Survey on Evaluation of LLM-based Agents

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Abstract

The emergence of LLM-based agents represents a paradigm shift in AI, enabling autonomous systems to plan, reason, use tools, and maintain memory while interacting with dynamic environments. This paper provides the first comprehensive survey of evaluation methodologies for these increasingly capable agents. We systematically analyze evaluation benchmarks and frameworks across four critical dimensions: (1) fundamental agent capabilities, including planning, tool use, self-reflection, and memory; (2) applicationspecific benchmarks for web, software engineering, scientific, and conversational agents; (3) benchmarks for generalist agents; and (4) frameworks for evaluating agents. Our analysis reveals emerging trends, including a shift toward more realistic, challenging evaluations with continuously updated benchmarks. We also identify critical gaps that future research must address—particularly in assessing costefficiency, safety, and robustness, and in developing fine-grained, and scalable evaluation methods. This survey maps the rapidly evolving landscape of agent evaluation, reveals the emerging trends in the field, identifies current limitations, and proposes directions for future research.

1 Introduction

Recent years saw a huge leap in the ability of Large Language Models (LLMs) to address a wide range of challenging tasks. Yet, LLMs are static models that are restricted to single-turn, text-to-text interactions. LLM-based agents, hereinafter also referred to as LLM agents, take the power of LLMs a step further by integrating them into a multi-step flow, while maintaining a state that is shared by multiple LLM calls, providing context and consistency. They also utilize external tools to perform computations, access external knowledge and interact with their environment. Agents are able to autonomously conceive, execute and adapt complex

plans in real-world environments. This newfound agency empowers them to address problems previously beyond the reach of AI, paving the way for innovative applications across a wide spectrum of domains.

Reliable evaluation of agents is critical to ensure their efficacy in real-world applications, and to guide further progress in this rapidly evolving field. Since agents are sometimes applied to "classical" text-to-text AI tasks, there is some overlap between their evaluation and standard LLM benchmarking. However, as their applicability is much broader, they require new types of evaluation methodologies, benchmarks, environments and metrics. The very characteristics that define LLM-based agents – their reliance on specific LLM abilities, their sequential operation within dynamic environments, and their capacity to undertake diverse, intricate tasks – introduce novel challenges for their evaluation. ¹

This survey provides the first comprehensive mapping of LLM-based agent evaluation, serving four key audiences: (1) LLM agent developers assessing the capabilities of their systems, (2) practitioners deploying agents in domain-specific applications, (3) benchmark developers addressing evaluation challenges, (4) AI researchers broadly studying current capabilities, risks and limitations of agents.

We begin by discussing the evaluation of fundamental agentic capabilities (§2), which are commonly employed by agents across different domains and applications. These include planning and multi-step reasoning, tool use, self-reflection,

¹The terminology for more complex systems that utilize LLMs as core components varies across the literature. Common terms include "LLM-based Agents", 'LLM Agents', "Language Agents", "AI Agents", "Agents," and "Agentic Systems". We adopt the terms "LLM-based agents" and "LLM agents" to emphasize both the foundational technology (LLMs) and the agentic capabilities that extend beyond single model inference.

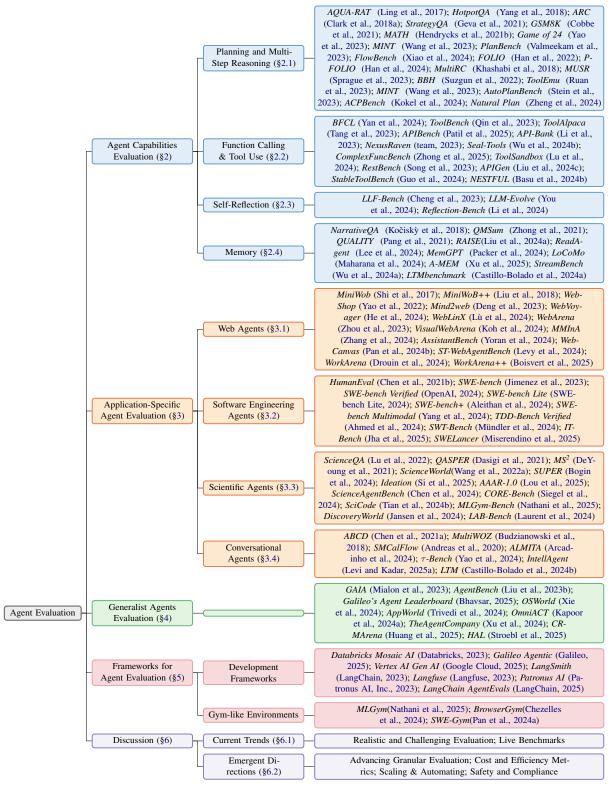


Figure 1: Overview of the paper.

and memory. We then review benchmarks and evaluation strategies for prominent types of agentic applications: web agents, software engineering agents, scientific agents and conversational agents (§3).

Next, we describe benchmarks and leaderboards

for evaluating general-purpose agents (§4), which assess the agent's ability to perform different tasks that require diverse skills. The next section (§5) reviews current evaluation frameworks for agent developers. These frameworks integrate with the agent's development environment, and support its

evaluation throughout the entire development cycle. We conclude with a discussion (§6) of current trends and emerging research directions in agent evaluation. Figure 1 provides a visual overview of the structure of our survey. Our survey is intended to offer researchers and practitioners a comprehensive understanding of the current state of agent evaluation and to highlight key areas for future innovation.

Scope In this survey, we specifically focus on evaluation methodologies for LLM-based agents. Consequently, widely-used single-call LLM benchmarks, such as MMLU, AlpacaEval, GSM8K, or similar standardized evaluation datasets, won't be extensively discussed. Additionally, detailed introduction to LLM-based agents, modeling choices and architectures, and design considerations are outside our focus, given their comprehensive treatment in existing surveys (e.g., Wang et al. (2024a)). Similarly, while we mention topics such as interactions between multi-agent systems, game agents, and embodied agents in some sections, they are not the main focus of this survey. Instead, our objective is to provide a comprehensive overview of evaluation methods for LLM-based agents.

2 Agent Capabilities Evaluation

LLM-based agents have evolved to rely on specific design patterns that encapsulate a core suite of LLM abilities. Evaluating these capabilities is paramount to understanding the potential and limitations of LLM-based agents. Here we focus on four foundational capabilities of LLM-based agents.

2.1 Planning and Multi-Step Reasoning

Planning and multi-step reasoning form the foundation of an LLM agent's ability to tackle complex tasks effectively which enables agents to decompose problems into smaller, more manageable subtasks and create strategic execution paths toward solutions (Gao et al., 2023a).

Multi-step reasoning in LLMs typically involves executing sequential logical operations—typically requiring 3-10 intermediate steps—to arrive at solutions that cannot be derived through single-step inference (Cobbe et al., 2021; Yang et al., 2018; Suzgun et al., 2022). This foundational need for multi-step planning has led to the development of specialized benchmarks and evaluation frameworks that systematically assess these capabilities

across diverse domains, including: mathematical reasoning (GSM8K (Cobbe et al., 2021), MATH (Hendrycks et al., 2021b), AQUA-RAT (Ling et al., 2017)), multi-hop question answering (HotpotQA (Yang et al., 2018), StrategyQA (Geva et al., 2021), MultiRC (Khashabi et al., 2018)), scientific reasoning (ARC (Clark et al., 2018a)), logical reasoning (FOLIO, P-FOLIO (Han et al., 2024, 2022)) constraint satisfaction puzzles (Game of 24 (Yao et al., 2023)), everyday common sense (MUSR (Sprague et al., 2023)), and challenging reasoning tasks (BBH (Suzgun et al., 2022)). Several of these benchmarks, particularly HotpotQA, ALF-Worlds, and Game of 24, have been specifically adapted for evaluating agent-based approaches like ReAct, where planning and calling the tools proposed by the agent are interleaved in interactive problem-solving settings.

Recent work has developed more specialized frameworks targeting LLM planning capabilities. ToolEmu (Ruan et al., 2023) introduces a simulator-based approach for evaluating tool-using agents, revealing that successful planning requires explicit state tracking and the ability to recover from errors. The MINT benchmark (Wang et al., 2023) evaluates planning in interactive environments, showing that even advanced LLMs struggle with long-horizon tasks requiring multiple steps.

PlanBench (Valmeekam et al., 2023) provides a comprehensive evaluation framework specifically designed to assess planning capabilities in LLM agents across diverse domains, revealing that current models excel at short-term tactical planning but struggle with strategic long-horizon planning. Complementing this, AutoPlanBench (Stein et al., 2023) focuses on evaluating planning in everyday scenarios, demonstrating that even SoTA LLM agents lag behind classical symbolic planners.

FlowBench (Xiao et al., 2024) evaluates workflow planning abilities, focusing on expertise-intensive tasks. ACPBench (Kokel et al., 2024) focuses on evaluating LLMs on core reasoning skills. The Natural Plan benchmark (Zheng et al., 2024) is designed to evaluate how LLMs handle real-world planning tasks presented in natural language. SoTA LLM agents perform poorly on this benchmark, particularly as complexity increases.

These benchmarks highlight key abilities essential for effective agent planning: (1) task decomposition for breaking down complex problems, (2) state tracking and belief maintenance for accurate multi-step reasoning, (3) self-correction to detect

and recover from errors, (4) causal understanding to predict action outcomes, and (5) meta-planning to refine planning strategies.

2.2 Function Calling & Tool Use

The ability of LLMs to interact with external tools through function calling is fundamental for building intelligent agents capable of delivering realtime, contextually accurate responses (Qin et al., 2023; Tang et al., 2023). Early works utilized targeted tools, such as retrieval in approaches by augmented language models with retrieval capabilities (Lewis et al., 2020; Gao et al., 2023b; Nakano et al., 2021). Later developments included more generalpurpose tools, exemplified by ToolFormer (Schick et al., 2023), Chameleon (Lu et al., 2023), and MRKL (Karpas et al., 2022).

Function calling involves several sub-tasks that work together seamlessly. Intent recognition identifies when a function is needed based on user requests. Function selection determines the most appropriate tool for the task. Parameter-value-pair mapping extracts relevant arguments from the conversation and assigns them to function parameters. Function execution invokes the selected function with those parameters to interact with external systems. Finally, response generation processes the function output and incorporates it into the LLM's reply to the user. This integrated process ensures accurate and efficient function calling within the LLM's workflow.

Early evaluation efforts offered approaches to evaluate the above sub-tasks while focusing on relatively simple, one-step interactions with explicitly provided parameters. Benchmarks such as ToolAlpaca (Tang et al., 2023), APIBench (Patil et al., 2025), ToolBench (Qin et al., 2023), and the Berkeley Function Calling Leaderboard v1 (BFCL) (Yan et al., 2024) exemplify this phase, employing synthetic datasets and rule-based matching (e.g., via Abstract Syntax Trees) to establish baseline metrics like pass rates and structural accuracy. However, these methods were limited in capturing the complexities of real-world scenarios, which might include multistep conversations, parameters that are not explicitly mentioned in the conversation, and tools with complex input structures and long, intricate outputs.

The live nature of BFCL aimed to bridge some of these gaps by introducing BFCL v2, which includes organizational tools, and BFCL v3, which incorporates integrated multi-turn and multi-step

evaluation logic. These enhancements provide a closer approximation of real-world complexity and emphasize the importance of continuous state management.

Complementing this evolution, several benchmarks have broadened the evaluation landscape. For example, ToolSandbox (Lu et al., 2024) differs from previous benchmarks by incorporating stateful tool execution, implicit state dependencies, on-policy conversational evaluation with a built-in user simulator, and dynamic evaluation strategies for intermediate and final milestones across arbitrary trajectories. Seal-Tools (Wu et al., 2024b) adopts a self-instruct (Wang et al., 2022b) methodology to generate nested tool calls, effectively modeling layered and interdependent interactions. In parallel, API-Bank (Li et al., 2023) emphasizes realistic API engagements by utilizing dialoguebased evaluations and extensive training datasets. Frameworks like NexusRaven (team, 2023) further enrich this landscape by focusing on generalized tool-use scenarios that mirror the diverse challenges encountered in practice. API-Blend (Basu et al., 2024a) suggested a comprehensive approach focusing on identifying, curating, and transforming existing datasets into a large corpus for training and systematic testing of tool-augmented LLMs. API-Blend mimics real-world scenarios involving API tasks such as API/tool detection, slot filling, and sequencing of detected APIs, providing utility for both training and benchmarking purposes. Rest-Bench (Song et al., 2023) facilitates exploration of utilizing multiple APIs to address complex realworld user instructions. APIGen (Liu et al., 2024c) provides a comprehensive automated data generation pipeline that synthesizes high-quality functioncalling datasets verified through hierarchical stages. StableToolBench (Guo et al., 2024) addresses the challenges of function-calling evaluation by introducing a virtual API server with caching and simulators to alleviate API status changes.

Addressing the inherent complexity of multistep interactions, ComplexFuncBench (Zhong et al., 2025) was specifically designed to assess scenarios requiring implicit parameter inference, adherence to user-defined constraints, and efficient long-context processing. NESTFUL (Basu et al., 2024b) focuses on adding complexity by evaluating LLMs on nested sequences of API calls where outputs from one call serve as inputs to subsequent calls.

2.3 Self-Reflection

An emerging line of research focuses on whether agents can self-reflect and improve their reasoning through interactive feedback, thereby reducing errors in multi-step interactions. This requires the model to understand the feedback and dynamically update its beliefs to carry out adjusted actions or reasoning steps over extensive trajectories.

Early efforts to gauge LLM agent self-reflection were often indirect, repurposing existing reasoning or planning tasks, such as AGIEval (Zhong et al., 2023), MedMCQA (Pal et al., 2022), ALF-World (Shridhar et al., 2021), MiniWoB++ (Liu et al., 2018), etc., into multi-turn feedback loops, to see if models could recognize or correct their own errors given external feedback in confined settings (Renze and Guven, 2024; Huang et al., 2024; Shinn et al., 2023; You et al., 2024; Sun et al., 2023; Liu et al., 2025). Improvement was typically measured by determining if the final answer was corrected, providing only a coarse evaluation and potentially ill-defined measurement, as observed improvements may depend on specific prompting techniques lacking proper standardization (Huang et al., 2024; Liu et al., 2025).

As a dedicated effort to establish a standardized benchmark for interactive self-reflection, LLF-Bench (Cheng et al., 2023) was proposed. This benchmark extends diverse decision-making tasks and incorporates task instructions as part of the environment rather than as part of the agent. To mitigate overfitting to specific environments, LLF-Bench offers options to randomize textual descriptions of task instructions and feedback received by agents.

Similarly, LLM-Evolve (You et al., 2024) was introduced to evaluate LLM agents' self-reflection capabilities on standard benchmarks such as MMLU (Hendrycks et al., 2020). This approach evaluates agents based on past experiences by collecting previous queries with feedback and extracting them as in-context demonstrations. To provide more granular insights into different feedback types, (Pan et al., 2025) focused specifically on coding agents, extending existing coding benchmarks like APPS (Hendrycks et al., 2021a) and LiveCodeBench (Jain et al., 2024) to interactive settings.

From a cognitive science perspective, Reflection-Bench (Li et al., 2024) was designed to assess LLMs' cognitive reflection capabilities, breaking down reflection into components like perception of

new information, memory usage, belief updating following surprise, decision-making adjustments, counterfactual reasoning, and meta-reflection.

2.4 Memory

Memory mechanisms in LLM-based agents improve their handling of long contexts and information retrieval, overcoming static knowledge limits and supporting reasoning and planning in dynamic scenarios (Park et al., 2023). Unlike tool use, which connects agents to external resources, memory ensures context retention for extended interactions like processing documents or maintaining conversations. Agents rely on short-term memory for real-time responses and long-term memory for deeper understanding and applying knowledge over time. Together, these memory systems allow LLM-based agents to adapt, learn, and make well-informed decisions in tasks requiring persistent information access.

One prominent line of research focuses on addressing the challenge of limited context lengths in LLMs by incorporating memory mechanisms to enhance reasoning and retrieval across extended contexts and conversations. Recent works, such as ReadAgent (Lee et al., 2024), MemGPT (Packer et al., 2024), and A-MEM (Xu et al., 2025), investigate these methods and evaluate their efficacy through reasoning and retrieval metrics.

Specifically, ReadAgent structures reading by grouping content, condensing episodes into memories, and retrieving passages, with effectiveness shown on datasets like QUALITY (Pang et al., 2021), NarrativeQA (Kočiskỳ et al., 2018), and QMSum (Zhong et al., 2021).

Similarly, A-MEM introduces an advanced memory architecture evaluated using the Lo-CoMo benchmark (Maharana et al., 2024), while MemGPT manages a tiered memory system tested on NaturalQuestions-Open (Liu et al., 2024b) and multi-session chat datasets (Xu et al., 2021).

For episodic memory evaluation, (Huet et al., 2025) proposes a specialized benchmark to assess how LLMs generate and manage memories that capture specific events with contextual details. This benchmark utilizes synthetically created book chapters and events with LLMs-based judge evaluation metrics to measure accuracy and relevance. StreamBench (Wu et al., 2024a) represents a more challenging setting, evaluating how agents leverage external memory components—including the memory of previous interactions and external feed-

back—to continuously improve performance over time, with quality and efficiency assessed across diverse datasets including text-to-SQL tasks (e.g., Spider (Yu et al., 2018)), ToolBench (Xu et al., 2023), and HotpotQA (Yang et al., 2018).

Beyond context length optimization, memory mechanisms also enhance real-time decisionmaking and learning in agent settings, focusing on action optimization (Liu et al., 2024a; Shinn et al., 2023; Wang et al., 2024b). For example, Reflexion (Shinn et al., 2023) tracks success rate on tasks like HotPotQA (Yang et al., 2018) and ALFWorld (Shridhar et al., 2021), while RAISE (Liu et al., 2024a) enhances the ReAct framework with a two-part memory system evaluated through human judgment on quality metrics and efficiency. Similarly, KARMA (Wang et al., 2024b) tests memory in household tasks using metrics such as success rate, retrieval accuracy, and memory hit rate, demonstrating how memory mechanisms significantly improve agent performance across diverse domains requiring complex reasoning and persistent information retention. LTMbenchmark (Castillo-Bolado et al., 2024a) evaluates conversational agents through extended, multitask interactions with frequent context switching to test long-term memory and information integration capabilities. The results demonstrate that while LLMs generally perform well in single-task scenarios, they struggle with interleaved tasks, and interestingly, short-context LLMs equipped with long-term memory systems can match or exceed the performance of models with larger context windows.

3 Application-Specific Agents Evaluation

The landscape of application-specific agents is rapidly expanding, with an increasing number of specialized agents emerging across popular categories such as tools, web, software, game, embodied, and scientific agents (Wang et al., 2024a). In this section, we focus on four prominent categories that exemplify the diversity and potential of these agents, offering insights into their evaluation frameworks and performance metrics tailored to their unique applications.

Agent benchmarks offer a systematic framework for assessing the diverse capabilities of LLM-based agents by integrating three key elements. First, they utilize a **dataset** of clearly defined tasks—ranging from website navigation to com-

plex scientific problem-solving—that outline what agents are expected to achieve. Second, they establish the operating **environment**, which may be simulated (whether static or dynamic) or real-world, and can incorporate user simulations, a variety of tools, and specific policies to adhere to. Third, they apply **evaluation metrics**, such as success rate, efficiency, and accuracy, to measure performance. These metrics can be applied with varying degrees of granularity, from tracking individual actions and milestones to assessing overall, end-to-end task completion.

3.1 Web Agents

Web agents are AI systems designed to interact with websites to perform tasks such as booking flights or shopping. Their evaluation involves testing how effectively they complete tasks, navigate web environments, and adhere to safety and compliance rules. As these agents have evolved, so too have the benchmarks used to assess them, with recent developments capturing an increasingly complex range of real-world interactions.

Initial efforts in web-agent evaluation focused on basic simulation environments. Early benchmarks such as MiniWob (Shi et al., 2017) and MiniWoB++ (Liu et al., 2018) provided fundamental frameworks for assessing navigation and task automation capabilities. These pioneering studies established essential evaluation protocols and highlighted key challenges in executing web-based tasks, laying the groundwork for more sophisticated assessments.

Building on these early efforts, subsequent research introduced static datasets that enable offline, reproducible evaluation. For example, WebShop (Yao et al., 2022) simulates online shopping scenarios, requiring agents to perform tasks ranging from product search to checkout processes. Similarly, Mind2Web (Deng et al., 2023) and WebVoyager (He et al., 2024) extend this paradigm by incorporating a broader spectrum of web interactions, thereby allowing for comprehensive assessments of an agent's ability to navigate complex website structures and achieve intermediate goals. These benchmarks have been instrumental in standardizing the evaluation process, and facilitating direct comparisons across different methodologies.

More recent efforts have shifted toward dynamic, online benchmarks that more closely mimic real-world conditions. WebLinX (Lù et al., 2024) introduces a dynamic interaction model in which agents must adapt to continuous changes in the web

interface, testing the robustness of their decisionmaking processes. WebArena (Zhou et al., 2023) and its visual variant, Visual-WebArena (Koh et al., 2024), incorporate realistic user interface elements and visual cues, requiring agents to not only follow predefined workflows but also interpret and respond to visual information. In addition, WorkArena (Drouin et al., 2024) and WorkArena++ (Boisvert et al., 2025) simulate complex, multistep tasks typical of office or enterprise environments, where coordinating several actions is necessary to achieve long-term objectives. MMInA (Zhang et al., 2024) provides multimodal, Multihop, holistic evaluation. AssistantBench (Yoran et al., 2024) focuses on realistic multi-site timeconsuming tasks. Notably, WebCanvas (Pan et al., 2024b) refines the dynamic evaluation framework by specifically measuring the completion rates of key navigational nodes, thereby offering a more granular analysis of agent performance.

Recent advances have further broadened the evaluation landscape. The introduction of ST-WebAgentBench (Levy et al., 2024) represents an effort to assess web agents in settings that integrate both static and dynamic elements, providing insights into agents' performance under varied conditions. While these benchmarks have significantly advanced our understanding of web-agent capabilities, most of them continue to focus primarily on task completion and navigational efficiency. Critical aspects such as policy compliance, risk mitigation, and adherence to organizational safety protocols remain underexplored. As web agents move closer to real-world deployment, addressing these gaps will be essential for ensuring both their practical utility and safe operation.

3.2 Software Engineering Agents

The evaluation of software engineering (SWE) agents began with benchmarks that measured fundamental coding capabilities, such as HumanEval (Chen et al., 2021b) and MBPP (Austin et al., 2021). These early benchmarks focused on short, self-contained, algorithm-specific tasks, offering an initial glimpse into the potential of LLMs for code generation. More recently, open-domain coding benchmarks (Wang et al., 2022c; Lai et al., 2022) have emerged as a notable step forward by incorporating application-specific scenarios and interactions with diverse libraries and tools. However, while these benchmarks mark clear progress, they generally evaluate simpler intents and limited tool

usage, thus falling short of addressing the full complexity of real-world SWE tasks.

SWE-bench (Jimenez et al., 2023) was introduced to address the above shortcomings. It is constructed from real-world GitHub issues and offers an end-to-end evaluation framework, including detailed issue descriptions, complete code repositories, execution environments (e.g., Docker), and validation tests. To enhance evaluation reliability, several variants have been proposed. SWE-bench Lite (SWE-bench Lite, 2024) focuses on a subset of 300 issues involving bug fixing, filtering out tasks requiring complicated multi-file edits or extraneous elements. SWE-bench LiteS (Xia et al., 2024) further refines the dataset by removing tasks with exact patches or insufficient descriptive information, while SWE-bench Verified (OpenAI, 2024) includes only those issues with clear, informative descriptions and robust test cases. More recently, SWE-bench+ (Aleithan et al., 2024) has been introduced to mitigate critical evaluation flaws such as solution leakage and weak test cases, thereby providing a more robust benchmark for assessing SWE agents. Additionally, a Java version of SWE-bench was introduced in (Zan et al., 2024). SWE-bench Multimodal (Yang et al., 2024) evaluates agents in visual software domains, targeting JavaScript-based applications with visual elements in problems and tests. It highlights challenges in visual problem-solving and cross-language generalization, with top systems showing lower resolution rates. TDD-Bench Verified (Ahmed et al., 2024) and SWT-Bench (Mündler et al., 2024) evaluate the agent's ability to generate tests from user issues in real-world Github repositories. ITBench (Jha et al., 2025) offers a benchmark for evaluating challenging real-world IT automation tasks.

Complementing these developments, Agent-Bench (Liu et al., 2023b) has emerged as a dedicated framework for evaluating the interactive capabilities of SWE agents. AgentBench provides insights into agent performance in dynamic settings through real-time interaction and environment manipulation. Finally, the introduction of SWE-Lancer (Miserendino et al., 2025) represents the latest trend in benchmark development. By targeting freelance coding tasks, SWELancer links agent performance to monetary value, underscoring the challenges in achieving long-term reasoning and decision-making in complex, real-world scenarios.

3.3 Scientific Agents

The evaluation of scientific agents has evolved from early benchmarks assessing basic reasoning to comprehensive frameworks evaluating diverse scientific research capabilities. Initial benchmarks emphasized scientific knowledge recall and reasoning—examples include ARC (Clark et al., 2018b), ScienceQA (Lu et al., 2022), and ScienceWorld (Wang et al., 2022a). Others focused on the synthesis and contextualization of scientific literature, such as QASPER (Dasigi et al., 2021), QASA (Lee et al., 2023), and MS²(DeYoung et al., 2021). More recent benchmarks, like SciRiff (Wadden et al., 2024), have expanded to evaluate a broader range of tasks, emphasizing the ability to follow user instructions across scientific domains.

Recent advancements have shifted the focus toward developing and assessing scientific agents in accelerating scientific research. Emerging benchmarks now cover various stages of the scientific research process: (1) Scientific Ideation: This stage explores whether scientific agents can autonomously generate novel, expert-level research ideas that are comparable to those proposed by human experts (Si et al., 2025). The emphasis is on creativity, relevance, and feasibility in scientific thinking. (2) Experiment Design: Benchmarks like the AAAR-1.0 dataset (Lou et al., 2025) assess an agent's ability to systematically plan experiments. This includes formulating hypotheses, selecting appropriate methodologies, and outlining experimental procedures that adhere to scientific rigor. (3) Code Generation for Experiment Execution: Benchmarks such as SciCode (Tian et al., 2024a), ScienceAgentBench (Chen et al., 2025), SUPER (Bogin et al., 2024), and CORE-Bench (Siegel et al., 2024) are pivotal in verifying whether agents can produce accurate, executable scientific code. These benchmarks ensure the code aligns with the specific demands of scientific protocols and maintains computational accuracy. (4) Peer-Review Generation: It examines whether agents can provide comprehensive, substantive feedback that matches or surpasses the quality of human peer reviewers (Chamoun et al., 2024).

Beyond the individual task-specific benchmarks described above, there is a growing interest in unified frameworks that integrate multiple, interrelated scientific tasks into single platforms. AAAR-1.0 (Lou et al., 2025) evaluates scientific agents

across four core research tasks, i.e., equation inference, experiment design, paper weakness identification, and review critique, focusing on tasks that require deep domain expertise. MLGym (Nathani et al., 2025) introduces a gym-like environment for AI research tasks, covering 13 diverse challenges that simulate real-world research workflows, from hypothesis generation to experimentation and analysis. DiscoveryWorld (Jansen et al., 2024) offers a virtual, text-based environment for simulating complete scientific discovery cycles across 120 diverse tasks, emphasizing hypothesis formation, experimentation, and result interpretation. LAB-Bench (Laurent et al., 2024) offers a domainspecific evaluation tailored to biological research. It challenges agents with tasks ranging from experimental design to the interpretation of texts, images, and tables.

3.4 Conversational Agents

Customer-facing agents are required to handle user requests, while adhering to the company's policies and procedures. Successful completion of such tasks requires the agent to engage with a user in a multi-turn, task-oriented dialogue, while performing a sequence of actions that involve various function calls.

A common benchmarking approach for these agents is to collect ground truth trajectories with user and agent messages, and function calls. Given a prefix of such a trajectory, the agent is evaluated on predicting the next step. A more flexible approach simulates both the environment and the user. The agent is assessed on its ability to bring the environment to the desired state and communicate the right answer to the user.

The Action-Based Conversations Dataset (ABCD) (Chen et al., 2021a) includes over 10K customer-agent conversations, collected via crowdsourcing. These dialogues contain 55 distinct user intents, each requiring a unique sequence of actions defined by the corresponding policy. Additional examples of crowdsourced task-oriented dialogue benchmarks are MultiWOZ (Budzianowski et al., 2018) and SMCalFlow (Andreas et al., 2020).

A fully automated pipeline for generating tests for conversational AI agents in the customer service domain is described in (Arcadinho et al., 2024). Utilizing an LLM as a generator at each step, they create a set of intents, a procedure defining how each intent should be handled by the agent, tool

APIs to be called by the agent, a flow graph and a conversation graph, from which conversation paths are sampled. Finally, prefixes of the conversation path are extracted as tests. Their manually-filtered ALMITA benchmark includes 192 conversations for 14 intents, resulting in 1420 tests.

The τ -Bench benchmark (Yao et al., 2024) emulates dynamic conversations between an agent and an LLM-simulated user in two customer service domains, *airline* and *retail*. The benchmark was constructed manually, with some LM assistance. Each domain includes several databases, associated APIs, and a domain policy provided to the agent as a system prompt. Task instances include an instruction for the user simulation and ground truth annotation for the expected database write operation and the required output for the user's question. The dataset includes 115 retail tasks and 50 airline tasks.

IntellAgent (Levi and Kadar, 2025a) provides an open-source framework for automatic benchmarking of conversational agents, taking a schema of the system database and a company policies document as input. It constructs a policy graph, from which a list of policies is sampled. It then creates an event addressing these policies, and simulates a dialogue between the tested agent and a user agent, based on the event information. Finally, a critique agent analyzes the dialogue and provides detailed feedback on the tested policies.

4 Generalist Agents Evaluation

Building on the evaluation of basic agentic capabilities and application-specific ones, we now turn to examine benchmarks for general agents. As LLMs evolved from task-specific to general-purpose, agents are now transitioning from application-specific to more general-purpose ones. These agents integrate core LLM abilities with skills like web navigation, information retrieval, and code execution to tackle complex challenges. This shift necessitates broader evaluation methods, leading to the development of benchmarks that assess their diverse capabilities.

A primary category of these benchmarks focuses on evaluating general capabilities that emphasize multi-step reasoning, interactive problem-solving, and proficient tool use. The GAIA benchmark (Mialon et al., 2023) includes 466 human-crafted, real-world questions that test an agent's reasoning, multimodal understanding, web navigation, and gen-

eral tool-use abilities. Similarly, Galileo's Agent Leaderboard (Galileo, 2025) emphasizes the evaluation of agents' abilities to perform function calls and API invocations in real-world applications such as database queries, online calculators, and web services. AgentBench (Liu et al., 2023a) introduces a suite of interactive environments that include operating system commands, SQL databases, digital games, and household tasks. These benchmarks collectively highlight the core competencies required for general agents—flexibility, multi-step reasoning, and adaptive tool use.

Beyond general reasoning and tool use, another crucial dimension in evaluating general agents lies in their performance within full-scale computer operating environments. Benchmarks like OS-World (Xie et al., 2024), OmniACT (Kapoor et al., 2024a), and AppWorld (Trivedi et al., 2024) test whether agents can navigate real-world computer systems, execute complex tasks, and coordinate actions across multiple applications. In these settings, agents must write and modify interactive code, handle complex control flows, and ensure robust execution without causing unintended system changes.

Motivated by the need to assess how general agents perform in realistic professional settings, recent benchmarks extend evaluation into digital work environments, where agents must manage tasks akin to those of human employees. The Agent-Company (Xu et al., 2024) creates an extensible environment resembling a small software company, in which agents browse internal websites, write code, run programs, and communicate with coworkers. CRMArena (Huang et al., 2025) focuses on customer relationship management (CRM), simulating a large-scale CRM environment filled with interconnected data about accounts, orders, knowledge articles, and cases. It examines whether agents can perform multi-step operations using both UI and API access, adhere to domain-specific policies, and integrate various pieces of information to complete complex enterprise tasks.

As benchmarks diversify, there is a growing need for unified platforms that consolidate testing criteria. Holistic Agent Leaderboard (HAL) (Stroebl et al., 2025) serves as a standardized evaluation platform that aggregates multiple benchmarks, covering coding, interactive applications, and safety assessments.

5 Frameworks for Agent Evaluation

In response to the growing need for systematic assessment of LLM agents, several frameworks have recently emerged, providing developers with essential tools to evaluate, refine, and improve their performance, quality, and efficiency. Unlike the benchmarks discussed in the preceding section, which compare the performance of fully developed systems across predefined scenarios, these frameworks serve as integral components of the development ecosystem, enabling continuous monitoring and indepth error analysis across both development and deployment. Rather than supplying standardized test data, they allow developers to design and evaluate their own scenarios, offering greater flexibility. Moreover, these frameworks are designed to be highly general, supporting a wide range of development use cases rather than focusing on specific tasks, making them versatile tools for AI research and application.

While earlier evaluation frameworks for LLM-based applications primarily focused on assessing a model's task completion ability through single-call interactions (e.g. OpenAI Evals (OpenAI, 2023)), the rise of agentic workflows has created a need for more advanced evaluation frameworks capable of assessing multi-step reasoning, trajectory analysis, and specific agent capabilities such as tool usage.

There are many frameworks supporting the evaluation of a wide range of agent types, including LangSmith (LangChain, 2023), Langfuse (Langfuse, 2023), Google Vertex AI evaluation service (Google Cloud, 2025), Arize AI's Evaluation Framework (Arize AI, Inc, 2025), Galileo Agentic Evaluation (Galileo, 2025), Patronus AI (Patronus AI, Inc., 2023), LangChains' AgentEvals (LangChain, 2025); Databricks Mosaic AI Agent Evaluation (Databricks, 2023) which is mostly designed for RAG like tasks, Botpress Multi-Agent Evaluation System (Kargwal, 2025) and AutoGen (Dibia et al., 2024) for multi-agent systems, and more.

All evaluation platforms provide continuous monitoring of agent trajectories, assessing key performance metrics such as task completion rates, latency, execution speed, and, in some cases, throughput and memory usage (LangChain, 2023). Some frameworks utilize the OpenTelemetry (Blanco, 2023) observability framework and their infrastructure, including Langfuse (Langfuse, 2023) and Google Vertex AI (Google Cloud, 2025). Beyond

observability and monitoring, each framework incorporates unique methodologies for quality assessment, providing additional layers of evaluation.

Evaluating agentic workflows occurs at multiple levels of granularity, each focusing on different aspects of the agent's dynamics.

Final Response Evaluation. Frameworks often incorporate LLM-based judges to evaluate agent responses against predefined criteria, with some offering proprietary judge models (e.g. Databricks Mosaic (Databricks, 2023), and PatronusAI (Patronus AI, Inc., 2023)). Additionally, most platforms allow for customizable assessment metrics, enabling domain-specific evaluation of output quality and relevance.

Stepwise Evaluation. Most evaluation frameworks support granular assessments of individual agent actions or LLM calls, facilitating root cause analysis of errors. This includes assessing textual output with predefined judges, and assessing tool selection and execution by either comparing the selected tool against an expected tool for a given step, or using an automated judge to verify the tool choice, its parameters, and the correctness of the execution output. Furthermore, Galileo Agentic Evaluation (Galileo, 2025) introduces an action advancement metric, which measures whether each step successfully contributes to or advances toward a user-defined goal. This approach refines stepwise evaluation by assessing progress rather than solely relying on binary success/failure outcomes.

A key challenge in the current stepwise evaluation schemes lies in the scope and reliability of the automated judges. Many judges are task-specific, making them well-suited for particular evaluations but difficult to generalize across complex workflows. Conversely, more general-purpose judges may offer broad applicability but lack clear quality guarantees.

Trajectory-Based Assessment. In addition to stepwise evaluation, some platforms—such as Google Vertex AI (Google Cloud, 2025) and Lang-Smith (LangChain, 2023) support trajectory-based assessments, which analyze the sequence of steps taken by an agent in relation to an expected optimal path. This method evaluates the agent's decision-making process, particularly regarding tool selection and sequencing. AgentEvals (LangChain, 2025) also enables LLM-as-judge evaluation of agent trajectories, with or without a reference trajectory. Additionally, it supports graph evaluation for frameworks like LangGraph, which model

Framework	Stepwise Assessment	Monitoring	Trajectory Assessment	Human in the Loop	Synthetic Data Generation	A/B Comparisons
LangSmith (LangChain)	✓	√	✓	✓	×	✓
Langfuse (Langfuse)	✓	✓	×	✓	×	✓
Google Vertex AI evaluation (Google Cloud)	✓	✓	✓	×	×	✓
Arize AI's Evaluation (Arize AI, Inc)	✓	✓	×	✓	✓	✓
Galileo Agentic Evaluation (Galileo)	✓	✓	×	✓	×	✓
Patronus AI (Patronus AI, Inc.)	✓	✓	×	✓	✓	✓
AgentsEval (LangChain)	×	×	✓	×	×	×
Mosaic AI (Databricks)	✓	✓	×	✓	✓	✓

Table 1: Supported evaluation capabilities of major agent frameworks. Note that some of these capabilities are still in initial phases of development, as discussed further in the text.

agents as graphs, by assessing whether an agent follows the expected workflow and correctly invokes the appropriate nodes and transitions. However, the reliance on reference sequences, combined with the non-deterministic nature of agentic workflows and the existence of multiple valid solutions, introduces significant challenges in defining and benchmarking optimal trajectories.

Datasets. A critical aspect of agent evaluation is input data curation and annotation. Most frameworks provide integrated annotation tools, support human-in-the-loop evaluation, where human feedback is collected from production runs to refine model configurations, and enable the extraction of evaluation datasets from production logs, leveraging real-world interactions to enhance assessment quality. Additionally, platforms such as Patronus AI (Patronus AI, Inc., 2023), and Databricks Mosaic (Databricks, 2023) facilitate synthetic data generation using proprietary seed data.

A/B comparisons. Current evaluation frameworks support A/B comparisons, enabling the side-by-side analysis of inputs, outputs, and metrics from at least two test runs. In some cases—such as Patronus AI (Patronus AI, Inc., 2023)—these frameworks also facilitate the comparison of aggregated results across multiple runs from distinct experimental setups. Additionally, these frameworks provide the capability to drill down into individual trajectories, identifying specific failure points. However, obtaining large-scale insights at the trajectory or stepwise level remains a significant challenge.

Table 1 presents key frameworks for agent evaluation along with their support for the evaluation features discussed in this section.

Gym-like Environments.

The frameworks discussed primarily monitor and assess agent behavior passively in real-world scenarios. However, evaluation often requires a controlled, interactive setting with a simulated environ-

ment, provided by Gym-like frameworks. Inspired by OpenAI Gym (Brockman et al., 2016), which was originally designed for training and evaluating Reinforcement Learning algorithms, these frameworks have been adapted to the training and evaluation of LLM agents using realistic task simulations, allowing LLM agents to interact with dynamic environments. Moreover, these frameworks enable standardized evaluation across various benchmarks, with proposals made for web agents (Chezelles et al., 2024), AI research agents (Nathani et al., 2025) and SWE agents (Pan et al., 2024a).

6 Discussion

6.1 Current Trends

Our review of the evolution of agent benchmarking highlights several converging trends shaping the field. We identify two primary motives exhibited in the development of new evaluation methodologies, which we outline in the subsequent discussion.

Realistic and Challenging Evaluation. Early agent evaluations often relied on simplified, static environments. However, there is a clear shift toward benchmarks that more accurately reflect realworld complexities. In web agent evaluation, for example, we have moved from basic simulations like MiniWob to dynamic online environments like WebArena and VisualWebArena, and from LAB-Bench which is static and narrow to Discovery-World for scientific agents. In software engineering, SWE-bench utilizes real-world GitHub issues, moving beyond synthetic coding problems. This shift toward realism is key to evaluating agents in real-world scenarios, capturing interaction nuances missed by simpler benchmarks. Benchmarks like Natural Plan, which incorporates simulated API results from real-world tools like Google Calendar and Maps, further exemplify this drive for realistic task settings. Concurrently, to keep pace with increasingly capable agents and ensure benchmarks remain challenging, there is a distinct trend toward

greater task complexity and difficulty. This is evident from benchmarks like *SWE-bench* and *SWE-Lancer* targeting complex coding tasks, *CORE-Bench* for scientific computational reproducibility, and intricate general agent benchmarks like *GAIA* and *TheAgentCompany*. A key indicator of their difficulty is the low score of the best-performing agents in their papers, sometimes as low as 2%. This increased challenge is crucial for stress-testing agents, revealing limitations, and driving advances in long-horizon planning, robust reasoning, and tool use.

Live Benchmarks. The rapid pace of LLM and agent development necessitates evaluation methodologies that are adaptive and continuously updated. Static benchmarks can quickly become outdated as models improve, potentially leading to benchmark saturation and a reduced ability to differentiate between systems. We observe this dynamic approach in the evolution of BFCL, which has progressed through multiple versions, incorporating live datasets, organizational tools, and multiturn evaluation logic to remain relevant. Similarly, the continuous refinement and variant creation within the SWE-bench family (SWE-bench Lite, SWE-bench Verified, SWE-bench+) along with the development of *IntellAgent* based on τ -Bench , demonstrates an ongoing effort to enhance and adapt agent benchmarks to meet evolving evaluation needs. This dynamic approach is essential for maintaining the relevance of benchmarks in this rapidly advancing field.

6.2 Emergent Directions

Observed but not yet fully established trends point to promising future research opportunities for advancing agent evaluation.

Advancing Granular Evaluation. Many current benchmarks rely on coarse-grained, end-to-end success metrics that, while useful for gauging overall performance, fall short in diagnosing specific agent failures. This lack of granularity obscures insights into intermediate decision processes such as tool selection and reasoning quality. Addressing this limitation calls for the development of standardized, fine-grained evaluation metrics that capture the trajectory of an agent's task execution. Future work should explore detailed, step-by-step assessments—similar to those emerging in benchmarks like WebCanvas (Pan et al., 2024b) and frameworks like LangSmith and Galileo Agentic Evaluations (Galileo, 2025) —to provide richer feedback and

guide targeted improvements.

Cost and Efficiency Metrics. As observed by Kapoor et al. (2024b), current evaluations often prioritize accuracy while overlooking cost and efficiency measurements. This emphasis can inadvertently drive the development of highly capable but resource-intensive agents, limiting their practical deployment. Future evaluation frameworks should integrate cost efficiency as a core metric, tracking factors such as token usage, API expenses, inference time, and overall resource consumption. Establishing standardized cost metrics will help guide the development of agents that balance performance with operational viability.

Scaling & Automating. The reliance on static human annotated evaluation poses significant scalability challenges, as these methods can be resourceintensive and quickly outdated in a rapidly evolving field. This shortcoming underscores the need for scalable, automated evaluation approaches. Future directions include leveraging synthetic data generation techniques to create diverse and realistic task scenarios—imitated by efforts such as IntellAgent (Levi and Kadar, 2025b) and Mosaic AI Agent Evaluation (Databricks, 2023). Another avenue is automating evaluation by employing LLM-based agents as evaluators, termed Agent-as-a-Judge. As highlighted by Zhuge et al. (2024), this approach not only reduces the reliance on resource-intensive human annotation but also holds the potential to capture more nuanced aspects of agent performance through agentic evaluation processes. By harnessing these approaches, the community can achieve continuous, fine-grained, and cost-effective assessment of agent performance.

Safety and Compliance. A notable shortcoming in current benchmarks is the limited focus on safety, trustworthiness, and policy compliance. While early efforts (e.g., *AgentHarm* (Andriushchenko et al., 2024) and *ST-WebAgentBench*) have begun to address these dimensions, evaluations still lack comprehensive tests for robustness against adversarial inputs, bias mitigation, and organizational and societal policy compliance. Future research should prioritize developing multi-dimensional safety benchmarks that simulate real-world scenarios, particularly in multi-agent scenarios where emergent risks may arise (Hammond et al., 2025). This can ensure that agents are not only effective but also safe and secure.

7 Conclusion

The field of LLM-based agent evaluation is rapidly advancing, driven by the need to assess increasingly complex and autonomous systems. While significant progress has been made in creating more realistic, dynamic, and challenging benchmarks, critical gaps remain, particularly in the areas of safety, fine-grained evaluation, and cost-efficiency. Addressing these shortcomings and pursuing the outlined future directions will be crucial for ensuring the responsible development and effective deployment of LLM-based agents in real-world applications.

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