

Agent Systems with Harness Engineering

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Abstract

Developing effective agent systems has been a long-standing frontier in artificial intelligence. The recent emergence of LLM-based agents marks a paradigm shift, yet even highly capable models deployed without adequate system support exhibit systematic failures in long-horizon settings, including loss of intermediate goals, incorrect tool invocation, and inability to incorporate environmental feedback. These failures reflect not gaps in model training but a structural mismatch between the single-turn generative interface of LLMs and the stateful, iterative nature of real-world problem solving. In this paper, we formalize the surrounding infrastructure as the *harness* and introduce *harness engineering* as the joint optimization of both the harness and the model it supports. The relationship between the two is inherently *synergistic*: a well-designed harness unlocks latent model potential through structured memory, error recovery, and adaptive context management, while a capable model enables the harness to implement sophisticated workflows that would be infeasible with a weaker reasoner. We present a structured taxonomy of harness components, spanning agent workflows, memory systems, skill libraries, and multi-agent orchestration, and analyze how each contributes to system-level performance, distilling design principles and architectural trade-offs from current practice. We further review optimization strategies from both the scaffold side and the model side, and summarize evaluation benchmarks across software engineering, deep research, tool use, computer use, and scientific discovery. By shifting focus from *what* agents can accomplish to *how* the surrounding infrastructure enables them to do so, this paper aims to serve as a practical reference for building reliable, scalable, and controllable agent systems through principled harness engineering.

Keywords: Harness Engineering, Agent Systems

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1 Introduction

Developing effective agent systems has been a long-standing frontier in artificial intelligence [1], tracing back to early symbolic agents [2] and rule-based designs [3] that excelled in simplified, structured environments but struggled with complexity and scalability. Over the decades, progress through reinforcement learning [4] and robotic agents [5] brought adaptive behaviors; yet real-world deployment remained hindered by brittle decision-making and limited generalization.

The recent emergence of large language model (LLM)-based agent systems [6] has marked a paradigm shift: by leveraging rich commonsense knowledge, natural language interaction, and complex reasoning, LLMs empower agents to plan, use tools, and adapt in open-ended scenarios—dramatically enhancing their practicality for real-world applications such as software automation [7, 8], scientific discovery [9, 10], and personal assistance [11, 12]. Given these remarkable capabilities, initial LLM-based agent development placed significant emphasis on the models themselves rather than on the supporting mechanisms within the agent systems.

However, as tasks grow increasingly complicated, a fundamental challenge has emerged: even highly capable LLMs deployed without adequate system support exhibit systematic failures in long-horizon settings [13, 14]. For example, models frequently lose track of intermediate goals during multi-step planning, invoke tools with incorrect arguments or at inappropriate moments, and fail to incorporate environmental feedback to correct earlier mistakes [15]. These shortcomings are not merely gaps in model training that future scaling will close; they reflect a structural mismatch between the single-turn generative interface of LLMs and the stateful, iterative nature of real-world problem solving. A growing consensus has consequently emerged: the practical capability of an AI system depends as much on the design of its supporting harness as on the generative capacity of the underlying model.

Therefore, it is equally important to consider the design and development of supporting systems. In the context of LLMs, agent systems were initially defined as holistic frameworks comprising key modules—memory, tools, planning, and action—built atop LLMs. The field has since expanded to encompass prompt and context engineering [16, 17], which improves LLM capacities without altering model weights. More recently, agentic frameworks have advanced by redesigning the agent–environment interface itself. Unlike earlier systems relying on free-form text actions or limited tool calls, modern frameworks such as OpenClaw [11] and Hermes Agent [12] introduce highly capable action spaces (*e.g.*, bash commands, file edits, search operations), stateful sandboxed execution environments, and direct computer control—aiming to enable autonomous, long-horizon task execution without human oversight. These design choices shift the bottleneck from raw LLM reasoning to robust system scaffolding, transforming agents from fragile proof-of-concepts into deployable systems for real-world tasks.

This recognition—that practical capability depends as much on system scaffolding as on the model itself—naturally invites a more precise characterization of what this “supporting system” entails. In recent literature, the term harness has been adopted to refer specifically to the infrastructure that surrounds and extends a foundation model [13, 14]. We accordingly decompose an agent system into two fundamental components: a foundation model that serves as the reasoning engine responsible for language understanding, generation, and decision-making, and a supporting harness that governs execution flow, tool invocation, memory management, context construction, safety enforcement, and multi-step coordination with external environments [18, 19, 20, 21]. Without a harness, a model remains a passive text generator; only when embedded within a properly engineered harness does it become a functional agent.

Crucially, the relationship between these two components is not merely compositional but inherently *synergistic*: improvements to one component unlock latent potential in the other, producing system-level gains that neither could achieve in isolation. A more capable model, for instance, can follow more nuanced instructions, enabling the harness to implement sophisticated multi-step workflows that would be infeasible with a weaker reasoner. Conversely, a well-designed harness that provides structured memory retrieval, error recovery mechanisms, and adaptive context management allows even a moderately capable model to sustain coherent performance over long-horizon tasks that would otherwise exceed its standalone capacity. Harness engineering advances this synergy along two complementary fronts. On the scaffold side, it designs more effective workflows, memory architectures, skill libraries, and orchestration mechanisms that structure and channel model behavior. On the model side, it adapts the foundation model itself through context engineering and agentic training to



Figure 1: Timeline of representative agent systems with harness engineering. The lower portion presents scaffold-side optimization, encompassing four categories: **agent workflow**, **memory systems**, **skill libraries**, and **multi-agent orchestration**. The upper portion presents model-side adaptation, comprising two categories: **context engineering** and **agentic training**. These two dimensions are inherently synergistic—scaffold design shapes the interaction patterns that inform model adaptation, while improved model capabilities in turn enable more sophisticated scaffold architectures—together driving the development of more capable, robust, and generalizable agent systems.

more effectively exploit the capabilities afforded by the harness. We accordingly formalize *harness engineering* as the joint optimization of both components: designing the harness to accommodate the model’s strengths and limitations, while simultaneously adapting the model to leverage the harness’s affordances. It is precisely this bidirectional synergistic optimization that endows agent systems with the reliability, adaptability, and controllability required for complex real-world tasks.

In this paper, we focus on examining how the supporting infrastructure enables effective agent behavior, shifting the analytical focus from agent capabilities to the mechanisms that produce them. Specifically, the contributions of this paper are threefold:

- We formalize harness engineering as a distinct research paradigm, establishing its conceptual foundations and clarifying its relationship to adjacent paradigms. This provides a unified vocabulary for understanding the infrastructure that elevates language models into autonomous agents.
- We present a structured taxonomy of harness components, spanning agent workflows, memory systems, skill libraries, and multi-agent orchestration, and systematically analyze how each contributes to system-level performance, distilling design principles, architectural trade-offs, and empirical best practices from current practice.
- We comprehensively review optimization strategies that operate across both the scaffold and the underlying model, and summarize evaluation benchmarks that assess harness effectiveness in domains such as deep research, software engineering, tool use, computer use, and scientific discovery.

The remainder of this paper is organized as follows. Section 2 establishes the conceptual foundations of harness engineering. Section 3 details the principal components of harness design. Section 4 examines model adaptation techniques, including context engineering and agentic training. Section 5 summarizes evaluation benchmarks across deep research, software engineering, tool use, computer use, and scientific research. Section 6 identifies open challenges and future directions.

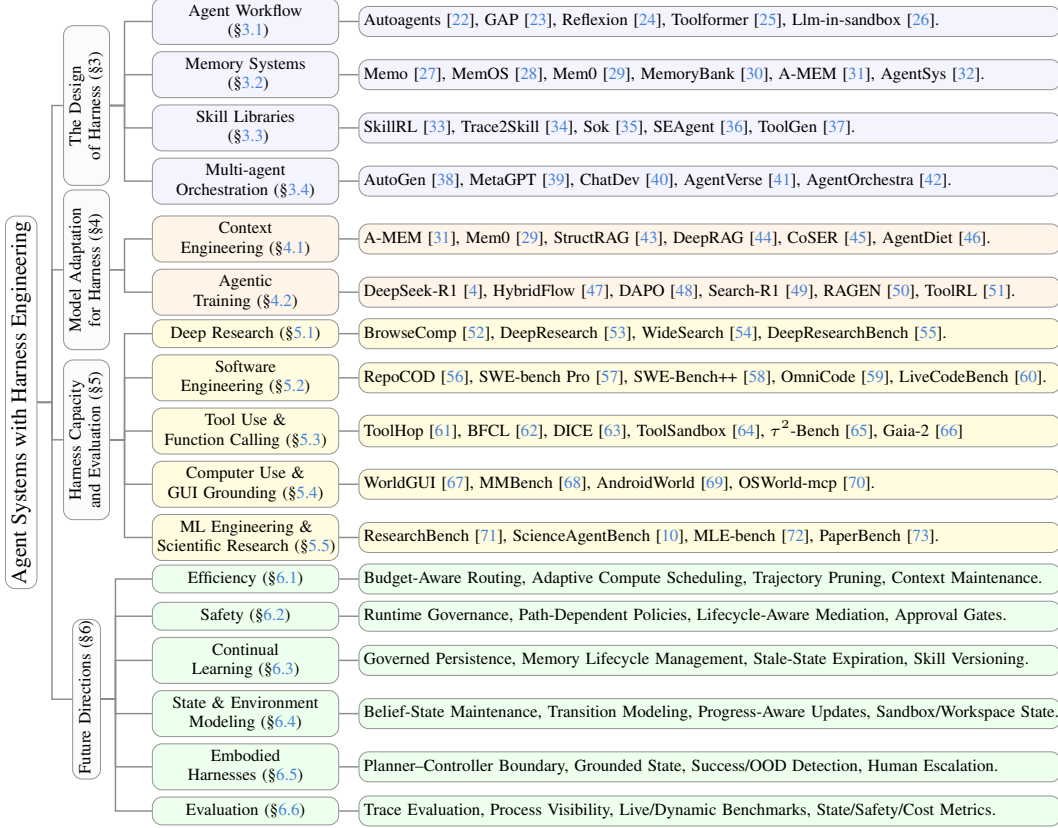


Figure 2: Overview of the structure of this paper.

2 Foundations of Harness Engineering

The practical capability of an agent system depends not only on the foundation model but equally on the orchestration layer that supports it [74, 75]. This layer structures reasoning steps, mediates tool interactions, and governs iterative execution across extended task horizons [76, 77]. We refer to its systematic study and design as *harness engineering*, with particular attention to how its scope expands as agentic systems evolve from simple model-environment coupling to increasingly capable and persistent forms of assistance. In this section, we introduce the concept through three progressively broader perspectives (Section 2.1), trace its evolution across three evolutionary phases (Section 2.2), and clarify its relationship to related concepts (Section 2.3).

2.1 The Concept of Harness Engineering

The notion of harness engineering admits multiple interpretations. We organize these into three progressively broader perspectives, each subsuming the previous one.

Perspective I: Harness Engineering as Structural Decomposition. The first and most basic perspective offers a structural decomposition: an agent system consists of two constitutive elements, a foundation model and its supporting harness. The foundation model provides core capabilities in language understanding, reasoning, and generation, while the harness constitutes the orchestration layer that mediates all interactions between the model and the external environment. Concretely, the harness governs tool invocation (*e.g.*, API calls and code execution), context maintenance (*e.g.*, conversation history and memory management), state persistence (*e.g.*, storage of intermediate results), and execution control (*e.g.*, termination conditions and retry policies). System-level performance is thus jointly determined by both components: a foundation model without a harness remains a reasoning engine capable of producing outputs yet unable to engage in sustained, goal-directed behavior; only when coupled with a properly designed harness does it become a fully functional

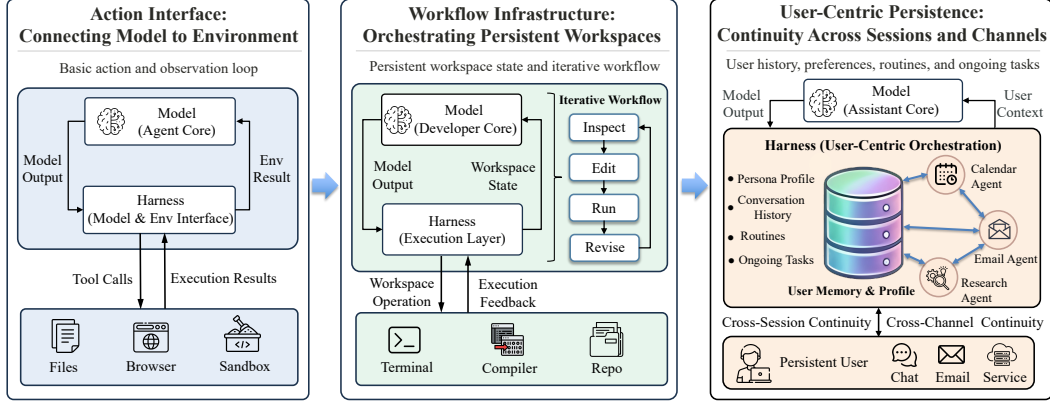


Figure 3: Three layers in the evolution of harness architecture, illustrating the progressive expansion of its scope and responsibility. **Layer 1 (Action Interface: Connecting Model to Environment):** The harness translates model outputs into executable tool calls (e.g., file operations, browser interactions, sandbox execution) and returns environmental observations, establishing a basic action-observation loop. **Layer 2 (Workflow Infrastructure: Orchestrating Persistent Workspaces):** The harness maintains persistent workspace state and orchestrates iterative workflows of inspecting code, applying edits, running commands, and revising based on execution feedback within technical environments such as terminals, compilers, and version-control systems. **Layer 3 (User-Centric Persistence: Continuity Across Sessions and Channels):** The harness manages user profiles, memory, conversation history, routines, and ongoing tasks, coordinating multiple specialized agents and providing cross-session and cross-channel continuity.

agent that can execute tasks in real-world environments. This perspective, however, remains primarily descriptive, for it identifies what surrounds the model without prescribing how the supporting structure should be designed or improved.

Perspective II: Harness Engineering as Framework Construction. The second perspective moves from description to implementation by equating harness engineering with the design and construction of agent frameworks. From this viewpoint, building a harness extends well beyond wrapping a model with a thin interface layer; it entails creating a complete, reusable software infrastructure that supports multi-step interaction, tool integration, and complex agentic workflows. The objectives of harness engineering, under this interpretation, coincide with those of agent framework development: to furnish developers with extensible, robust, and ready-to-deploy infrastructure for constructing agentic applications. While this perspective captures much of the practical engineering effort, it focuses on a single direction of optimization and does not address the complementary question of how the model itself can be adapted to better exploit the supporting infrastructure.

Perspective III: Harness Engineering as Synergistic Enhancement. This paper adopts a broader and more integrated view. Rather than treating harness engineering as either structural decomposition (Perspective I) or framework construction (Perspective II), we position it as a synergistic optimization methodology for agent systems. Whereas Perspective I focuses on the question “what constitutes an agent system?” and Perspective II examines “how to build the scaffold around a model?”, Perspective III explores “how can the scaffold and the model be jointly optimized to maximize system-level performance?” This synergistic formulation encompasses two complementary directions. The first direction targets optimizations of the scaffold supporting the model (Section 3), including the construction of agent workflows, the design of memory systems, the curation of skill libraries, and the orchestration of multi-agent collaboration. The second direction targets optimizations of the model itself to better cooperate with the harness (Section 4), encompassing context engineering and agentic training. Neither direction alone is sufficient: a well-architected scaffold cannot compensate for a model lacking fundamental reasoning capabilities, nor can a highly capable model realize its full potential within a poorly structured system. It is through the synergistic optimization of both sides that agent systems can attain the reliability, scalability, and controllability required for complex, long-horizon tasks in real-world settings.

2.2 Evolution of Harness Engineering

As agentic systems have been deployed in increasingly complex environments, the harness has had to support a broader range of actions, longer-horizon states, and more powerful forms of delegated control. To meet these growing demands, harness engineering has evolved through three distinct phases, each expanding the scope of what the orchestration layer is responsible for. In the first phase, the harness serves primarily as an interface between the model and the environment. In the second phase, it becomes the execution layer for developer assistants operating within persistent technical workspaces. In the third phase, it functions as the backbone of personal assistants that maintain continuity with individual users over time and across communication channels.

2.2.1 Action Interface: Connecting Model to Environment

The foundational layer of the harness establishes the connection between a model and its external environment. At this layer, the harness links the model with external tools such as file systems [78], browsers [79], and executable runtimes [80], translating outputs into executable actions and routing environmental results back for the next reasoning step. This closed-loop structure elevates a foundation model from a passive text generator to an agent capable of acting upon its environment [81].

The core mechanism is a repeating cycle of reasoning, action, and observation: the model generates an action, observes the outcome, and adjusts its next step based on the updated environmental state [82, 80]. A representative example is ReAct [82], which makes this loop explicit by directly interleaving reasoning traces with environment interactions. Subsequent work extends the same principle by incorporating program execution [80], API calls [25], and diverse external tools [83]. More recently, agent systems have organized these interactions within unified runtimes, enabling actions and observations to be handled consistently across different tools and environments [84, 78].

2.2.2 Workflow Infrastructure: Orchestrating Persistent Workspaces

Building upon the action interface, the second layer introduces persistent workspace management and multi-step workflow orchestration. The harness at this layer no longer merely bridges the model and individual tools; instead, it manages workspace state, coordinates sequences of development actions, and carries execution context across steps, enabling the model to inspect code [7], apply edits [85], run commands [86], and use results to guide subsequent actions [8]. This closed-loop development cycle elevates the model from a one-shot code generator to a developer assistant capable of iteratively refining its output until the task is complete [87].

The core mechanism at this layer is a repeating cycle of generation, execution, and revision: the model produces code, the harness executes it within the workspace, observes outcomes such as test results or error messages, and feeds these back for the next iteration [74, 88]. A representative example is SWE-agent [7], which demonstrates that strong task performance depends not only on code generation quality but critically on how the harness structures navigation, feedback, and iterative correction. Systems such as OpenHands [74] and Claude Code [88] further extend this principle by placing the model within realistic development environments with full access to shells, file systems, and version control, supporting sustained cycles of editing and validation rather than isolated generation. Beyond software engineering, LLM-in-Sandbox [26] shows that the same workspace infrastructure, virtualized as a minimal code sandbox, brings consistent gains across general non-coding tasks.

2.2.3 User-Centric Persistence: Continuity Across Sessions and Channels

The third layer extends the harness beyond single-session task execution by introducing continuity with individual users across sessions, tasks, and communication channels. Where the previous layer maintains workspace state within a task, this layer manages user history, preferences, routines, and ongoing tasks as persistent state, enabling personalized assistance that builds upon the prior interactions [89, 90]. This longitudinal interaction loop elevates the model from a stateless task executor to a personal assistant capable of sustained, context-aware engagement over time [91, 92].

The defining requirement at this layer is continuity with the same user over time, even when tasks span different sessions or communication channels [93, 90]. This enables longer-term, personalized assistance that accumulates knowledge of user needs and adapts accordingly. A representative example is OpenClaw [94], which treats the assistant as a persistent, user-oriented agent with support for memory, profile management, and delegated action across realistic tools and long-horizon interactions.

2.3 Connections with Related Concepts

Harness engineering is an emerging concept that intersects with several established notions in agent systems research. In this subsection, we clarify how harness engineering connects to and builds upon these related concepts.

Agent Framework. The concept most closely connected to harness engineering is the agent framework. Such frameworks provide reusable infrastructure for building, deploying, and managing agentic applications, typically covering tool interfaces, execution environments, interaction protocols, and support for multi-step task completion [76, 84]. Their core contribution is a concrete implementation foundation that turns agentic behavior into a working process. While the two concepts share common ground, they operate at different levels and address fundamentally different questions. Agent frameworks focus on the engineering question of *how to implement* an agent system — that is, realizing designs through concrete code and software architecture. Harness engineering, by contrast, addresses the methodological question of *how to systematically optimize* the overall performance of an agent system, encompassing not only improvements to the scaffold but also adaptations of the model itself. These optimization strategies are general across different frameworks and models and do not depend on the implementation details of any specific framework. An agent framework can therefore be seen as one concrete instantiation of a harness, while harness engineering serves as a meta-level discipline that guides the design of such instantiations. In this paper, we adopt this broader view and systematically examine design principles for building more effective agent systems through two complementary directions: scaffold optimization and model optimization.

Other Related Concepts. Beyond agent frameworks, three other families of concepts are closely related to harness engineering, each contributing an essential ingredient that harness engineering integrates into a unified system-level methodology.

- *Prompt engineering* and *context engineering* focus on crafting or structuring inputs to elicit better responses from LLMs [95, 96, 97]. Harness engineering subsumes these techniques as part of its model-side optimization, while further organizing multi-step execution, state management, and control flow across the entire agent workflow.
- *Tool use* examines whether and how LLMs can invoke external functions or APIs [98, 99]. Harness engineering incorporates tool use as a component within its scaffold design, additionally addressing when to invoke a tool, how to handle failures and integrate observations into subsequent reasoning.
- *Developer assistants* and *personal assistants* categorize agentic systems by their application roles (e.g., coding support or everyday task assistance [74, 89]). Harness engineering provides the underlying orchestration structures, including context management, progress tracking, and robust execution, that enable such assistant roles to function effectively.

3 The Design of the Harness

Having established the conceptual framework of harness engineering in Section 2, we now turn to the scaffold side: the architectural components that wrap around the foundation model and shape its agentic behavior. Rather than operating as isolated modules, these components form an integrated pipeline. The agent workflow orchestrates perception, planning, and action in a closed loop; memory systems extend the agent’s effective horizon beyond a single context window; skill libraries accumulate reusable behavioral units; and multi-agent orchestration scales the system to tasks that exceed the capacity of any single model instance. We examine each component in turn, focusing on design principles that have proven effective in deployed systems.

3.1 Agent Workflow

The agent workflow is the operational core of the agentic harness, transforming a stateless language model into a goal-directed system [100, 101]. Because a language model performs a single forward pass and terminates, what appears as persistent behavior is entirely constructed by the harness, which maintains message history and replays it on every invocation [102]. The harness compensates for this statelessness by wrapping the model in a loop: call the model, parse the response, execute the indicated tool, and feed the result back for the next iteration. This loop gives rise to three tightly

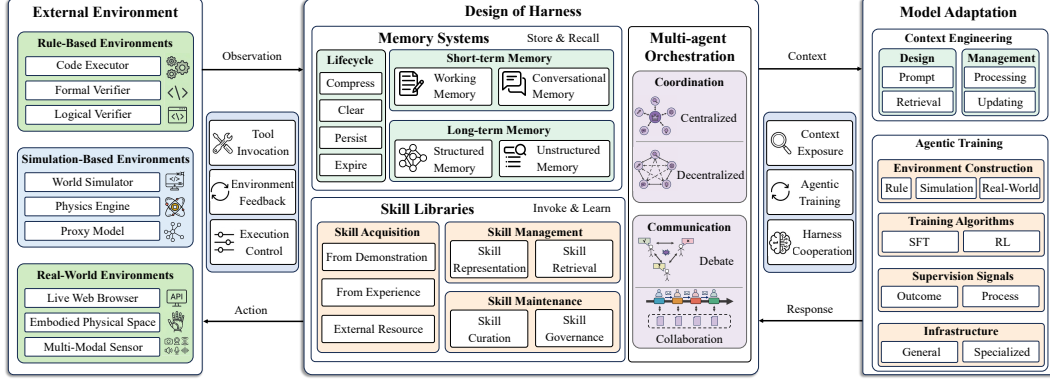


Figure 4: Overview of the harness design space and its interaction with external environments and model adaptation. **Left:** External environments provide grounding signals for agent execution and learning. **Center:** The four principal scaffold-side components that collectively form the harness infrastructure. The agent workflow governs the perceive-plan-act execution cycle; memory systems maintain persistent context across steps and sessions; skill libraries accumulate reusable capabilities to prevent redundant exploration; and multi-agent orchestration decomposes complex tasks across specialized agents. **Right:** Model-side adaptation through context engineering and agentic training, which complements the scaffold by shaping both the input information and the reasoning behavior of the underlying model. Together, scaffold-side construction and model-side adaptation form the two complementary pillars of harness engineering, and their synergistic optimization jointly shapes overall agent capability.

coupled phases. The harness first perceives the environment to gather task-relevant information (Section 3.1.1), then plans the next step based on accumulated state (Section 3.1.2), and finally executes the chosen action whose outcome becomes the input for the next iteration (Section 3.1.3).

3.1.1 Environment Perception

Environment perception is the entry point of each loop iteration. Before an agent can plan or act, the harness must construct a representation of the current environment that is both accurate and compact enough to fit within the context budget. This involves two complementary challenges: extracting task-relevant information from the raw environment, and encoding it into a form that downstream planning can reliably consume.

Observation Extraction. The central challenge is extracting spatial and logical relationships from complex interfaces, whether web pages [103, 104], desktop applications [105, 106], or mobile apps [69]. Early approaches extract structured features from UI hierarchies and convert them into textual representations [107, 108]. These representations are straightforward to parse but often large and redundant, motivating compression techniques that prune task-irrelevant content while preserving interactive elements [109]. Purely textual representations lack visual grounding and fail when layouts deviate from expected hierarchies [110]. Visual extraction based on screenshots addresses this limitation, with further gains from pretraining on large-scale GUI corpora [111] and reinforcement learning on interaction traces [112, 113]. However, purely visual methods still suffer from spatial ambiguity. The current state of practice therefore combines both channels through multimodal extraction, parsing structured metadata alongside screenshots to obtain element-level descriptions including widget type, text content, and spatial attributes [114]. This progression from textual to visual to multimodal extraction is not simply a march toward richer input; each step introduces its own cost. It reflects a fundamental trade-off among information completeness, token efficiency, and extraction reliability. Each additional perceptual channel provides a more complete picture of the environment but consumes more of the context budget, while every conversion step introduces opportunities for noise. Richer perception does not always yield better downstream decisions; the engineering challenge lies in maximizing useful signal per token for a given task.

State Representation. Once information has been extracted, the harness must encode it into a representation the model can use for planning. Common approaches employ structured markup

such as JSON [115], DOM-style trees [7, 108], or code formats [116] to produce compact textual descriptions. When these descriptions grow long, they exceed the context window or degrade planning quality through information overload [117]. Simple heuristics such as masking irrelevant attributes, truncating beyond a token budget, or retaining only recent observations can manage this growth effectively [109, 118]. Beyond such surface-level pruning, some methods use a secondary model to summarize or filter environment state [119], though these approaches do not capture how elements relate to one another. To model such relations, recent work distills the full environment into compact, task-oriented world models that retain only relevant objects, properties, and transitions [120], or builds explicit structures such as scene graphs [121, 122] that compress the environment into a small set of entities and spatial configurations most useful for planning. Industrial practice takes this filtering idea further and treats it as a core design principle: the perceptual interface should be designed as an Agent-Computer Interface rather than a Human-Computer Interface [123]. The harness surfaces only the few signals that materially affect decisions in the context window, while writing verbose details to files that the agent can query on demand. This ensures the context budget is spent on tokens with the highest decision-making value.

3.1.2 Task Planning

Task planning determines how the harness decomposes goals and maintains the plan state across loop iterations. Complex tasks cannot be solved in a single inference step because of two coupled constraints: autoregressive error accumulation causes success rates to drop sharply once reasoning depth exceeds what the model can sustain in one pass, and the finite context window cannot simultaneously hold the goal, full environment state, and all relevant constraints. Task decomposition addresses both constraints by segmenting a long reasoning chain into shorter chains separated by calibration points, where each new chain begins from a state confirmed through tool execution rather than from an unverified intermediate token. Finer decomposition inserts more calibration points and raises end-to-end reliability, at the cost of additional loop iterations and greater total token consumption. Existing work addresses this from two perspectives: how a complex goal is split into intermediate subtasks, and how those subtasks are converted into executable action sequences.

Task Decomposition. Early work organized intermediate reasoning into increasingly flexible structures, progressing from linear chains [95, 124] to branching trees [125] and graphs that allow path merging and reuse [126]. These approaches rely on predefined reasoning structures not adapted to specific tasks. More recent methods [127, 128] mitigate this mismatch by allowing agents to analyze the task and select suitable reasoning strategies before execution begins. Two emerging directions move beyond static structures altogether. The first is cross-session incremental decomposition [129]. When a task spans multiple context windows, single-pass planning breaks down because no single session holds the full problem state. A practical solution has the initial agent produce a complete functional requirements document that subsequent agents use to recover planning state, together with intermediate artifacts and version control history. Each new context window introduces a fresh agent that rebuilds task understanding from this externalized state before continuing where the previous session left off. The second is adaptive decomposition driven by external verifiers [123]. For tasks that resist natural parallelization, a known-good oracle can serve as a reference point. In one deployed example, multiple agents collaborate to build a C compiler; the harness assigns source file subsets to the agent-built compiler, compiles the rest with GCC, and cross-compares outputs to detect discrepancies. This turns an inherently sequential task into parallelizable subtasks whose boundaries are determined dynamically by runtime feedback rather than fixed in advance.

Plan Generation. Beyond decomposition, plan quality improves when each step incorporates explicit tool-use specifications [130] and when linear sequences are replaced with dependency-aware structures that enable independent subtasks to run in parallel [23]. The representation format of a plan also affects loop efficiency. A plan described in natural language may consume hundreds of tokens, whereas the same plan expressed as structured tool names and arguments requires far fewer. However, compressing too aggressively strips away the intent and assumptions behind each step, noticeably degrading the quality of retry attempts when replanning is needed after a failure [129]. This tension suggests that plan generation is best treated not as a one-time output but as a living artifact that the harness loop continuously verifies and adjusts.

3.1.3 Action Execution

Once a plan has been generated, the agent must translate it into concrete operations that affect the external environment. We examine action execution from two perspectives: how agents select and call discrete external tools, and how they operate within dynamic, stateful environments.

Tool Invocation. Tool invocation concerns how the harness enables an agent to select and call the appropriate tool for a given task. Early work [25] embedded tool tokens directly into the model’s vocabulary, supporting only sequential single-tool calls. Subsequent methods [131] parse agent outputs into executable function calls, enabling branching and multi-step composition. To ground these capabilities in deployed settings, practical systems [7, 132] expose components such as file systems and shell commands as structured tool interfaces with explicit schemas. A converging line of work demonstrates that reliable tool invocation must be learned through executable environment feedback rather than specified in advance. Methods that train agents via reinforcement learning using runtime execution outcomes as direct signals show consistent gains in both single-tool reliability and multi-step composition [133, 134, 135]. Beyond the invocation mechanism, the granularity of the tool interface is a key harness design choice. A general-purpose interface such as bash offers maximum flexibility but leaves the harness with little ability to enforce whitelists, validate arguments, or isolate permissions. Specialized interfaces with explicit schemas, such as those defined in the Model Context Protocol, trade flexibility for interface-level safety checks [136]. Similarly, domain-specific systems such as SquRL [137] provide specialized interfaces by abstracting task-oriented tools [138] from the target domain. The right balance depends on the security requirements of the deployment domain. A related scaling challenge arises when the number of available tools is in the hundreds. Under the conventional pattern, every tool result returns to the context window, and long tool chains accumulate substantial token overhead. Code Execution with MCP [139] addresses this by having the model write a single code block that invokes multiple tools in sequence within a sandbox; only the final result returns to the context, collapsing a multi-round tool chain into a single model call.

Environment Interaction. Environment interaction concerns how agents execute actions in stateful environments whose consequences persist across steps. Early work [82] placed agents in raw environments with unbounded action spaces, making it difficult to reliably translate intentions into executable actions. Subsequent work [7] introduced structured agent-environment interfaces that expose available actions, expected formats, and resulting state changes. Building on this, filtering methods [140] combine the current plan with environment-based reward signals to discard infeasible or irrelevant actions before execution. Even with well-structured and filtered actions, reliable interaction requires that execution be isolated from the host system. Sandbox mechanisms [79, 78] confine agent behavior to controlled containers that restrict file system access, limit network exposure, and enable clean state resets between attempts. However, containment alone does not guarantee safety; recent analysis [141] shows that sandboxed agents still exhibit systematic vulnerabilities at planning, memory, and execution boundaries that require active trace-level auditing to detect.

Discussion

- The finite context window is a shared budget that perception, planning, and execution compete for: enriching one phase necessarily starves the others.
- The core value of agentic loops is not stepping through subtasks, but creating calibration points where external feedback corrects accumulated model drift.
- Loop reliability depends more on harness design; without proper support, agents compress all work into a single context window and prematurely terminate near the limit.

3.2 Memory Systems

Beyond the immediate execution loop, a capable harness must maintain agent coherence across reasoning steps that exceed the capacity of any single context window. This requires explicit memory systems that govern what to keep, what to compress, and what to offload. The guiding principle is not to remember as much as possible, but to persist only information that has reuse value for future decisions [142, 129]. We examine memory systems along these two dimensions: *short-term memory* (Section 3.2.1) manages information within a single session, while *long-term memory* (Section 3.2.2) accumulates knowledge that persists beyond the immediate context.

3.2.1 Short-term Memory

Short-term memory governs how an agent tracks and utilizes information within a single session. The harness must actively decide what intermediate state to preserve, compress, or discard within the context window. The key design insight is to distinguish between reconstructible information, such as tool outputs that can be re-fetched and are thus safe to discard, and irreplaceable information, such as reasoning conclusions and user decisions that must be retained or compressed [142]. We discuss two complementary aspects: *working memory*, which manages intermediate states during active reasoning, and *conversational memory*, which maintains dialogue history across turns.

Working Memory. Working memory provides a dynamic store for intermediate states generated during task execution. Early designs relied on linear traces that interleave reasoning steps, actions, and observations [82, 143], but linear formats struggle with non-linear reasoning involving branching or backtracking, often leading to duplicated information [144] or loss of critical context [27]. Subsequent work introduced structured alternatives: graph-based methods [145] organize intermediate thoughts as connected nodes supporting branching and recombination, while workflow-based methods [146] further organize execution states through reusable structures. Beyond format, industrial practice reveals that not all intermediate states share the same lifecycle. Tool call results can often be re-fetched and should be cleared first; task progress checkpoints must persist to support cross-window resumption [142, 129]. This lifecycle-aware decomposition moves working memory management from uniform compression toward selective retention based on reconstructibility.

Conversational Memory. In long dialogues, important information from earlier turns, such as user preferences or prior decisions, can be lost as history grows beyond the context window. Early methods stored conversation history externally and used hierarchical buffers [147] or paging mechanisms [148] to retrieve relevant content on demand, but these operate at coarse granularity and can split related context apart [149]. Later work achieved finer-grained segmentation by partitioning history into functional units such as task state [150] and user profile [151], though still treating each segment in isolation. Recent studies [152, 153] recover cross-segment dependencies through explicit links between memory elements, while the most recent efforts [154, 155] move toward adaptive management that learns what to retain, update, or discard based on the evolving dialogue state. This adaptive approach has already been deployed at scale. Claude Code, for instance, uses compaction during long sessions to produce structured summaries that preserve key decisions while reclaiming context budget [142], demonstrating that the distinction between reconstructible and irreplaceable information can be operationalized in production systems.

3.2.2 Long-term Memory

While short-term memory manages the active context window, long-term memory enables agents to accumulate knowledge that persists across sessions. Since the model maintains no persistent state between invocations, all mechanisms for storing, indexing, and retrieving long-term knowledge must be implemented by the harness. From a functional perspective, long-term memory divides into three categories with distinct lifecycles [156, 157]: semantic memory (facts, user preferences, project knowledge), episodic memory (past interactions, failure and success trajectories), and procedural memory (task rules and workflows). Each category requires different writing strategies and retrieval mechanisms. Moreover, not all long-term memory should be written in real time; preferences that must take effect immediately belong to hot-path memory, while experience extraction and conflict resolution are better handled asynchronously after the task completes [157]. We examine two organizational forms: *structured memory*, which maintains knowledge in explicit relational formats, and *unstructured memory*, which stores information as flat text.

Structured Memory. Structured memory organizes accumulated knowledge in relational forms such as knowledge graphs [158] or explicitly linked entry sequences [31]. Early graph-based designs [159, 160] store knowledge as nodes and relationships as edges, enabling efficient traversal but typically accommodating only one information type. Later approaches [161, 162] unified multiple types within a single structure using node tags, yet still require a fixed schema specified in advance, limiting generalization to unseen tasks. More recent work [31, 29] removes this rigidity by allowing each entry to carry its own contextual description and link to others based on semantic similarity and usage patterns rather than predefined types.

Unstructured Memory. Real-world experience often exists as flat text that lacks explicit relational organization [163]. Early work [148, 30] stored free-form text and used similarity matching for retrieval, but lengthy entries consume substantial space and outdated information is difficult to update. A subsequent line of work [24, 164] makes memory explicit by preserving past interactions and reflections in natural language, making it easier to inspect, edit, and distill into reusable guidelines. However, these systems rely on hand-designed rules for deciding what to store or discard. Recent work [154, 165, 166, 167, 168] treats memory operations as learnable decisions rather than fixed heuristics, with extensions to long-horizon personalization [169] and on-demand memory expansion [170].

Looking forward, long-term memory is evolving from an internal component of individual agents into a shared infrastructure layer. Systems such as Mem0 [171] and OpenMemory [172] abstract memory into a portable personal context layer, exposing standardized interfaces through protocols like MCP so that different agents can access the same memory on demand. At the technical level, memory becomes a reusable service rather than something each framework implements independently. At the ownership level, local-first designs store data on the user’s machine, making memory persist across ephemeral agent sessions and enabling cross-application context continuity. This architectural shift also blurs the boundary between memory and skills: when an agent repeatedly distills reusable procedures from episodic memory and packages them as executable instructions, memory transitions from episodic to procedural form and eventually becomes a callable skill [173]. In this sense, skill libraries, discussed in the next section, can be viewed as an advanced form of memory systems.

Discussion

- The central challenge of memory is no longer capacity but governance: unbounded accumulation introduces stale conflicts, retrieval degradation, and persistent behavioral corruption.
- Context budget should be treated as a first-class runtime resource to be actively monitored and defended, not a passive container the model fills until it overflows.
- Agent state is not homogeneous—conversation history, tool results, task checkpoints, and long-term knowledge differ in persistence and update frequency, and must be managed separately rather than mixed into one undifferentiated context.
- The harness should enforce a disciplined lifecycle: compaction and clearing handle intra-session bloat, while only cross-session knowledge that remains valuable enters the persistent layer; reusable procedures further graduate from episodic memory into callable skills.
- Memory is evolving from an internal module into a shared, portable infrastructure layer: agents are ephemeral, but memory is long-lived, enabling cross-application continuity with user-owned context [171, 173].

3.3 Skill Libraries

While agent workflows enable action and memory systems preserve state, neither prevents the agent from rediscovering solutions to previously solved problems. Skill libraries close this gap by persisting reusable behavioral units that the agent can invoke when similar situations recur [35, 174, 175]. Conceptually, skill libraries occupy a continuum with the memory systems discussed in Section 3.2. When an agent repeatedly extracts actionable procedures from episodic memory and encodes them as executable instructions, memory gradually transitions from episodic to procedural form [176]. In production, this transition is increasingly explicit: skills are authored, versioned, and distributed as self-contained packages of instructions, scripts, and resources [177, 178]. The scope of skill library design therefore extends beyond learning alone to encompass construction, runtime routing, and lifecycle governance [179, 180]. This section examines the three core problems that arise when building and operating such libraries: how skills are acquired (Section 3.3.1), how they are organized and retrieved at runtime (Section 3.3.2), and how the library is maintained as it grows (Section 3.3.3).

3.3.1 Skill Acquisition

Skill acquisition converts successful behavior into reusable capabilities. The harness intercepts successful trajectories, triggers extraction routines, and persists the results for later retrieval. The central difficulty is generalization: a behavior observed in one trajectory must be abstracted sufficiently to transfer beyond the original context. Existing approaches address this from three directions.

Learning from Demonstration. The most direct route is to derive skills from prior successful behavior [35, 174]. Early methods imitate tool-call logs [25, 181, 182, 183] or replay expert trajectories [184, 185], yielding skills that reproduce observed actions but generalize poorly [186]. Injecting full trajectories into context also introduces redundancy [187]. Subsequent work therefore decomposes trajectories into atomic units that can be recombined into higher-level capabilities [34, 188], or identifies reusable structures within prior records as seeds for broader skill creation [189]. More recent methods further integrate textual knowledge as structured guidance during composition [190, 191].

Learning from Experience. Rather than relying on external demonstrations, agents can acquire skills through their own environment interactions. Early reinforcement learning formulations [192, 193] produce task-specific policies that transfer poorly [194, 33]. Later work reframes the problem as discovering reusable behavioral structures from interaction [195, 196, 197, 198, 199, 200]: successful action sequences are packaged into skills that persist beyond the originating episode. Recent approaches further improve coverage by guiding exploration toward regions of the environment likely to yield novel, generalizable behaviors [201, 36, 202]. In an extreme case, Tool-R0 [203] removes the need for any predefined task specification, training tool-calling skills entirely through self-play with executable environment feedback as the sole learning signal.

Learning from External Resources. Skills need not originate from agent trajectories at all. Industrial practice increasingly constructs them from documentation, code repositories, and API definitions [204, 177]. Anthropic’s Agent Skills framework [177, 205] defines skills as directory-based packages of instructions, scripts, and resources that agents discover and load at runtime. OpenAI’s Skills API [178] extends this model with versioned bundles that can be uploaded, managed, and mounted in hosted environments. In these systems, skills function as versioned software artifacts with lifecycle management analogous to traditional packages.

3.3.2 Skill Management

Once a library contains a large number of skills, two organizational problems arise: how to represent skills for efficient access, and how to select the right skill at runtime without overwhelming the model’s context [206].

Skill Representation. Early work [184, 35] encodes skills as continuous embeddings, enabling similarity-based indexing but sacrificing internal structure. Later approaches adopt programmatic formats such as executable code fragments [190], structured reasoning procedures [34, 195, 207], or unified tool-use schemas [208, 37], making composition and transfer more explicit [194]. Production systems take this further by representing skills as complete packages containing instructions, scripts, metadata, and tests [177, 178]. This package-level design enables progressive disclosure: the agent initially loads only metadata or a directory-level summary and expands into full instructions on demand [177, 209]. Because only a fraction of any skill occupies the context at a given time, the library can scale well beyond what full-injection approaches support [210, 179].

Skill Retrieval. Embedding-based similarity [195, 184] provides a natural method for retrieval but degrades when tasks require composing multiple skills, as in multi-agent coordination [211, 212] or embodied manipulation [213]. Hierarchical retrieval mitigates this by first resolving coarse intent and then searching within a narrower subset [208, 210]. Context-sensitive retrieval conditions selection on environmental states, prior trajectories, or intermediate failures [214, 215], turning retrieval into an iterative decision process [216]. At the production scale, where libraries contain thousands of overlapping entries, retrieval becomes a learned routing problem. SkillRouter [179, 206] demonstrates this with a retrieve-and-rerank pipeline that operates over full skill text, showing that exposing only names and descriptions degrades routing accuracy. This finding indicates that skill content itself is a critical routing signal and that dedicated learned routers outperform metadata-only matching.

3.3.3 Skill Maintenance

As libraries grow, the challenge shifts from acquisition and retrieval to long-term health. A static library inevitably accumulates redundant, outdated, or conflicting entries that degrade retrieval precision and execution reliability.

Library Curation. Skills decay in real environments as tool APIs change and external dependencies evolve [217, 218]. The harness must detect execution failures, trace them to specific skills, and trigger targeted updates. At the library level, growth introduces overlap and staleness that impair the retriever’s ability to discriminate among candidates [179, 210]. Active curation, including merging redundant entries, pruning ineffective ones, and hierarchically organizing surviving skills, is therefore essential to sustained performance.

Skill Governance. When skills are treated as versioned executable packages [178, 219], they inherit the governance requirements of traditional software. New versions require correctness testing, and existing skills require regression checks as environments change [219]. Distribution across platforms further introduces supply-chain risks: incorrect or malicious skills can persistently corrupt agent behavior [220, 177]. Reliable operation at scale therefore demands version control, compatibility checking, conflict detection, and principled deprecation.

Discussion

- A fundamental tension persists between specificity and generality: trajectory-extracted skills tend to be narrow and brittle, while highly abstract skills lack the operational precision needed for reliable execution.
- Once skills become versioned artifacts, they inherit software lifecycle burdens—API changes, environment migration, and silent error propagation—that demand active maintenance, not just extraction.
- The boundary between memory and skills is blurring: repeatedly distilled episodic memory becomes indistinguishable from skills, suggesting future harnesses should unify experience accumulation, procedural extraction, and skill maintenance into a single governed pipeline.

3.4 Multi-agent Orchestration

Single-agent harnesses, however well designed, face inherent limits in parallelism, specialization, and fault tolerance. Multi-agent orchestration addresses these limits by coordinating multiple agents, where each runs its own workflow and memory, toward a shared task objective. Product practice identifies three axes along which multi-agent systems deliver value [221]: context protection, where each agent operates in an isolated context window; parallelization, which trades token consumption for shorter wall-clock time; and specialization, where splitting agents by domain avoids the performance degradation that occurs when a single agent is loaded with too many tools. This principle shapes the two central design questions explored below: *coordination architectures*, which define how agents are structurally organized, and *communication mechanisms*, which define how agents exchange information within these structures.

3.4.1 Coordination Architectures

Coordination architectures define how control authority, task assignment, and result aggregation are distributed across agents. Existing approaches divide by whether the system relies on a core agent: *centralized architectures* employ a controller to manage the entire system, while *decentralized architectures* achieve coordination through interaction among equal agents.

Centralized Architectures. Centralized architectures use one central agent to decompose tasks, assign subtasks to specialized subagents, and aggregate their results. Early systems such as MetaGPT [39] and ChatDev [40] organize role-specialized agents through manually designed workflows, but these patterns are costly to build and difficult to transfer across tasks. Subsequent work shifts toward autonomous coordination: AutoGen [38] treats scheduling as a configurable conversation and routing layer, while MegaAgent [222] enables agents to negotiate responsibilities at runtime, allowing organization to emerge without predefined orchestration [223, 22, 224, 225]. A particularly successful centralized pattern in production is the verification subagent [221], where a dedicated subagent tests or verifies the primary agent’s work. This pattern succeeds because verification requires minimal context transfer: the verifier can black-box test the system without knowing its full construction history, avoiding the context degradation that occurs when reasoning passes between agents. However, scaling centralized systems is not as simple as adding more subagents. Recent findings [226] show that smaller teams with well-designed memory can outperform larger ones,

suggesting that the quality of each agent’s coordination infrastructure matters more than team size alone.

Decentralized Architectures. Decentralized architectures [227] explore how collaboration can emerge from interactions among equal agents without a central coordinator. AgentVerse [41] demonstrated that agents can spontaneously form roles and divide labor through interaction alone, and DyLAN [228] extended this with a dynamic collaboration graph that evolves as the task progresses [42, 229, 230]. A known risk of this design is premature consensus: if agents agree too quickly, minority but correct viewpoints can be overlooked. CONSENSAGENT [231] addresses this by assigning asymmetric roles so that minority positions receive structured consideration before a final decision. Decentralized coordination does not always require a purpose-built communication protocol. In a large-scale multi-agent coding project [232], 16 agents coordinated without direct communication: each claimed a task by writing a file to a shared directory, and conflicts were surfaced through git merge conflicts. This demonstrates that existing software infrastructure, such as file systems and version control, can serve as the coordination substrate. The shared-state pattern [233] generalizes this: agents collaborate through a shared state space, building on each other’s findings without a central router, which eliminates single-point failure but risks duplicate work and conflicting decisions.

3.4.2 Communication Mechanisms

Communication mechanisms address how agents exchange information within a multi-agent system. Without well-designed communication, even a well-structured coordination architecture degrades into disconnected model calls rather than a coherent collaborative system. The central challenge is deciding what information to share and at what granularity. Sharing only final results is insufficient, because actions carry implicit decisions, agents that lack the reasoning behind a result are likely to make conflicting choices [234]. Sharing full agent traces preserves maximal information but creates prohibitive communication overhead. A practical compromise is to compress action histories into summaries of key decisions and events, preserving information density while controlling cost [234]. Existing work addresses this challenge from two directions: *debate-based methods*, which improve output quality through critique and disagreement, and *collaboration-based methods*, which support coordinated execution across agents.

Debate-based Methods. Debate-based methods address a fundamental limitation of single agents: following one line of thought makes it difficult to uncover intermediate errors. A natural solution is to have multiple agents execute the same task from different roles [39, 235, 236] and stances [237, 238], so that agents challenge and refine each other’s outputs before forming a final answer [239]. However, multi-agent discussion does not automatically lead to better results [240]. Without a mechanism to integrate conflicting viewpoints, interaction can become repetitive or unstable. More recent work therefore organizes debate around explicit reflection loops [241] or consensus-oriented decision procedures [231] that summarize conflicting viewpoints and assemble them into a coherent result.

Collaboration-based Methods Collaboration-based methods coordinate agents into a coherent execution structure where different roles contribute complementary capabilities [242, 243, 40]. Early work relies on explicit role specialization and predefined workflows [244, 39], making systems controllable but fragile under dynamic task changes [223]. Recent research shifts toward more adaptive approaches, including graph-based planning that restructures coordination as execution evolves [245, 246], reinforcement learning that jointly optimizes collaboration policies [247, 248, 249, 250], and environment-aware coordination that adjusts strategies based on real-time progress [251]. Another emerging direction is artifact-mediated collaboration, where agents coordinate through durable shared project state—such as permission-scoped workspaces containing analyses, plans, and code—rather than transient conversational handoffs [252]. A practical challenge for collaboration is the read-write asymmetry identified in production systems [253]: multi-agent systems that primarily read are far easier to build than those that primarily write. When multiple agents write simultaneously, their implicit decisions can conflict, producing incompatible outputs that are difficult to merge [234]. This asymmetry suggests that collaborative writing tasks require stronger coordination protocols than parallel reading tasks.

Table 1: Design principles of representative agent systems across the four harness components.

Components	Claude Code	OpenClaw	Hermes Agent
Agent Workflow	- Plan-then-execute separation - Layered permission control - Interactive user confirmation	- Declarative context assembly - Context-driven tool selection - Unified multi-channel routing	- Budget-capped execution loop - Security-aware context filtering - Platform-adaptive prompt design
Memory Systems	- Automatic context compaction - Hierarchical file persistence - Typed cross-session memory	- Vector-based semantic retrieval - Wiki-based linked knowledge - Automatic memory capture and recall	- Threshold-triggered compression - Dialogue-driven user profiling - Snapshot-based memory loading
Skill Libraries	- User-authored slash commands - Agent-assisted skill creation - Persistent scheduled tasks	- Centralized skill registry - Standardized skill interfaces - Role-based skill assignment	- Agent-managed lifecycle control - Automatic curation and retirement - Security-verified activation
Multi-Agent Orchestration	- Role-based specialist subagents - Repository-level workspace isolation - Foreground and background execution	- Depth-limited agent spawning - Identity-based agent configuration - Cross-framework communication protocol	- Explicit orchestrator role - Persistent cross-agent task board - Parallel multi-model execution

Discussion

- Each coordination pattern carries an inherent tension: centralized designs risk single-point bottlenecks, while decentralized designs increase the difficulty of debugging and behavior prediction [233].
- Decomposition should follow context boundaries, not problem types: splitting by role creates persistent coordination overhead, whereas the agent holding the context should own all related subtasks [221].
- A single agent failure can redirect the entire exploration trajectory, creating cascading errors.
- Getting a multi-agent system to basically work takes $\sim 20\%$ of the effort, while making it reliable takes the remaining $\sim 80\%$ [233].
- Multi-agent orchestration may be retracing the path of single-agent systems: manually designed coordination patterns may eventually be internalized as native model capabilities.

3.5 A Comparative View of Representative Agent Systems

To make the preceding design principles concrete, we now examine how three representative agent systems, Claude Code [88], OpenClaw [11], and Hermes Agent [12], instantiate the four harness components in practice. Each agent system embodies a distinct design philosophy, and Table 1 summarizes the key differences.

Agent Workflow. The three systems govern the perceive, plan, and act loop in fundamentally different ways. Claude Code enforces a strict plan-then-execute separation: the agent first enters a read-only phase to explore the codebase and draft a structured plan, then requests interactive user confirmation before any modification is carried out, and every subsequent tool call passes through a layered permission control mechanism so that no consequential action proceeds without explicit consent. OpenClaw treats the loop as composable infrastructure, where declarative context assembly specifies how information enters, persists in, and leaves the context window, context-driven tool selection prunes the available tool set before each model call based on runtime signals such as authentication state or channel type, and unified multi-channel routing allows a single agent to serve dozens of messaging platforms through one dispatch interface. Hermes Agent emphasizes autonomous self-governance, implementing a budget-capped execution loop that bounds each task with an explicit step limit, security-aware context filtering that scans every loaded file for prompt-injection threats before it reaches the model, and platform-adaptive prompt design that tailors system instructions to the runtime environment, so that the agent can operate reliably without human oversight.

Memory Systems. The three systems differ sharply in how they manage working memory and long-term knowledge. Claude Code is context-window-centric: the conversation itself serves as working memory, and once it grows too long the system performs automatic context compaction by compressing it into a structured summary; long-term knowledge resides in hierarchical file persistence at the user, project, and directory level that is loaded automatically into every session, supplemented by a typed cross-session memory store that organizes persistent facts by category such as user preferences, feedback, and project state. OpenClaw adopts a dual-track design that pairs vector-based semantic retrieval, which surfaces relevant facts before each model call, with wiki-based linked knowledge that maintains human-readable, interlinked persistent articles, both underpinned by automatic memory capture and recall that records notable facts and retrieves them without explicit user commands. Hermes Agent focuses on streaming context management: threshold-triggered compression monitors token usage in real time and compacts the context once a configurable limit is crossed, while protecting the earliest and most recent messages so that task framing and recent state survive; for long-term user modeling it employs dialogue-driven user profiling through an external service that maintains an evolving user profile by reasoning over past conversations, and it adopts snapshot-based memory loading that ingests memory files as frozen snapshots at session start so that mid-session updates do not invalidate the prompt cache.

Skill Libraries. The three systems organize reusable capabilities at increasing levels of autonomy. Claude Code treats skills as user-authored slash commands, where each skill is a markdown file with structured metadata; a built-in helper enables agent-assisted skill creation so that the system can bootstrap new skills on its own, and persistent scheduled tasks let recurring jobs behave like durable skills, all governed by plugin blocklists and fine-grained permission allowlists. OpenClaw moves to a centralized skill registry that packages each skill with standardized skill interfaces and publishes them through a hub for discovery and installation, with role-based skill assignment ensuring that each agent only receives skills relevant to its designated role, cleanly separating skill authoring from consumption. Hermes Agent goes furthest by implementing agent-managed lifecycle control: skills are exposed through progressive disclosure in three tiers of increasing detail so that the agent loads only what it needs, automatic curation and retirement removes skills that have not been invoked within a configurable period, and security-verified activation validates every skill before it is enabled.

Multi-Agent Orchestration. All three systems support subagent delegation but differ in coordination philosophy. Claude Code follows a pattern of role-based specialist subagents, spawning agents with explicit role annotations such as explorer, planner, or general-purpose, each receiving a constrained tool set; repository-level workspace isolation gives each subagent its own working copy, and the option of foreground and background execution keeps each subagent in a clean context window of its own. OpenClaw takes a protocol-first stance, with depth-limited agent spawning that bounds recursion to prevent runaway chains, identity-based agent configuration that defines each agent's role, personality, and behavioral constraints through scoped configuration files, and a cross-framework communication protocol that enables agents built on different stacks to interoperate as a first-class concern. Hermes Agent offers the richest coordination toolkit by defining an explicit orchestrator role that separates coordinating agents from leaf agents that execute tasks, maintaining a persistent cross-agent task board for shared work tracking, and most distinctively supporting parallel multi-model execution that queries multiple language models simultaneously and synthesizes their outputs.

Discussion

- The same four harness components can be instantiated under very different design philosophies: Claude Code optimizes for human-in-the-loop safety, OpenClaw for composable extensibility, and Hermes Agent for autonomous self-governance.
- These trade-offs directly reflect deployment context: interactive developer assistance, multi-channel platform orchestration, and autonomous terminal execution demand fundamentally different balances of control, flexibility, and autonomy.

4 Model Adaptation for Harness

Within the synergistic framework of harness engineering, designing the surrounding harness must be complemented by model-side adaptation. Standard LLMs are trained for general text generation

and lack the built-in capacity to invoke tools, follow multi-step workflows, or process environmental feedback. We organize model adaptation into two categories: *Context Engineering* (Section 4.1), which shapes model behavior at inference time through the information exposed by the harness, and *Agentic Training* (Section 4.2), which internalizes agent-specific behaviors into model parameters through imitation and reinforcement learning.

4.1 Context Engineering

The contextual information provided during inference determines both the behavior and the capability ceiling of an LLM agent. As discussed in Section 3, the harness governs what the model observes at each step, including task instructions, tool descriptions, retrieved knowledge, and interaction history. Context engineering adapts model behavior by deciding what information to expose, how to structure it, and how to update it throughout multi-turn interactions. Unlike general prompting, context engineering for agentic harnesses specifically targets tool use, workflow execution, and long-horizon decision making under limited context budgets. We cover two complementary stages: *Context Design*, which constructs high-quality inputs before the model acts, and *Context Management*, which compresses and maintains contextual state over extended interactions.

4.1.1 Context Design

Context design focuses on constructing optimal input before an agent reasons or acts. This relies on two core strategies: *Prompt Engineering*, which structures instructions provided to the model, and *Context Retrieval*, which expands the model’s knowledge by incorporating external information.

Prompt Engineering. Prompt engineering steers model behavior through carefully crafted inputs without parameter updates. Early work focuses on structuring task instructions and demonstrations [254, 255, 125, 126], while subsequent studies show that explicit role descriptions can effectively elicit targeted behaviors [256, 227]. This proves particularly useful in multi-agent systems where agents assume specialized roles and coordinate within shared workflows [159, 45]. A common limitation of manual prompt design is its heavy reliance on human effort. To address this, automated prompt optimization enables models to refine their own prompts. APE [16] uses the LLM itself to generate and select candidate instructions, while subsequent methods eliminate human intervention entirely through self-refining loops [257, 258, 259].

Context Retrieval. Context retrieval dynamically integrates external knowledge to overcome the limitations of parametric memory. Traditional retrieval-augmented generation (RAG) relies on a static retrieve-once paradigm with flat text chunks, which struggles with complex multi-hop queries [260]. Subsequent methods advance retrieval along two dimensions: *retrieval timing* and *knowledge structure*. For retrieval timing, active mechanisms allow models to interleave reasoning with information gathering, dynamically deciding when to retrieve and how to rewrite queries based on intermediate states [261, 262, 263, 264, 265, 266, 44]. For knowledge structure, graph- or table-based indexes capture explicit relations among retrieved items [267, 268, 269, 43]. Building on these advances, agentic retrieval integrates retrieval operations directly into the model’s iterative execution loop. Pioneered by ReAct [82], this paradigm enables agents to alternate between reasoning and querying. Subsequent frameworks further abstract retrieval into automatically constructed modules [270] and hierarchical strategies [271], while multi-agent ecosystems distribute retrieval across specialized roles to handle complex tasks through collaborative reasoning [272].

4.1.2 Context Management

Raw context is often noisy and excessively long, risking both context overflow and reasoning degradation [273]. Context management involves two processes: *Context Processing*, which compresses information for immediate inference, and *Context Updating*, which maintains accumulated experience across interactions.

Context Processing. Context processing compresses the assembled context to maintain maximal information density within the model’s limited window. Early methods shorten input text by pruning tokens based on importance [274, 275, 276]. While effective for single-turn queries, these methods overlook the sequential dynamics of autonomous agents. To prevent context overflow in long-

horizon tasks, recent frameworks design compression specifically for multi-turn agent trajectories. Acon [277] applies reinforcement learning over interaction histories to minimize context usage while maintaining long-term memory. AgentDiet [46] prunes redundant information to reduce inference costs, AgentFold [278] condenses sub-tasks through hierarchical consolidation, and SWE-Pruner [279] performs task-aware adaptive pruning for coding agents. Beyond pruning existing traces, IterResearch [280, 281] reframes context management as workspace reconstruction, replacing full-history replay with a compact state consisting of the original question, an evolving report, and the latest action-observation pair.

Context Updating. Context updating dynamically maintains and evolves an agent’s contextual state across extended interactions, deciding what to remember, what to forget, and how to reorganize experience. At the foundational level, agents accumulate experience through reflection. Reflexion [24] pioneers this by having agents summarize failure causes for future attempts, while AWM [146] distills reusable workflow patterns from successful trajectories. As experience grows, flat storage becomes impractical, prompting hierarchical memory architectures [148] that partition memory into a fast context window and slow external storage with autonomous page-swapping. Subsequent frameworks enhance this with graph databases [29], streaming caches [282], and time-decay forgetting [30]. However, passive storage alone cannot support active memory lifecycle management. Recent studies empower agents to organize interconnected knowledge [32, 283, 284], highlight important memories [31], and delete outdated information [285, 286].

4.2 Agentic Training

While context engineering adapts model behavior at inference time, its effectiveness is bounded by the model’s inherent capabilities since parameters remain fixed. Agentic training complements this by internalizing domain knowledge and agent-specific behaviors directly into model parameters through two broad paradigms: *supervised fine-tuning* (SFT), which learns from demonstrations or teacher-generated trajectories, and *reinforcement learning* (RL), which refines policies through environment interaction feedback. Applying these methods to agents introduces unique challenges: constructing interactive environments, assigning credit under sparse rewards, stabilizing policy optimization, and managing large-scale engineering overhead. We discuss four aspects: *Environment Construction* (Section 4.2.1) explores how to build interactive training environments; *Reward Design* (Section 4.2.3) examines how to acquire stable reward signals; *Training Optimization Algorithms* (Section 4.2.2) discusses both SFT-based and RL-based policy updates; and *Infrastructure* (Section 4.2.4) discusses systems for large-scale distributed training.

4.2.1 Environment Construction

Training environments form the foundation of agentic training. Since the harness mediates interaction between the model and the external world, environment fidelity determines whether learned policies transfer to real-world deployment. Existing environments fall into three types based on feedback mechanism: *rule-based environments* provide deterministic binary rewards from execution outcomes; *simulation-based environments* use proxy models to approximate real-world dynamics; and *real-world environments* place agents directly in live systems with authentic feedback.

Rule-Based Environments. Rule-based environments have evolved from predefined sandboxes to strictly verifiable metrics. Early studies [287] train agents in rule-based sandboxes with predefined state transitions, supporting household [288] or e-commerce [289] scenarios. However, predefined actions require manual design and struggle to generalize to complex reasoning with large action spaces. Recent work [290, 291, 292, 293] demonstrates that with reliable binary outcome feedback, agents can continuously self-improve without human annotations. This principle is rapidly adopted in mathematical [294, 295, 10] and coding [296, 132] domains where precise verifiers provide reliable feedback. More recent environments further extend this through procedurally generated reasoning tasks [297] and stateful enterprise sandboxes supporting long-horizon planning [298]. In software engineering, Scale-SWE [299] scales environment construction by turning raw GitHub pull requests into verified Dockerized SWE tasks and training trajectories via a sandboxed multi-agent workflow.

Simulation-Based Environments. Simulation-based environments use proxy models to provide low-cost feedback approximating real-world dynamics. A critical challenge is that LLM-as-simulator

approaches are susceptible to hallucinations in physical scenarios. To improve fidelity, some approaches [300] train world models on large-scale interaction data for cross-domain generalization, while neural simulators extend this to operating-system interfaces by modeling screen transitions [301]. Beyond fidelity, improving rollout efficiency is equally important. Hardware-accelerated physics engines support massively parallel multi-agent rollouts [302, 303], while RAP [304] shifts simulation inside the model itself, allowing it to compare possible outcomes before acting. To further improve accuracy, recent works [305] replace generative proxies with deterministic database-backed mechanisms that execute actions as SQL transactions.

Real-World Environments. Real-world environments place agents directly into live digital or physical systems with authentic, constantly changing feedback. Early research [108, 306, 307] used controlled static websites, but these lack realism. Later work introduced actual digital noise such as network delays and dynamic content loading [113, 308, 309, 310]. To further scale up, some studies [311, 312, 313] let agents freely browse the live web using real-time operational logs as feedback. The physical world is the most complex environment because robotic actions must follow real physics and obey strict safety rules. Embodied environments [314, 315, 316] combine live sensor data with physics-based safety checks, enabling agents to translate high-level reasoning into real physical movements.

4.2.2 Training Optimization Algorithms

After constructing interaction environments and reward signals, agentic training requires optimization algorithms to update model parameters. Existing methods follow two broad paradigms: *supervised fine-tuning*, which learns agentic behaviors by imitating demonstrations or self-generated trajectories, and *reinforcement learning*, which refines policies through trial-and-error interaction with environment feedback.

Supervised Fine-Tuning. Supervised fine-tuning transfers agentic capabilities into the target model through direct optimization on multi-turn trajectories containing intermediate plans, tool calls, and environment observations. Based on data origin, methods are divided into off-policy distillation from teacher models and on-policy generation from the student itself. Off-policy distillation trains on trajectories pre-generated by stronger models. FireAct [317] first applies this to agentic scenarios, showing that fine-tuned small models can outperform larger ones on tool-use tasks. Since agent-only data may degrade general capabilities, later studies improve data quality through trajectory-instruction mixing [318], format and reasoning signal disentanglement [319], and unified multi-turn formatting [320]. To improve scalability, recent work synthesizes training data through environment interaction and systematic data engineering [119, 321, 322, 323, 299]. Within this line of work, ClawGym [324] introduces a scalable synthesis-centered framework for Claw-style personal agents, generating workspace-grounded tasks and further linking them to agent training and diagnostic benchmark construction. When trajectories contain both planning and execution signals, multi-teacher supervision [325, 326] or segment-specific losses [327] can separate these components for better transfer. On-policy distillation addresses the train-test distribution mismatch by letting the student generate its own trajectories while the teacher provides dense supervision. Early methods optimize divergence objectives such as forward KL [328] and reverse KL [329]. To stabilize training under large capability gaps, subsequent methods adjust target logits [330] or clip reward signals [331]. Beyond imitation, ExOPD [332] combines distillation with KL-regularized RL to push the student beyond the teacher, while GAD [333] extends on-policy distillation to black-box teachers using discriminator-based feedback.

Reinforcement Learning Approaches. While supervised fine-tuning internalizes agentic behaviors, it cannot support exploration beyond the training distribution. Reinforcement learning addresses this by refining policies through trial-and-error with reward feedback. Based on whether a value network is used, methods are divided into critic-based and critic-free algorithms. Critic-based algorithms introduce a value network to estimate advantages and guide stable policy updates. PPO [334] is the representative method, with improvements including value pre-training [335] and reward normalization [336, 337]. However, standard PPO struggles with long-horizon agents because credit assignment across multi-step trajectories is inherently difficult. Recent methods address this by decomposing interactions into planning levels [338, 339] or reasoning trees [340], and by assigning separate critics to different agents in multi-agent settings [341]. Critic-free algorithms remove the

value network to reduce memory and computation costs. One line uses offline preference learning such as DPO [342], KTO [343], SimPO [344], and ORPO [345] to avoid expensive online exploration. Another preserves online exploration but estimates advantages directly from rewards: GRPO [346] and ReMax [347] use parameter-free estimators based on group-level or maximum-return signals. For agentic workloads, recent studies further introduce hierarchical sampling and tree-structured exploration [50, 348, 349], token-level loss weighting [48], dynamic sampling [350, 351], and entropy balancing [351, 352, 353] to stabilize long-horizon exploration.

4.2.3 Supervision Signals

After environments are constructed, reward signals evaluate agent behaviors and guide policy improvement. Based on supervision granularity, two complementary paradigms emerge: *outcome-level signals* provide feedback only upon task completion, while *process-level signals* offer dense supervision after each step.

Outcome-Level Signals. Outcome-level signals evaluate the final state of a task, working well in domains that are easy to verify but hard to solve. In mathematical [354, 355], code generation [356, 357], software engineering [358], and deep research [49, 312, 359] tasks, objective execution feedback serves as a natural outcome signal. A common approach [358, 360] uses binary signals to let models learn from both correct and incorrect trajectories, driving large-scale self-play and iterative repair. To further reduce reliance on human labels, TTRL [361] estimates rewards through majority voting over sampled solutions, enabling RL without gold annotations. In formal theorem proving where signals are extremely sparse, DeepSeek-Prover-v1.5 [362] combines proof assistant feedback with tree-based search and exploration rewards.

Process-Level Rewards. Outcome-level rewards suffer from signal sparsity in long-horizon tasks, as models cannot determine which specific steps lead to success or failure. Process Reward Models (PRMs) address this by providing dense supervision at each reasoning or action step. The evolution of PRMs involves two aspects: *supervision signal construction* and *architectural design*. For signal construction, early methods [363] relied on expensive human annotations. Subsequent work automated this through Monte Carlo sampling [364] and Monte Carlo Tree Search [365]. Recent extensions introduce continuous spatial rewards for GUI grounding [366] and fine-grained rewards for tool selection [51]. For architectural design, traditional PRMs are discriminative models that assign a single score per step [363], but they are difficult to interpret and prone to bias. Generative methods [367] address this by performing step verification through natural language reasoning, using chain-of-thought to explain correctness, yielding more transparent reward signals. Complementary to reward-based optimization, supervised fine-tuning on curated trajectories offers a more direct signal: high-quality trajectories are sourced from human specialists [368] or distilled from strong models via rejection sampling [258], with many systems combining both to bootstrap capability [4].

4.2.4 Infrastructure

Large-scale agentic training requires coordinated scheduling of model inference, environment interaction, gradient computation, and parameter synchronization. The efficiency of the system infrastructure directly limits the speed and scalability of optimization.

General-Purpose Frameworks. General-purpose agentic frameworks coordinate the core RL components (actor, critic, reward, and reference models) across distributed clusters while supporting multi-turn interactions and continuous environment feedback. For flexible scheduling, some systems [369, 370, 47, 371] dynamically assign models to specific GPU partitions, optimizing data transfer across training stages. To improve throughput, asynchronous architectures [372, 373] separate the slower generation stage from gradient updates, scaling efficiently to thousands of GPUs. For environment integration, standardized APIs [374, 375] wrap various simulators into unified interfaces for cross-environment training. However, the multi-turn nature of agents causes load imbalance among fast generation, slow environment interaction, and heavy gradient updates. Recent frameworks address this by either interleaving generation and environment execution within a single workflow [50, 348, 376, 377, 378, 379], or physically separating stages across machines [380, 381].

Specialized Frameworks. Specialized frameworks extend general-purpose infrastructure for advanced settings such as multi-agent coordination and omni-modal interaction. For multi-agent systems, multiple agents interact through long-horizon interdependent trajectories, making rollout scheduling far harder than in single-agent settings [382]. Dedicated frameworks [383, 382, 341, 384, 385] introduce centralized multi-agent interaction, distributed policy training, and asynchronous multi-turn rollouts. For omni-modal agentic training, heterogeneous observations and feedback across text, images, and videos pose unique challenges [386]. Recent studies introduce specialized rubric rewards for multimodal grounding [386, 387] and multimodal search environments [388], extending agentic training beyond standard textual single-agent settings.

5 Harness Capacity and Evaluation

In this part, we review representative benchmarks and evaluation methods for agentic harnesses. The capability of an agentic system depends not only on the underlying model but equally on the harness that organizes context, tools, execution, and feedback. We refer to this overall ability, which sustains effective behavior under tool use, partial observability, long execution trajectories, and changing environmental feedback, as *harness capacity*. Measuring harness capacity requires going beyond single-step correctness; evaluation must assess whether a system can maintain goal-directed progress across multi-step interaction with external environments. Recent benchmarks embody this perspective by situating agents in increasingly realistic environments, extending task horizons and statefulness, and incorporating richer evaluation signals including execution results, environment states, rubric-based judgments, and run-to-run reliability [108, 389, 105, 390, 132, 53, 62, 60, 73, 391, 392, 59, 393, 68, 394]. Benchmark design has thus become an integral part of harness engineering itself, as it determines which aspects of orchestration—context management, tool coordination, error recovery—are made visible and measurable.

5.1 Deep Research

Deep research benchmarks evaluate whether an agent can support open-ended information seeking beyond short-answer retrieval. The field has progressed from difficult browsing questions to broader search, citation-grounded reporting, and rubric-based evaluation of synthesis quality.

Broad and Complex Search. An early direction focuses on information-heavy search rather than short-answer lookup. BrowseComp and WideSearch evaluate whether an agent can sustain multi-step exploration, compare evidence across search branches, and preserve useful intermediate findings [52, 53, 54, 391]. LiveDRBench is particularly notable for characterizing deep research in terms of breadth, logical nesting, and search intensity rather than report length alone. Compared with classical retrieval settings, these benchmarks stress search planning, evidence accumulation, and the harness’s ability to maintain coverage as the search space expands.

Research Reports. A second line of work shifts attention from information collection to citation-grounded long-form reporting. DeepResearch Bench, ReportBench, and LiveResearchBench evaluate whether an agent can organize retrieved evidence into coherent outputs whose claims, citations, and structure can be directly inspected [55, 395, 396, 392, 397, 398, 399]. This direction places greater weight on report organization, citation quality, and faithfulness between statements and sources, revealing how much performance depends on the harness’s ability to manage notes, compress documents, and preserve grounding during generation.

Survey Generation and Evaluation. More recent benchmarks move toward survey-style synthesis with explicit quality evaluation. ResearchRubrics pairs deep-research prompts with expert-designed rubrics, making coverage, grounding, and analytical quality first-class evaluation targets [400, 392, 397]. This marks a shift from asking whether an agent can produce a plausible artifact to asking whether the synthesis is complete, well-supported, and genuinely useful under structured judgment. Even so, current deep-research benchmarks still under-evaluate source credibility, citation faithfulness under changing web content, cross-session persistence, and the cost-latency trade-offs that matter in practical research assistants.

Table 2: Representative benchmarks across major task domains in agentic harness engineering.

Benchmark	Date	Tasks	Evaluation Mechanism
Deep Research			
BrowseComp	2025.04	Browsing-based information seeking	Rule-based
Deep Research Bench	2025.05	Web research	Rule-based
DeepResearch Bench	2025.06	Deep research report generation	Rule-based
ResearcherBench	2025.07	Frontier scientific inquiry	Rule-based / LLM Judge
ReportBench	2025.08	Academic survey / report generation	Rule-based
Characterizing Deep Research	2025.08	Deep research benchmarking	Rule-based
WideSearch	2025.08	Agentic broad information seeking	Rule-based
PDR-Bench	2025.09	Personalized deep research	LLM Judge
LiveResearchBench	2025.10	User-centric deep research in the wild	LLM Judge
ResearchRubrics	2025.11	Prompt-and-rubric-based deep research evaluation	LLM Judge / Human Judge
DEER	2025.12	Deep-research expert reports	LLM Judge
DeepSynth-Eval	2026.01	Information consolidation in deep survey writing	Rule-based
VideoDR-Benchmark	2026.01	Video deep research on open web	Rule-based
DeepResearch Bench II	2026.01	Rubric-based diagnosis of deep research reports	Rule-based
MMDeepResearch-Bench	2026.01	Multimodal deep research	Rule-based / LLM Judge
DeepSurvey-Bench	2026.01	Academic value of generated scientific surveys	Human Judge
DeepSearchQA	2026.01	Exhaustive answer-set generation	Rule-based / LLM Judge
deepsynth-bench	2026.02	Deep information synthesis	Rule-based / LLM Judge
Software Engineering			
RepoBench	2023.06	Repository-level code auto-completion	Rule-based
SWE-bench	2023.10	Real-world GitHub issue resolution	Rule-based
CodeAgent	2024.01	Tool-integrated repo-level coding challenges	Rule-based
LiveCodeBench	2024.03	Holistic contamination-free code evaluation	Rule-based
DevEval	2024.05	Repository-aligned code generation	Rule-based
BigCodeBench	2024.06	Function calls and complex code generation	Rule-based
REPOCOD	2024.10	Realistic repository-level coding	Rule-based
HumanEval Pro /MBPP Pro	2024.12	Self-invoking code generation	Rule-based
Commit0	2024.12	Library generation from scratch	Rule-based
FEA-Bench	2025.03	Repository-level feature implementation	Rule-based
AutoCodeBench	2025.08	Automatic code benchmark generation	Rule-based
SWE-Bench Pro	2025.09	Long-horizon software engineering tasks	Rule-based
SWE-Sharp-Bench	2025.11	Reproducible C# software engineering tasks	Rule-based
LoCoBench-Agent	2025.11	Long-context software engineering	Rule-based
NL2Repo-Bench	2025.12	Long-horizon repository generation	Rule-based
OmniCode	2026.02	Diverse software engineering agent tasks	Rule-based
SWE-Universe	2026.02	Scalable verifiable software environments	Rule-based
FeatureBench	2026.02	Complex feature development	Rule-based
BeyondSWE	2026.03	Beyond single-repo bug fixing	Rule-based
Tool Use and Function Calling			
API-Bank	2023.04	API planning and tool invocation	Rule-based
ToolLLM / ToolBench	2023.07	Large-scale real-world tool use	LLM Judge
AgentBench	2023.08	Multi-domain interactive agents	Rule-based
GAIA	2023.11	General AI assistant tasks	Rule-based
τ -bench	2024.06	Tool-agent-user interaction	Rule-based
AppWorld	2024.07	Controllable world of apps and people	Rule-based
AssistantBench	2024.07	Realistic web assistant tasks	Rule-based
ToolSandbox	2024.08	Stateful conversational tool use	Rule-based
ToolHop	2025.01	Query-driven multi-hop tool use	Rule-based
DICE-BENCH	2025.06	Multi-round, multi-party dialogue tool use	Rule-based
τ^2 -Bench	2025.06	Conversational agents in dual-control settings	Rule-based
BFCL	2025.07	Function calling and agentic evaluation	Rule-based
FuncBenchGen	2025.09	Controllable multi-step function calling	Rule-based
GAIA2	2025.09	Real-life assistant tasks	Rule-based
CCTU	2026.03	Tool use under complex constraints	Rule-based
Computer Use and GUI Grounding			
Mind2Web	2023.06	Generalist web agent interaction	Rule-based
WebArena	2023.07	Realistic web navigation	Rule-based
Android in the Wild	2023.07	Android device control	Rule-based
VisualWebArena	2024.01	Multimodal visual web tasks	Rule-based
WorkArena	2024.03	Common knowledge-work web tasks	Rule-based
OSWorld	2024.04	Open-ended real computer use	Rule-based
AndroidWorld	2024.05	Dynamic Android interaction environment	Rule-based
Windows Agent Arena	2024.09	Multi-modal desktop OS tasks	Rule-based
WorldGUI	2025.02	Dynamic testing for desktop GUI automation	Rule-based
ScreenSpot-Pro	2025.04	Professional high-resolution GUI grounding	Rule-based
MMBench-GUI	2025.07	Hierarchical multi-platform GUI evaluation	Rule-based
OSWorld-MCP	2025.10	MCP tool invocation in computer-use agents	Rule-based
VenusBench-GD	2025.12	Multi-platform GUI grounding	Rule-based
ML Engineering and Scientific Research			
DS-1000	2022.11	Data science code generation	Rule-based
MLAgentBench	2023.10	Machine learning experimentation	Rule-based
DA-Code	2024.10	Agent data science code generation	Rule-based
ScienceAgentBench	2024.10	Data-driven scientific discovery	Rule-based
MLE-bench	2024.10	Machine learning engineering	Rule-based
PaperBench	2025.04	AI research replication	LLM Judge
TimeSeriesGym	2025.05	Time-series ML engineering	Rule-based
MLR-Bench	2025.05	Open-ended ML research	LLM Judge
FML-bench	2025.10	Automatic ML research	Rule-based
TRAJECT-Bench	2025.10	Trajectory-aware evaluation of agentic tool use	Rule-based / LLM Judge
ReplicatorBench	2026.02	Replicability in social and behavioral sciences	LLM Judge / Human Judge

5.2 Software Engineering

Software engineering benchmarks evaluate whether an agent can operate under realistic development conditions rather than merely generate standalone code. Evaluation has expanded from repository understanding and issue fixing to feature implementation and broader engineering workflows.

Repository Tasks. An early direction focuses on repository-grounded coding rather than isolated generation. These tasks ask whether an agent can work with project structure, cross-file dependencies, and documentation instead of relying only on a local prompt. RepoBench represents retrieval- and completion-oriented evaluation, while CodeAgentBench and REPOCOD move toward realistic repo-level generation with tool use and executable evaluation [401, 402, 56, 403]. Repository tasks primarily evaluate codebase grounding, context selection, and navigation, providing the foundation for later issue-resolution and engineering benchmarks.

Issue Resolution. A second line focuses on executable repair and issue-level debugging. SWE-bench makes real issue resolution the core task, SWE-Bench Pro extends this toward longer-horizon, multi-file, enterprise-grade problems, and LiveCodeBench adds executable, contamination-aware evaluation [404, 57, 60, 58, 405]. This direction emphasizes iterative correction, debugging, and responding to test feedback. As tasks grow longer-horizon, performance increasingly depends on whether the harness can retrieve context, run commands, inspect failures, and support repeated repair.

Broader Engineering Workflows. A third line broadens evaluation beyond issue repair to fuller engineering workflows. NL2Repo-Bench requires agents to design architecture, manage dependencies, and generate an installable repository from natural-language requirements [406]. FeatureBench focuses on feature-level implementation requiring coordinated edits across files [407]. BeyondSWE consolidates several beyond-bug-fixing regimes, including cross-repository reasoning, domain-specialized fixing, dependency migration, and doc-to-repo generation [408, 59]. These benchmarks collectively show that newer evaluations increasingly test global planning, cross-file consistency, and dependency management rather than local patch generation alone.

5.3 Tool Use and Function Calling

Tool use and function calling benchmarks evaluate whether an agent can invoke external capabilities correctly, relevantly, and consistently with task state. The overall trend moves from isolated function invocation toward multi-step, stateful, and conversational tool orchestration.

Function Calling. An early direction isolates the correctness of the call itself. API-Bank and BFCL evaluate whether a system can choose the appropriate function, supply valid arguments, and align the invocation with task requirements [409, 62, 393]. This targets a narrow but foundational layer of harness capacity: choosing and formatting the right action before longer trajectories begin.

Tool Use. A second line broadens scope from calling a tool to solving a task with tools. ToolBench, AgentBench, and GAIA evaluate whether agents can plan over APIs, integrate intermediate results, and use tools as part of broader task completion [115, 307, 410, 61]. These tasks emphasize tool routing, multi-step planning, and the ability to connect retrieved outputs to subsequent decisions, shifting evaluation from local call correctness toward coordinated tool-supported problem solving.

Stateful Interaction. More recent benchmarks move toward persistent orchestration across multiple turns and changing state. τ -bench and AssistantBench evaluate conversational interaction under user constraints, while AppWorld, ToolSandbox, and τ^2 -Bench require managing shared app or tool state across longer trajectories [390, 132, 411, 64, 65, 63, 412]. These benchmarks place greater weight on state tracking, multi-turn consistency, and correct sequencing of dependent actions, though they still leave gaps around permissions, safety boundaries, partial-failure recovery, and cross-session memory.

5.4 Computer Use and GUI Grounding

Computer use and GUI grounding benchmarks evaluate whether an agent can perceive and act within interactive digital environments such as browsers, desktops, and mobile systems. Recent benchmarks increasingly stress multimodal perception, richer environments, and explicit GUI grounding.

Web Navigation. An early direction is browser-based task completion. Mind2Web and WebArena establish web navigation as a central evaluation setting by requiring systems to interpret page content, choose actions, and make progress across realistic sequences of web states [107, 108]. These tasks emphasize observation, action choice, and trajectory management inside an interface, introducing the browser as a meaningful environment for evaluating agentic interaction.

Computer Use. A second line expands from websites to broader digital environments. VisualWebArena adds visually grounded web interaction, while WorkArena, Android in the Wild, OSWorld, AndroidWorld, and Windows Agent Arena extend evaluation to enterprise platforms, mobile tasks, desktop systems, and real Windows control [104, 389, 413, 105, 69, 414, 67]. These benchmarks place more emphasis on multimodal perception, environment state, and broader computer control, moving evaluation closer to the conditions under which practical agents are deployed.

GUI Grounding. More recent work moves toward explicit grounding of actions in graphical interfaces. ScreenSpot-Pro and OSWorld-MCP make element identification and interface-aligned control a direct part of the task rather than an implicit subproblem [415, 70, 416, 68]. This reflects a shift toward general multimodal computer use, where precise grounding becomes a central bottleneck for reliable action. Even so, a substantial gap still remains between sandboxed settings and live deployment, and issues such as intervention points, safety-sensitive actions, latency, and the live deployment gap are still only weakly evaluated.

5.5 ML Engineering and Scientific Research

Benchmarks in this category evaluate whether an agent can support experimental, engineering, and scientific workflows over longer horizons than ordinary coding tasks. The development moves from data-science problem solving toward research replication and open-ended research assistance.

ML Experimentation. An early direction focuses on executable experimentation in data science and machine learning. DS-1000 evaluates realistic data-science coding, while MLAgentBench asks whether agents can iteratively run and improve experiments rather than merely generate code [417, 418, 394]. This setting emphasizes experiment setup, data processing, and empirical feedback, measuring whether the harness can support an experimental loop instead of a single generation step.

Scientific Workflows. Building on executable experimentation, a second line extends evaluation toward workflow-oriented scientific and ML-engineering tasks. DA-Code, ScienceAgentBench, and MLE-bench emphasize broader data-science workflows, scientific task decomposition, and ML-engineering pipelines over dependent steps [419, 10, 72, 71]. Performance increasingly depends on whether the harness can organize context, execution, and verification over extended workflows.

Research Replication. More recent benchmarks move toward replication and open-ended scientific validation. PaperBench, MLR-Bench, FML-bench, and ReplicatorBench evaluate whether agents can reproduce research results, pursue open-ended ML research, and reconstruct scientific claims under longer-horizon conditions [73, 420, 421, 422]. This represents a broader shift toward benchmarks that ask whether the system can support meaningful scientific work over extended trajectories. Scientific usefulness remains harder to verify than engineering correctness, with validity, novelty, computational inequality, and long-horizon reliability still open challenges.

Discussion

- Benchmark design is evolving from single-signal final-answer checking toward multi-signal evaluation: execution-based, state-based, rubric-based, and trajectory-aware signals together form a progression from verifying *what* was produced to evaluating *how* it was produced.

- Critical gaps remain: safety and permission control, operational costs (latency, token budgets), and long-term memory persistence are all weakly or inconsistently evaluated across current benchmarks.
- Most fundamentally, current benchmarks rarely disentangle improvements attributable to the base model from those attributable to the harness, limiting actionable insight for harness engineers.
- Closing these gaps—particularly cost-aware evaluation, safety testing, and model-harness attribution—will be central to the next generation of benchmarks.

6 Future Directions

The development of agentic harnesses is shifting from constructing capable execution loops to governing long-running runtime systems. Early harness designs focused on enabling models to perceive environments, invoke tools, maintain context, and coordinate actions. As these capabilities mature, the central bottleneck moves to what happens when agents run over extended horizons, interact with uncontrolled environments, persist state across sessions, and act with increasing authority. In such settings, performance depends not only on whether the model can produce a plausible next action but also on whether the harness can allocate compute selectively, manage state lifecycles, maintain environment-aligned beliefs, constrain risky actions, and expose evidence for evaluation.

This shift frames future harness engineering as runtime governance under resource, state, and action constraints. Efficiency concerns how compute, context, and tools are allocated under explicit budgets. Safety concerns how tool access, memory writes, and delegation are mediated before model outputs become real-world actions. Continual learning concerns how persistent memories and skills are consolidated, updated, and protected from drift. State and environment modeling concerns how partial observations and tool feedback are maintained as coherent belief states. Embodied harnesses test these abstractions under physical constraints where actions are noisy and often irreversible. Evaluation must then move beyond final success rates toward trace-aware, safety-aware, and cost-aware protocols. The following subsections discuss these directions in turn.

6.1 Efficiency

As LLM agents move from single-turn generation to long-horizon execution, efficiency becomes a harness-level concern rather than a model-level one alone. Cost in agentic systems accumulates through repeated model calls, expanding action-observation histories, tool-result feedback, retrieval, reflection, and multi-agent delegation. A uniform execution loop that applies the same model, context budget, and reasoning depth to every subtask is inherently wasteful, yet most current harnesses adopt exactly this uniform strategy. Model routing work offers a first alternative by framing inference as a cost-quality trade-off, showing that weaker and stronger models can be selected dynamically without always invoking the most capable model [423]. The same principle extends to reasoning depth: analyses of chain-of-thought prompting caution that deeper reasoning traces are not universally beneficial, since additional reasoning can be brittle, task-specific, and costly when it does not generalize [424]. Taken together, these results suggest that agent efficiency should be studied as a scheduling problem: the harness must decide when deeper reasoning, stronger models, or retrieval are warranted, and when cheaper execution paths suffice.

While model selection and reasoning depth determine the cost of each individual step, a second bottleneck arises from what accumulates across steps: context and trajectory management. Long-running agents repeatedly reprocess growing histories, observations, tool outputs, and intermediate decisions. ACON addresses this by optimizing compression guidelines against downstream agent failures, showing that context compression must preserve task-relevant information rather than simply shorten text [277]. AgentDiet complements this finding from the removal side, demonstrating that long-horizon trajectories contain redundant and expired information that can be pruned at inference time without sacrificing task performance [425]. More recent frameworks move beyond such passive compression toward active context governance. ARC treats context as a dynamic reasoning state that can be monitored and revised when context rot appears, while Context as a Tool makes context maintenance a callable action inside long-horizon SWE agents [426, 427]. Together, these works

indicate that efficient harnesses should treat history not as an immutable transcript but as a managed resource whose fidelity, lifetime, and accessibility are governed by the runtime.

Beyond what the model computes and what context it sees, efficiency also depends on how tools and reasoning components are orchestrated. Tool use can reduce model burden by delegating computation to external systems, but poorly structured invocation introduces additional calls, long feedback traces, and expensive replanning that offset the delegation benefit. Recent work on layered tool orchestration shows that separating global dependency guidance from local reflective correction can reduce this overhead, avoiding full-trajectory replanning after each tool-level failure [428]. These three dimensions form a coherent efficiency stack: routing controls which model is used, context management controls what the model sees, trajectory reduction controls what history persists, and tool orchestration controls how much reasoning is spent coordinating external actions. Future harnesses should therefore treat computation as a budgeted runtime resource, allocating capacity where uncertainty or task risk justifies it while collapsing routine subtasks into cheaper model calls, compressed state, cached artifacts, or structured tool execution.

6.2 Safety

Safety in agentic systems is shifting from output alignment to runtime capability governance. When an agent only produces text, safety can be framed around harmful responses or preference alignment. Once the harness allows a model to browse untrusted content, call tools, write to external systems, store persistent memory, or delegate subtasks, the primary risk surface moves from generation into the observation-to-action loop. This expanded attack surface manifests at progressively deeper layers of the harness. At the tool-output level, AgentDojo showed that returned results can carry prompt-injection attacks that steer agents toward malicious actions [429]. At the tool-metadata level, MCPTox demonstrated that MCP-style ecosystems introduce poisoning risks before a tool is even executed [430]. At the memory level, AgentSys argues that indirect prompt injection becomes persistent when untrusted observations accumulate in working memory, and proposes hierarchical memory isolation as a defense [32]. This progression indicates that harness safety concerns not only what the model generates, but what information, tools, and authority the runtime allows to influence future actions.

Recognizing that the threat surface spans the entire runtime, recent work increasingly treats safety as a governance architecture problem. At the conceptual level, OpenPort Protocol frames tool access as a governance interface combining authorization-dependent discovery, scoped permissions, stable failure semantics, risk-gated execution, state revalidation, and structured audit events [431]. At the formal level, Runtime Governance for AI Agents shows that many safety policies are path-dependent, meaning that whether an action is acceptable depends on the agent identity, partial execution trace, and previous data accesses, not on the next action in isolation [432]. At the enforcement level, AgentSpec provides a domain-specific language for specifying triggers, predicates, and interventions over agent actions, while AARM proposes an action-interception layer that accumulates session context, checks policy alignment, and records tamper-evident receipts [433, 434]. SafeHarness integrates these concerns across the full agent lifecycle, combining adversarial context filtering, causal verification, privilege-separated tool control, and rollback with adaptive degradation [435]. Together, these works signal a shift from prompt-level safeguards toward lifecycle-aware mediation inside the harness.

These governance mechanisms, however, largely address individual actions or single-layer threats. The central open problem is compositional governance over long horizons, where unsafe behavior emerges not from any single impermissible step but from combinations of individually permissible ones: reading sensitive data before sending an email, invoking a benign tool after poisoned metadata, retrieving stale memory under a changed policy, or delegating partial context without preserving provenance. Addressing such compositional risks requires safety mechanisms that travel with state. Tool outputs, memory entries, retrieved documents, and planned actions should carry provenance, trust, and freshness metadata checkable before downstream use. High-risk actions should support approval gates, state revalidation, rollback when possible, and auditable receipts when execution cannot be undone. This formulation clarifies how harness-level safety differs from model-level alignment: alignment shapes behavioral tendencies, whereas harness governance determines which capabilities are exposed, which information persists, which actions may execute, and what evidence must be produced before and after execution.

6.3 Continual Learning

Continual learning in agentic systems should not be equated with continually updating model weights. Agents improve through multiple layers of adaptation: the model may be fine-tuned, the harness may update its tools, rules, and policies, and the context layer may accumulate memories, user preferences, and reusable skills. Recent product-side discussions make this layered view explicit by separating model-level, harness-level, and context-level learning. A useful theoretical grounding is the externalization view of LLM agents, which observes that memory externalizes state across time, skills externalize procedural expertise, protocols externalize interaction structure, and the harness coordinates these externalized components at runtime. Combining these perspectives, continual learning becomes less about whether an agent has a larger memory store, and more about how the harness maintains the external structures through which past experience influences future behavior [436].

If continual learning operates primarily over externalized state, the core challenge shifts from memory accumulation to context lifecycle management. Early systems such as MemGPT introduced structured memory tiers rather than treating the context window as an append-only transcript [148]. Subsequent work made memory operations themselves learnable: A-MEM differentiates memory construction and retrieval strategies, while Memory as Action treats memory editing as part of the agent policy rather than a fixed heuristic [31, 437]. Production deployments further validate this trend by operationalizing distinct lifecycle stages. Anthropic’s context-management guidance, for instance, separates compaction, tool-result clearing, and memory: compaction compresses the current conversation, tool-result clearing removes re-fetchable outputs, and memory persists structured notes across sessions [438]. The underlying insight is that different types of state require different lifecycle treatments: some should remain in active context, some should be summarized, some can be dropped because it is reconstructable, and some must persist outside the window for future sessions. Continual learning thus becomes a governed write-manage-read loop over states, not a simple retrieval problem.

The same lifecycle challenge becomes even more acute when it extends from declarative memories to procedural skills. Agent Workflow Memory shows that agents can induce reusable workflows from prior trajectories and retrieve them to guide future action sequences [146]. More recent skill-oriented systems treat such procedures as explicit packages: skills may include instructions, scripts, metadata, tests, and execution constraints, and can be dynamically discovered, loaded, shared, or versioned by the harness. Skills, however, are more tightly coupled to external dependencies than declarative memories, and consequently acquire software-like maintenance risks once they become durable objects. Summaries can overcompress rare exceptions, old beliefs can survive after environment changes, tool APIs can invalidate procedural routines, and low-quality memories can contaminate future behavior. Future work should therefore study continual learning as governed persistence: how to consolidate experience, preserve provenance, expire stale state, reconcile contradictory updates, version skills, and keep persistent structures aligned with the tools, environments, and users.

6.4 State and Environment Modeling

State and environment modeling in agentic harnesses is not primarily about whether an LLM contains latent commonsense knowledge. The more immediate question is whether the runtime can maintain a compact, updatable, and action-relevant representation of the environment over long trajectories. For practical agents, the external world is only partially exposed through observations such as web page changes, GUI layouts, repository files, tool responses, sandbox feedback, and intermediate artifacts. Because these observations are incomplete and transient, treating the full interaction history as a proxy for state is both inefficient and brittle: the history grows with redundant or expired information, while the model’s implicit belief may silently drift from the actual environment. A harness therefore needs explicit mechanisms for constructing and updating a belief state that supports planning, execution, and recovery, rather than relying on raw observation replay.

Recent research addresses this need from two complementary directions that correspond to two distinct planning requirements. The first direction focuses on explicit belief maintenance, which answers the question of where the agent currently stands. WorldCoder learns executable environment models by writing code and interacting with the environment, enabling planning over learned models rather than raw histories [439]. CoEx couples planning with a persistent neurosymbolic belief state updated from experience, while PABU shows that progress-aware belief updates can outperform full-history conditioning by retaining only decision-relevant state [440]. The second direction models

action-conditioned transitions, which answers the question of what will happen if the agent acts. Reinforcement World Model Learning trains agents to predict next states after actions and uses discrepancies between simulated and real feedback as learning signals, making state transition itself part of harness optimization. Related work in web, GUI, and mobile environments similarly uses state machines or transition graphs to represent interface dynamics and action consequences. Together, these two capabilities enable an agent to reason about both its current situation and the likely outcomes of candidate actions, which are the minimal requirements for informed planning.

While academic research pursues learned state models, deployed systems often achieve the same function through structured infrastructure. Coding and computer-use agents maintain environment state through repository files, terminal outputs, test results, execution logs, and sandbox permissions. Recent product-side runtimes make this explicit: controlled sandbox environments define what the agent can inspect, execute, and modify, while progressive disclosure determines which parts are surfaced at each step. Agent-World extends this view by arguing that robust agent development requires scalable environment synthesis, sandboxing, and realistic state transitions [441]. Whether realized through learned models or engineered infrastructure, the underlying challenge is the same: maintaining consistency between what the agent believes and what is actually true. Future work should therefore treat state modeling as a harness-level consistency problem: how to reconcile model priors, partial observations, tool feedback, memory, and changing external state; how to detect stale or uncertain beliefs; and how to expose reusable state-transition interfaces across web, code, GUI, and embodied settings.

6.5 Embodied Harnesses

Embodied settings provide a particularly demanding test for harness engineering because state is partially observable, execution is noisy, feedback is real-time, and actions are often irreversible. Earlier systems such as PaLM-E and RT-2 showed that multimodal models can connect visual and linguistic knowledge to embodied planning [314, 315], but these systems largely treated the model as a monolithic planner-to-actor pipeline. Recent work decomposes this pipeline into explicit harness layers. Gemini Robotics-ER 1.6 separates high-level embodied reasoning, including spatial reasoning, task planning, and success detection, from low-level VLA execution and user-defined functions. Green-VLA similarly frames generalist robot deployment as a staged control stack with task planning, progress prediction, out-of-distribution detection, and RL-based policy alignment above a unified action interface [442]. ACoT-VLA and ST4VLA reinforce this decomposition by making action-space reasoning and spatial grounding learning objectives within VLA training [443, 444]. The converging lesson is that embodied progress depends less on end-to-end action generation and more on an explicit runtime boundary between high-level semantic reasoning and low-level motor execution.

Once this boundary is established, grounded state management becomes the harness’s core responsibility at the semantic level. Unlike digital environments, the physical world does not expose complete or rollback-friendly state, so the harness must maintain an approximate belief state from camera streams, sensor readings, and execution feedback. Three runtime questions then arise continuously: whether the current observation is reliable enough to plan from, whether a candidate action remains valid given updated perception, and whether the task has progressed as expected or drifted out of distribution. Recent systems address these questions through concrete mechanisms: Gemini Robotics-ER 1.6 provides multi-view success detection and spatial pointing for progress assessment; Green-VLA adds real-time progress tracking and OOD monitoring for drift detection [442]; and RoboAgent decomposes embodied task planning into scheduler-mediated capabilities with separate contexts for reliability isolation [445]. The common architectural pattern is that embodied harnesses must connect perception, planning, belief update, and success detection into a continuous runtime loop, since treating perception as a one-shot input cannot sustain multi-step physical execution.

The irreversibility of physical actions further demands pre-execution validation and recovery protocols that go beyond what software agents require. In digital environments, failed actions can often be retried or sandboxed; in physical environments, a single unsafe grasp or collision may damage the scene or the robot itself. EmbodiedBench confirms that even strong multimodal models struggle with sustained grounding and robust action selection under these conditions [5]. The runtime therefore cannot rely on model capability alone but must verify that planned actions are compatible with current perception, physical constraints, and safety rules before dispatching them to the controller. AgentSpec provides one useful abstraction by treating such constraints as executable harness logic

rather than informal prompts [446]. Production robotics workflows operationalize the same principle at scale: NVIDIA’s simulation-to-production stack and Isaac Lab-Arena require simulation evaluation, software-in-the-loop testing, digital-twin fleet testing, and safety guardrails before real-world execution. When validation passes but execution still fails, the harness must then support re-observation, replanning, controller switching, safe-state retreat, and escalation to human supervision. In this sense, embodied harnesses serve less as a separate application domain than as a demanding testbed for whether the planning, state maintenance, validation, and recovery abstractions developed for digital agents can survive contact with physical reality.

6.6 Evaluation

Evaluation for agentic harnesses is shifting from measuring isolated task success to assessing the quality of complete execution runs. Recent benchmarks already move beyond static question answering by placing agents in longer, more interactive settings: BrowseComp and OSWorld stress multi-step browsing and computer-use trajectories, PaperBench and ReplicatorBench evaluate open-ended research workflows, and BeyondSWE targets software-engineering tasks whose failures emerge only after cross-repository reasoning [313, 105, 73, 422, 408]. These benchmarks extend task horizon and difficulty, yet they still permit evaluation based primarily on the final output. More recent benchmarks go further by making the environment itself dynamic, which forces evaluation to consider the entire execution trajectory. Gaia2 evaluates agents in asynchronous environments where state changes independently of agent actions, while Claw-Eval-Live separates refreshable workflow signals from reproducible snapshots and grades runs using execution traces, audit logs, and workspace artifacts [66, 447]. Once the environment can change mid-execution, a correct final answer no longer guarantees a sound process, making the agent run itself the necessary unit of measurement.

Treating the run as the evaluation object, however, immediately raises the question of what within that run should be measured. Final success rates hide whether an agent followed a dependable procedure or arrived at a correct end state by chance, excessive retries, or unobserved side effects. This attribution problem motivates a second evaluation requirement: process visibility. Existing benchmarks have begun exposing richer intermediate signals: ResearchRubrics evaluates long-form research through structured rubrics, OSWorld-MCP makes tool invocation patterns explicit, and AgentLongBench evaluates long-context agents through environment rollouts rather than passive retrieval [400, 70, 448]. These efforts point toward a broader standard: benchmarks should record how state is updated, which tools are called, what intermediate artifacts are produced, how failures are handled, and whether memory becomes stale over time. Without such trace-level evidence, it remains difficult to attribute performance to the model, the harness, the tools, or the surrounding execution environment.

Process visibility reveals what an agent did, but a complete evaluation must also judge whether what it did was safe and affordable. This motivates a third requirement: evaluating governance, safety, and cost as first-class metrics rather than secondary diagnostics. Agentic failures increasingly occur inside trajectories where they are invisible to output-only evaluation: unsafe tool calls, poisoned tools, contaminated memory, privacy leakage through internal messages, and missing approval steps may never surface in the final response. ATBench makes this trajectory-level safety problem explicit through heterogeneous tool pools and delayed-trigger risks, while AgentLeak demonstrates that output-only audits miss privacy leakage through inter-agent messages and shared memory [449, 450]. Cost exhibits a parallel evaluation gap. General AgentBench shows that test-time scaling is limited by context ceilings and verification gaps, implying that pass rates should be interpreted together with token use, latency, tool-call count, and verification budget [451]. Future harness benchmarks should therefore report path quality, state quality, safety quality, and cost quality as an integrated profile, distinguishing systems that merely solve benchmark instances from harnesses that are reliable, auditable, and deployable.

7 Conclusion

This paper presented a systematic review of agent systems from the perspective of harness engineering. Starting from the observation that practical capability depends as much on system scaffolding as on the underlying model, we formalized the harness as the orchestration layer governing execution flow, tool invocation, memory management, context construction, and safety enforcement, and framed

harness engineering as the joint optimization of both the scaffold and the model it supports. Under this framework, we examined how agent workflows, memory systems, skill libraries, and multi-agent orchestration collectively determine system-level performance, and reviewed optimization strategies spanning context engineering and agentic training, as well as evaluation benchmarks across software engineering, deep research, tool use, computer use, and scientific discovery.

This perspective shifted the analytical focus from what agents can accomplish to how the surrounding infrastructure enables reliable accomplishment. Our analysis revealed that many practical failures in deployed systems, including instability during long-horizon execution, inefficient tool utilization, context degradation, and suboptimal multi-agent coordination, frequently originated from inadequate harness design rather than model-level deficiency alone. These failures reflected a structural mismatch between the single-turn generative interface of LLMs and the stateful, iterative nature of real-world problem solving, reinforcing the central thesis that the relationship between model and harness is inherently synergistic: improvements to one unlock latent potential in the other.

Looking ahead, several directions merit investigation: improving the scalability and robustness of harness execution in long-horizon settings, developing principled methods for joint scaffold-model optimization, generalizing agent harnesses to physical and embodied domains, and establishing evaluation protocols that disentangle harness contributions from model capability. We hope this paper serves as a practical reference for building more reliable, scalable, and controllable agent systems through principled harness engineering.

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