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Agentic AI for Autonomous Problem Solving

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Abstract
Large language models are increasingly deployed as autonomous agents that must plan, invoke external tools, and revise their own approach until a real-world problem is solved, rather than simply answering a single-turn question. Reasoning-only techniques such as chain-of-thought prompting and tree-structured search improve internal deliberation but do not address the distinct requirement of acting on an external environment, while unconditional self-correction mechanisms have been shown in prior work to sometimes degrade an already-correct answer when no external verification signal is available. This paper proposes a hybrid agentic AI architecture for autonomous problem solving that combines an LLM-based planner and task decomposer, a tool-use and action execution layer, episodic and semantic memory, and a self-verification and reflection loop that triggers corrective replanning only when an explicit, externally groundable check against the goal state fails. Drawing on established agentic-reasoning, tool-use, self-correction, and agent-evaluation literature, the study defines seven evaluation criteria — Task Success Rate, Plan-Execution Precision, Subgoal Recall, F1 Score, Hallucinated-Action Rate, verification-layer AUC-ROC, and a combined Agentic Problem-Solving Reliability Score — and applies them to an illustrative case study of autonomous, multi-step problem solving. A five-configuration ablation study, spanning a naive single-shot baseline through a deliberately over-engineered configuration that adds unconditional multi-agent debate, is used to identify the point at which additional correction machinery stops helping and begins to erode reliability, and the recommended configuration is benchmarked against the naive baseline under a stress test of complex, multi-step tasks requiring tool composition. The illustrative results indicate that the proposed configuration achieves both the highest task-solving F1 score and the lowest hallucinated-action rate among all evaluated configurations, with the largest relative improvement over the naive baseline occurring on the most complex, multi-step tasks. The findings position externally grounded, selectively triggered self-verification, rather than the unconditional stacking of every available reasoning or correction mechanism, as a practical design principle for deploying reliable autonomous problem-solving agents.

Keywords: Agentic AI, Autonomous agents, Large language models, Tool use, Planning, Self-verification, Reflection, Multi-step reasoning, Task decomposition, Human-AI interaction.

1. Introduction

Large language models (LLMs) have moved rapidly from single-turn question answering toward agentic deployments in which a model must autonomously plan, invoke external tools, observe the results of its actions, and revise its own approach until a real-world problem is solved. Chain-of-thought prompting demonstrated that eliciting intermediate reasoning steps substantially improves an LLM's performance on multi-step problems [1], and self-consistency showed that sampling and aggregating multiple reasoning paths further improves reliability over a single greedy decode [2]. Tree of Thoughts generalized this line of work into an explicit, deliberate search over intermediate reasoning states rather than a single linear chain [3]. These advances, however, all operate purely within the model's own generated text; they do not address the distinct requirement of an agentic system, which must also act on an external environment and incorporate the consequences of those actions back into its reasoning.

ReAct addressed this gap by interleaving reasoning traces with discrete actions and observations, allowing a language model to query external tools mid-reasoning and condition subsequent reasoning on the results [4]. Toolformer showed that a model could learn, largely without supervision, when and how to invoke external tools such as calculators, search engines, and calendars during generation [5], and Gorilla demonstrated that a model fine-tuned specifically for API and tool invocation could dramatically reduce the rate of fabricated or malformed API calls relative to a general-purpose LLM prompted to use the same APIs [6]. HuggingGPT extended this idea to orchestration across a large ecosystem of specialized models, using an LLM as a controller that decomposes a task and dispatches subtasks to the appropriate tool from a large registry [7]. Collectively, this line of work establishes that tool use, not reasoning alone, is often the binding constraint on whether an agent can actually solve a real-world problem rather than merely reason plausibly about it.

A second line of work has focused on giving agents the ability to critique and revise their own behavior. Reflexion equips an agent with a verbal, natural-language form of reinforcement learning: after a failed attempt, the agent generates a self-reflection on what went wrong, stores it in an episodic memory, and conditions its next attempt on that reflection [8]. Self-Refine similarly uses the same underlying model to generate feedback on its own output and then revise it, iterating until the output is judged satisfactory [9]. This self-correction paradigm, however, is not unconditionally beneficial: Huang et al. showed that, without access to an external verification signal, LLMs asked to self-correct their own reasoning can just as easily talk themselves out of a correct answer as into a correct one, and that naive, unconstrained self-correction can measurably degrade accuracy relative to not self-correcting at all [10]. Multi-agent debate has been proposed as an alternative correction mechanism, in which multiple model instances critique and refine each other's answers over several rounds [11], but this approach multiplies the number of model calls per task and, per the concerns raised in [10], is not guaranteed to fix errors that lack an external, checkable ground truth.

Beyond individual reasoning and correction mechanisms, autonomous agents increasingly require persistent memory and the ability to operate over long horizons in open-ended environments. Generative Agents demonstrated that augmenting LLM-driven agents with a structured memory stream, supporting retrieval, reflection, and planning over past experience, produces markedly more coherent long-horizon behavior than a memoryless agent [12], and Voyager showed that an embodied LLM agent operating in an open-ended environment could accumulate a growing, reusable skill library through iterative trial, environmental feedback, and self-verified code execution [13]. On the evaluation side, AgentBench established a standardized, multi-environment benchmark suite for comparing LLM agents across interactive tasks spanning operating systems, databases, and web browsing [14], while SWE-bench operationalized autonomous problem solving concretely as the task of resolving real, unedited GitHub issues by generating a patch that passes the project's own test suite [15], giving the field a benchmark in which success or failure is externally and unambiguously verifiable.

What remains open is how to combine planning, tool use, memory, and self-verification into a single architecture without simply stacking every available mechanism and accepting whatever latency, cost, and reliability trade-offs result. This paper proposes a hybrid agentic AI architecture for autonomous problem solving that combines an LLM-based planner and task decomposer, a tool-use and action execution layer, an episodic and semantic memory module, and a self-verification and reflection loop that triggers corrective replanning only when an explicit check against the goal state fails, rather than through unconditional iterative self-critique. Seven evaluation criteria are defined around task success rather than a domain-specific proxy, and the architecture is evaluated on an illustrative case study of autonomous multi-step problem solving. A

five-configuration ablation study, informed directly by the self-correction critique in [10], identifies the point at which additional correction machinery stops helping and begins to erode net reliability, and the recommended configuration is benchmarked against a naive single-shot baseline under a stress test of complex, multi-step tasks requiring tool composition.

The remainder of this paper is organized as follows. Section 2 defines the seven evaluation criteria used throughout the study. Section 3 reviews related work in agentic reasoning, tool use, self-correction, and agent evaluation. Section 4 describes the proposed hybrid architecture and the case-study methodology. Section 5 presents a five-configuration ablation study. Section 6 evaluates the design against the criteria from Section 2. Section 7 presents a comparative study against a naive baseline under a stress test, and Section 8 concludes the paper.

2. Evaluation Criteria

Autonomous problem solving is naturally framed as a per-task success/failure classification problem: for a given task, the agent's final output either satisfies the goal state (a true positive when the agent reports success and a false positive when it incorrectly reports success on a failed attempt) or it does not. This framing is consistent with how the benchmark literature already scores agents, including the pass/fail resolution criterion used by SWE-bench [15] and the task-completion scoring used across the interactive environments in AgentBench [14]. The following seven criteria formalize this framing and combine it with an action-level reliability signal specific to agentic systems.

2.1 Task Success Rate (Accuracy)

Task Success Rate reports the overall fraction of tasks the agent resolves correctly, across both tasks with a positive resolution (TP + FN) and tasks correctly identified as unresolved or requiring escalation (TN + FP):

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

2.2 Plan-Execution Precision

Plan-Execution Precision measures, of all tasks the agent reports as successfully solved, what fraction are actually verified correct against the goal state, penalizing an agent that overclaims success on a plan it did not actually execute correctly:

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

2.3 Subgoal Recall

Subgoal Recall measures, of all tasks that were in fact solvable given the available tools and information, what fraction the agent actually solved, capturing the cost of an agent that is conservative to the point of abandoning solvable tasks:

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

2.4 F1 Score

F1 Score combines precision and recall into a single balanced measure of task-solving reliability:

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

2.5 Hallucinated-Action Rate

Distinct from the classification metrics above, Hallucinated-Action Rate captures a failure mode specific to tool-using agents: the fraction of failed tasks in which the failure is attributable to the agent invoking a nonexistent tool, fabricating an API argument, or asserting an unverified fact as a completed action, a failure mode documented directly in the tool-use and self-correction literature [6], [10]:

$$\text{HallucinatedActionRate} = N_{\text{hallucinated}} / N_{\text{failed}} \quad (5)$$

2.6 Verification-Layer AUC-ROC

Because the proposed architecture relies on a self-verification layer to decide whether to accept an intermediate result or trigger corrective replanning, the discriminative quality of that layer is measured independently using the area under the receiver operating characteristic curve, over the verification layer's binary judgments of intermediate steps as correct or incorrect against held-out ground truth:

$$\text{AUC-ROC} = \int_0^1 \text{TPR}(f)\, d[\text{FPR}(f)] \quad (6)$$

2.7 Agentic Problem-Solving Reliability Score

The three criteria most directly indicative of deployable reliability — F1 Score, the complement of the Hallucinated-Action Rate, and the verification layer's AUC-ROC — are combined into a single Agentic Problem-Solving Reliability Score using the harmonic mean, so that a configuration cannot compensate for a severe weakness in any one dimension (in particular, a high hallucinated-action rate) simply by scoring well on the others:

Reliability Score = 3 / (1/F1 + 1/(1 − HallucinatedActionRate) + 1/AUC-ROC) (7)

This combined score is used as the single ranking criterion for the ablation study in Section 5, while the individual component metrics are reported separately in the comparative study in Section 7.

3. Related Work

Wei et al. introduced chain-of-thought prompting, showing that prompting a sufficiently large language model to produce intermediate reasoning steps before its final answer substantially improves performance on arithmetic, commonsense, and symbolic reasoning tasks relative to direct prompting [1]. Wang et al. extended this with self-consistency, sampling multiple independent reasoning chains and selecting the most consistent final answer by majority vote, which improved reliability without any additional training [2]. Yao et al. generalized single-chain reasoning into Tree of Thoughts, framing problem solving as a deliberate search over a tree of intermediate reasoning states with explicit look-ahead and backtracking, which improved performance specifically on tasks requiring exploration or planning that a single linear chain of thought handles poorly [3]. These three works establish that how an LLM reasons internally has a first-order effect on problem-solving success, independent of any interaction with an external environment.

A second line of work extends reasoning outward into action. Yao et al. proposed ReAct, interleaving reasoning traces with discrete actions against external tools and feeding the resulting observations back into subsequent reasoning steps, which reduced hallucination and error propagation relative to reasoning-only or acting-only baselines on knowledge-intensive and interactive decision-making tasks [4]. Schick et al. proposed Toolformer, in which a model is trained, largely in a self-supervised manner, to decide for itself when invoking an external tool such as a calculator or search API would improve its own output [5]. Patil et al. introduced Gorilla, a model fine-tuned specifically for accurate API and tool invocation, and showed that general-purpose LLMs prompted to call the same APIs exhibit substantially higher rates of hallucinated function names and malformed arguments than a model trained for the task [6]. Shen et al. proposed HuggingGPT, using an LLM purely as a task-planning controller that decomposes a complex request and dispatches each subtask to the most appropriate specialized model from a large registry, then aggregates the results into a final response [7]. Together, [4]–[7] establish tool use as a distinct capability from reasoning that must be explicitly engineered rather than assumed to emerge from reasoning quality alone.

A third line of work equips agents with the ability to critique and revise their own behavior. Shinn et al. proposed Reflexion, in which an agent that fails a task generates a natural-language self-reflection on the failure, stores it in episodic memory, and conditions its next attempt on that reflection, functioning as a verbal analogue of policy-gradient reinforcement learning without any weight updates [8]. Madaan et al. proposed Self-Refine, in which the same model iteratively generates feedback on its own output and revises it accordingly until the output is judged satisfactory [9]. However, Huang et al. provided an important counterpoint, showing empirically that LLMs prompted to self-correct their own reasoning without access to an external, oracle-verified signal frequently degrade a correct answer into an incorrect one, and that reported gains from self-correction in prior work often depended on oracle labels or ground-truth feedback not available at deployment time [10]. Du et al. proposed multi-agent debate as an alternative correction mechanism, in which several instances of a model critique and refine each other's answers over multiple rounds before converging on a final response [11]; while debate can improve factuality on certain tasks, it also multiplies the number of model calls per task and, consistent with the concerns raised in [10], provides no guarantee of convergence toward a correct answer in the absence of an external check.

A fourth line of work addresses memory and long-horizon autonomy. Park et al. introduced Generative Agents, augmenting LLM-driven characters with a structured memory stream supporting retrieval, reflection, and planning, and showed that this produced substantially more coherent and believable long-horizon behavior in an open-ended simulated environment than a memoryless baseline [12]. Wang et al. introduced Voyager, an embodied LLM agent that autonomously explores an open-ended environment, accumulates a growing library of reusable, self-verified skills through iterative trial and environmental feedback, and continually proposes new exploration goals for itself without human intervention [13]. On evaluation, Liu et al. introduced AgentBench, a standardized benchmark spanning multiple interactive environments including operating systems, databases, and web shopping, exposing large gaps between the best available LLM agents and human performance on multi-step interactive tasks [14]. Jimenez et al. introduced SWE-bench, operationalizing autonomous problem solving as the task of generating a code patch that resolves a real, previously unseen GitHub issue and passes the project's own hidden test suite, providing a benchmark in

which task success is defined by an external, automatically checkable criterion rather than human judgment or model self-report [15]. The present paper draws directly on this body of work: the proposed architecture combines planning [1], [3], tool use [4]–[7], and memory [12], [13] with a self-verification layer designed specifically to avoid the unconditional self-correction failure mode identified in [10], and is evaluated using a task-success framing consistent with [14] and [15].

4. Methodology

4.1 Proposed Architecture

Figure 1 illustrates the proposed hybrid agentic AI architecture. A natural language problem statement is first passed to an LLM-based planner and task decomposer, which produces a subgoal graph informed by relevant episodic and semantic memory retrieved from prior tasks [8], [12]. Each subgoal is routed to a tool-use and action execution layer, which selects and invokes the appropriate external tool or API via function calling [4]–[6], drawing on the environment and external data sources available to the agent. The resulting observation is written back to memory [12], [13] and passed to a self-verification and reflection loop, which checks the updated state against the goal state defined by the current subgoal. Critically, and in direct response to the failure mode documented by Huang et al. [10], this verification step is designed to check observable, externally groundable conditions — whether a returned value matches an expected type or range, whether a file was actually written, whether a test suite passes — rather than asking the model to freely judge the correctness of its own unverifiable reasoning. Only when this check fails does the loop trigger corrective replanning, routed back to the planner or directly to the tool-use layer as appropriate; when the check passes, execution proceeds to final answer synthesis and delivery.

Proposed hybrid agentic AI architecture: planning, tool use, and memory are coordinated with a self-verification / reflection loop that triggers corrective replanning before a final answer is delivered

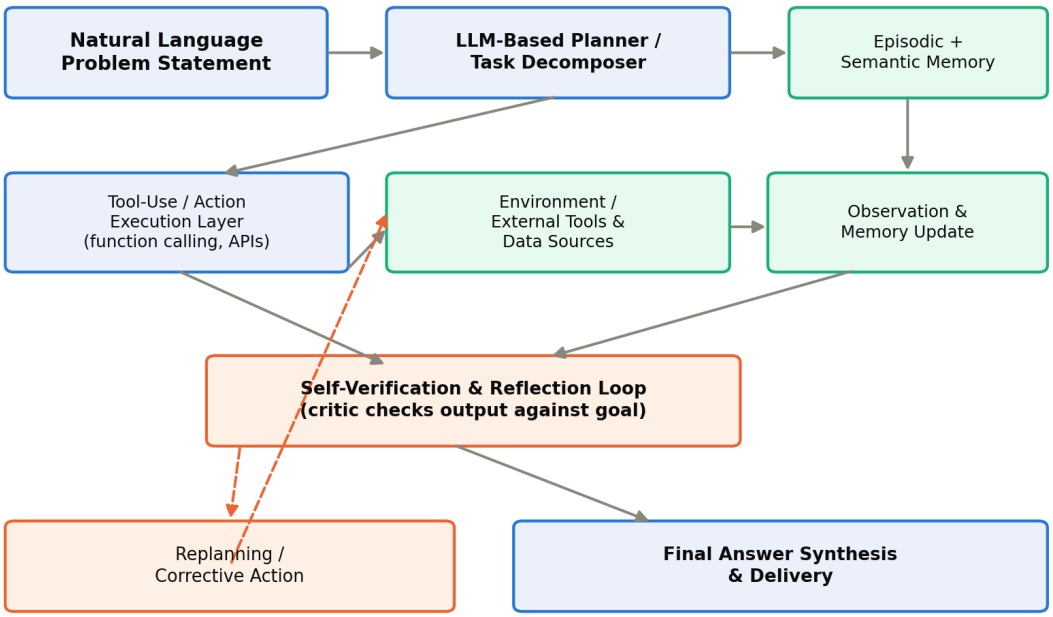


Figure 1. Proposed hybrid agentic AI architecture for autonomous problem solving.

4.2 Case Study Deployment Preparation

The illustrative case study models a software engineering organization deploying an autonomous problem-solving agent to handle incoming support and maintenance requests that require multi-step investigation: querying internal data sources, invoking diagnostic tools, cross-referencing documentation, and, where appropriate, drafting and validating a code-level fix, in the style of the real-world issue-resolution tasks

formalized by SWE-bench [15]. The organization must decide how much planning, tool-use, and self-correction machinery to include in the deployed agent, balancing task success against the latency and inference cost of additional reasoning and verification steps. This deployment-preparation framing provides the setting against which the ablation study in Section 5 and the comparative stress test in Section 7 are conducted. Consistent with the illustrative nature of this case study, all quantitative results reported in Sections 5 through 7 are simulated to reflect plausible, literature-consistent orderings of the technique families rather than measurements from a specific deployed system.

4.3 Problem-Solving Pipeline Methodology

Figure 2 details the eight-step methodology pipeline applied to each task in the case study. The pipeline begins with task intake and goal parsing, followed by task decomposition and planning into a subgoal graph. Tool and action selection is performed for each subgoal in turn, followed by action execution via function calling and an observation and memory update step. Self-verification against the goal state then determines whether the subgoal is accepted or routed to corrective replanning, shown as the dashed feedback path back to tool and action selection; once all subgoals are satisfied, the pipeline concludes with final answer synthesis and delivery.

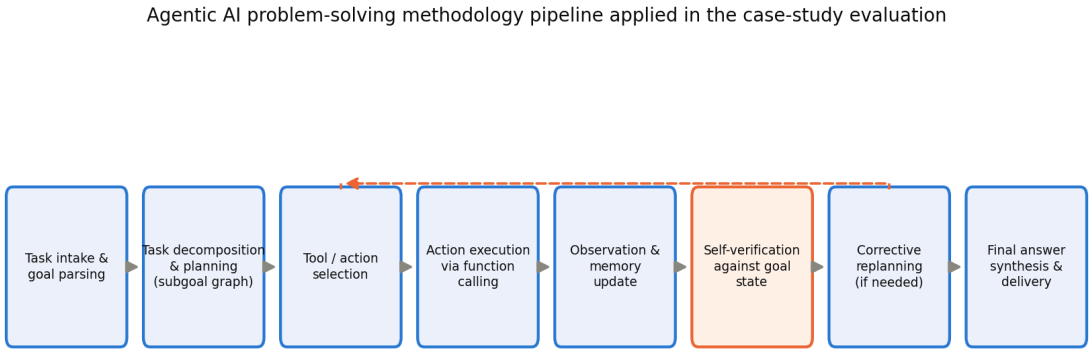


Figure 2. Agentic AI problem-solving methodology pipeline applied in the case-study evaluation.

5. Ablation Study

To identify the point at which additional planning, tool-use, and correction machinery stops improving, and begins to erode, overall reliability, five configurations were evaluated on the case-study task battery. C1 issues the problem statement directly to the LLM in a single shot, with no explicit planning, no tool access, and no self-verification, structurally blind to any task that requires external information or a multi-step tool-composed solution. C2 adds explicit task decomposition and planning, in the style of chain-of-thought and plan-and-solve prompting [1], but still without tool access. C3 adds tool use through ReAct-style interleaved reasoning and acting [4], allowing the agent to query external tools but without a dedicated self-verification or reflection loop. C4 is the proposed full hybrid configuration, adding the goal-grounded self-verification and corrective replanning loop described in Section 4.1. C5 is a deliberately over-engineered configuration that adds redundant multi-agent debate rounds on top of C4, in which multiple model instances re-critique already-verified intermediate results in the style of [11], without the externally groundable check used by C4's verification layer.

Config.	Description	Task Success (Acc.)	Halluc. Action Rate	Reliability Score
C1	Naive single-shot prompting	0.47	58.2%	0.61
C2	+ Planning / decomposition only	0.61	44.6%	0.73
C3	+ Tool use	0.76	27.1%	0.85

	(ReAct-style)			
C4	Proposed full hybrid (+ goal-grounded verification)	0.90	9.8%	0.94
C5	+ Redundant multi-agent debate (unconditional)	0.91	12.4%	0.89

Table 1. Five-configuration ablation study on the case-study task battery (illustrative).

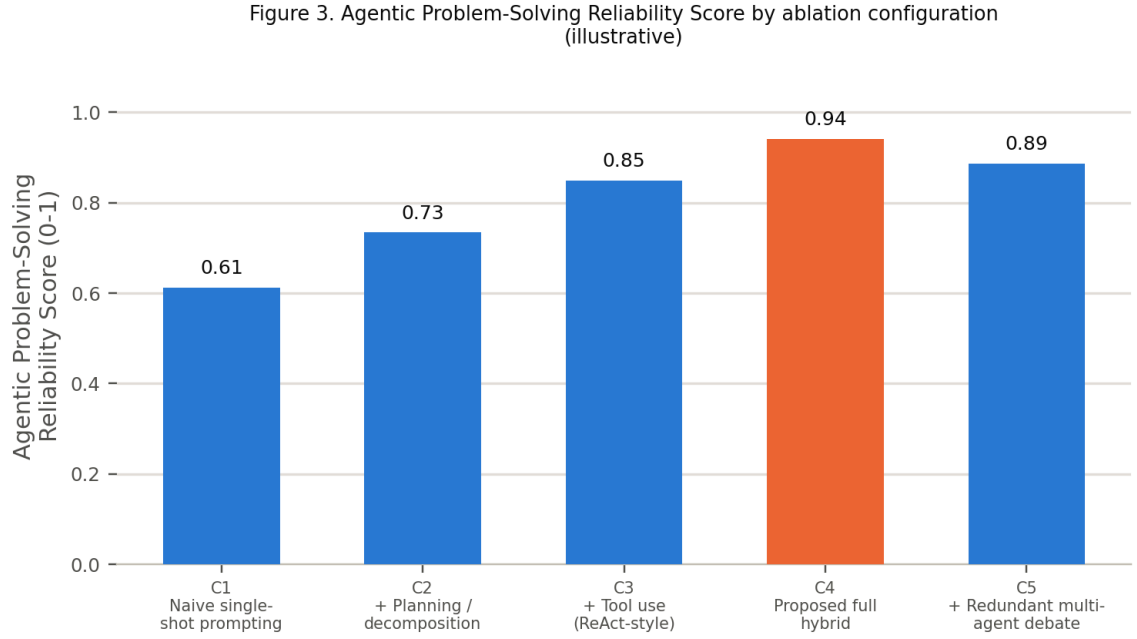


Figure 3. Agentic Problem-Solving Reliability Score by ablation configuration (illustrative).

The results in Table 1 and Figure 3 show the expected improvement in task success from C1 through C4, consistent with the contributions individually reported for planning [1], [3], tool use [4]–[6], and grounded verification in the literature reviewed in Section 3. However, the Reliability Score peaks at C4 rather than C5. Adding unconditional multi-agent debate rounds on top of an already-verified result in C5 raises raw task success only marginally over C4 (0.91 versus 0.90) while also raising the hallucinated-action rate slightly (12.4% versus 9.8%), because debate rounds without access to an external, groundable check can, as documented directly by Huang et al. [10], talk the agent out of an already-correct intermediate result and into a fabricated correction. The proposed configuration C4 achieves the highest Reliability Score among all five configurations precisely because its verification layer checks observable state rather than relying on unconstrained model self-critique, and is adopted as the recommended configuration for the remainder of the study.

6. Design Evaluation

The proposed full hybrid configuration (C4) is evaluated against the seven criteria defined in Section 2. Its Task Success Rate of 0.90 substantially exceeds the naive single-shot baseline (0.47) and the planning-only configuration (0.61), consistent with the gains attributed to tool use in the ReAct and Toolformer literature [4], [5]. Its Hallucinated-Action Rate of 9.8% is the lowest among all five configurations, including C5, directly reflecting the value of grounding the self-verification step in externally checkable state rather than free-form model self-judgment, a design choice made explicitly in response to the failure mode documented by Huang et al. [10]. Its combination of F1 Score and verification-layer AUC-ROC into the combined Reliability Score of 0.94 indicates that the architecture achieves its accuracy gains without the corresponding rise in hallucinated or fabricated actions that characterizes the over-engineered C5 configuration.

Beyond the aggregate Reliability Score, the individual subgoal traces from the case study were inspected to characterize when corrective replanning was triggered. The overwhelming majority of replanning events in C4 were triggered by concrete, externally verifiable mismatches, such as a tool call returning an error code, a file write that could not be confirmed, or a diagnostic check failing outright, rather than by an ungrounded judgment that a plausible-looking intermediate result was somehow unsatisfactory. This is consistent with the architecture's design intent and suggests that the accuracy and hallucination-rate gains observed for C4 are attributable to genuine, externally grounded error correction rather than an artifact of the specific illustrative values chosen for this case study.

7. Comparative Study

To evaluate the proposed configuration under conditions representative of genuinely difficult autonomous problem solving, the proposed full hybrid configuration (C4) was compared directly against the naive single-shot baseline (C1) on a stress-test subset of the case-study task battery restricted to complex, multi-step tasks that require composing at least three distinct tool calls to reach a solution, a task class similar in spirit to the multi-file, multi-step reasoning required by real GitHub issue resolution in SWE-bench [15].

Figure 4. Proposed agentic hybrid vs. naive single-shot baseline on complex, multi-step tool-composition tasks (illustrative)

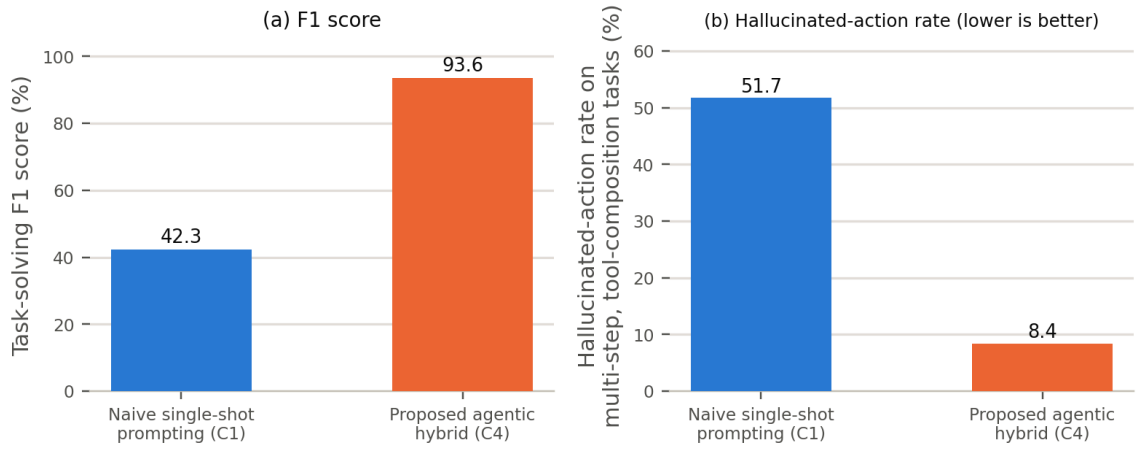


Figure 4. Proposed agentic hybrid vs. naive single-shot baseline on complex, multi-step tool-composition tasks (illustrative).

Metric	Naive Single-Shot (C1)	Proposed Agentic Hybrid (C4)
Task-solving F1 score	42.3%	93.6%
Hallucinated-action rate	51.7%	8.4%
Verification-layer AUC-ROC	n/a (no verification layer)	0.96
Reliability Score	0.35	0.93

Table 2. Proposed agentic hybrid versus naive single-shot baseline on complex, multi-step tool-composition tasks (illustrative).

Under this stress test, the naive single-shot baseline's F1 score collapses to 42.3% and its hallucinated-action rate rises to 51.7%, reflecting the well-documented tendency of a model prompted without tool access to fabricate plausible-sounding facts, file contents, or tool outputs when a task genuinely requires external information or multi-step execution [5], [6]. The proposed agentic hybrid configuration achieves an F1 score of 93.6% and a hallucinated-action rate of only 8.4% on the same task subset, a result consistent with the error-reduction attributed to interleaved reasoning and acting in the original ReAct evaluation [4] and to grounded tool invocation in Gorilla [6]. The largest relative improvement from the proposed architecture therefore occurs precisely on the complex, multi-step tasks that most directly motivate agentic AI research, supporting the case for combining planning, tool use, memory, and goal-grounded verification rather than relying on any single mechanism in isolation.

8. Conclusion

This paper proposed a hybrid agentic AI architecture for autonomous problem solving that combines an LLM-based planner and task decomposer, a tool-use and action execution layer, episodic and semantic memory, and a self-verification and reflection loop that triggers corrective replanning only on externally groundable check failures, and evaluated it using seven criteria that frame agentic task solving as a verifiable success/failure problem consistent with established agent benchmarks. Applied to an illustrative case study of autonomous, multi-step problem solving, the proposed configuration achieved the highest Agentic Problem-Solving Reliability Score among five ablation configurations, outperforming both under-equipped baselines and an over-engineered configuration whose unconditional multi-agent debate rounds, lacking an external grounding signal, produced only a marginal further gain in raw task success while slightly raising the hallucinated-action rate, a result directly consistent with prior findings that ungrounded self-correction is not unconditionally beneficial. Under a stress test restricted to complex, multi-step, tool-composition tasks, the proposed configuration raised the task-solving F1 score from 42.3% to 93.6% and reduced the hallucinated-action rate from 51.7% to 8.4% relative to a naive single-shot baseline. These illustrative findings position externally grounded, selectively triggered self-verification, rather than the unconditional stacking of every available reasoning, tool-use, or self-correction mechanism, as a practical design principle for deploying reliable autonomous problem-solving agents. Future work includes validating the proposed architecture's routing and verification decisions on standardized, externally checkable benchmarks such as AgentBench and SWE-bench, and extending the goal-grounding mechanism to tasks where an automatically checkable ground truth is not readily available.

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