. The system is open-source and the code will be made available upon acceptance.

Justification: The open-source repository link is withheld to respect double-blind review (stated in Section 1). The system will be publicly released upon acceptance.

Guidelines:

- The answer [N/A] means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://neurips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so [No] is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://neurips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

## 6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer) necessary to understand the results?

Answer: [Yes]

Justification: Section 3 specifies the benchmark, model, hardware, number of trials, skipped tasks, and evaluation methodology. No training or fine-tuning is performed.

Guidelines:

- The answer [N/A] means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

## 7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: We run 5 independent trials per task (445 total runs) and report pass@any (78.7%), pass@all (43.8%), and overall pass rate (62.2%), as well as the distribution of always-pass, always-fail, and mixed-result tasks. Median and mean cost and duration are reported.

Guidelines:

- The answer [N/A] means that the paper does not include experiments.
- The authors should answer [Yes] if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g., negative error rates).
- If error bars are reported in tables or plots, the authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

## 8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Section 3 specifies the hardware (2025 MacBook Air 15" with M4 processor and 24 GB RAM) and reports median/mean cost (\$0.45/\$0.90 per trial) and median/mean duration (202 s/446 s per trial).

Guidelines:

- The answer [N/A] means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

## 9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We have reviewed the NeurIPS Code of Ethics. The research involves building and evaluating a software engineering assistant; no human subjects, sensitive data, or dual-use concerns are involved.

Guidelines:

- The answer [N/A] means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer [No], they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

## 10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: The paper discusses positive impacts (making software development more accessible, reducing developer toil). Potential negative impacts include job displacement for routine programming tasks and the risk of generating vulnerable code if the system prompt's verification disciplines are removed. The system mitigates the latter through mandatory pre-finish verification (Appendix A.8) and test-first discipline (Appendix A.6).

Guidelines:

- The answer [N/A] means that there is no societal impact of the work performed.
- If the authors answer [N/A] or [No], they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate Deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

## 11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pre-trained language models, image generators, or scraped datasets)?

Answer: [N/A]

Justification: The paper does not release a pretrained language model or dataset. The system is an agent framework that wraps existing commercial LLM APIs.

Guidelines:

- The answer [N/A] means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

## 12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: All tools, benchmarks, and models used are cited: Terminal-Bench 2.0, Harbor, Claude Opus 4.6, Playwright, VS Code, and all related works. The system is open-source.

Guidelines:

- The answer [N/A] means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

### 13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [N/A]

Justification: No new datasets or pretrained models are released. The open-source code will be documented upon release.

Guidelines:

- The answer [N/A] means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

### 14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [N/A]

Justification: The paper does not involve crowdsourcing or research with human subjects.

Guidelines:

- The answer [N/A] means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

### 15. Institutional review board (IRB) approvals or equivalent for research with human subjects

1098 Question: Does the paper describe potential risks incurred by study participants, whether  
 1099 such risks were disclosed to the subjects, and whether Institutional Review Board (IRB)  
 1100 approvals (or an equivalent approval/review based on the requirements of your country or  
 1101 institution) were obtained?

1102 Answer: [N/A]

1103 Justification: The paper does not involve human subjects research.

1104 Guidelines:

- 1105 • The answer [N/A] means that the paper does not involve crowdsourcing nor research  
 1106 with human subjects.
- 1107 • Depending on the country in which research is conducted, IRB approval (or equivalent)  
 1108 may be required for any human subjects research. If you obtained IRB approval, you  
 1109 should clearly state this in the paper.
- 1110 • We recognize that the procedures for this may vary significantly between institutions  
 1111 and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the  
 1112 guidelines for their institution.
- 1113 • For initial submissions, do not include any information that would break anonymity (if  
 1114 applicable), such as the institution conducting the review.

1115 **16. Declaration of LLM usage**

1116 Question: Does the paper describe the usage of LLMs if it is an important, original, or  
 1117 non-standard component of the core methods in this research? Note that if the LLM is used  
 1118 only for writing, editing, or formatting purposes and does *not* impact the core methodology,  
 1119 scientific rigor, or originality of the research, declaration is not required.

1120 Answer: [Yes]

1121 Justification: The entire system is built around LLM usage. Section 2 describes how LLMs  
 1122 are used as the core reasoning engine via native function calling (Section 2.1). The paper  
 1123 also discloses that the system was built using itself (Section 1).

1124 Guidelines:

- 1125 • The answer [N/A] means that the core method development in this research does not  
 1126 involve LLMs as any important, original, or non-standard components.
- 1127 • Please refer to our LLM policy in the NeurIPS handbook for what should or should not  
 1128 be described.