Environments Matter: A Survey of Scaling Interactive Experience Collection for LLM Agents

Anonymous ACL submission

Abstract

LLM-based agents can autonomously accomplish complex tasks across various domains. However, to further cultivate capabilities such as adaptive behavior and long-term decision-making, training on static datasets built from human-level knowledge is insufficient. These datasets are costly to construct and lack dynamism, failing to capture the interactive nature of real-world scenarios. A growing consensus is that agents should instead interact directly with environments and learn from experience through reinforcement learning. We formalize this process as the *Generation-Execution-Feedback (GEF) loop*, where environments generate tasks to challenge agents, return observations in response to agents' actions during task execution, and provide feedback on trajectories, yielding experience for subsequent training. Under this paradigm, environments become the primary engines for experience generation, making their scaling in complexity, dynamism, and interactivity a prerequisite for collecting high-quality trajectories at scale. In this survey, we adopt an environment-centric lens and organize existing advances into a unified taxonomy along the *GEF loop*. Beyond taxonomy, we further analyze underlying implementation frameworks, identify open problems, and outline critical future directions, arguing that the deliberate engineering of interactive environments will be a decisive frontier in the pursuit of generalist agents.

1 Introduction

The rapid progress of large language models (LLMs) has catalyzed a transformative shift in artificial intelligence, precipitating a surge of research on LLM-based agents (Luo et al., 2025a; Xi et al., 2025). Such agents inherit strong reasoning and task-decomposition capabilities from their base models and, when augmented with modules for tool use and memory, can execute actions, interact with real or simulated environments, accumulate experience over time, and progressively improve their own behavior. This design has achieved remarkable progress across diverse domains, including automated coding (Qwen Team, 2025; Anthropic, 2025), interactive web navigation (Wei et al., 2025; Qi et al., 2025), tool use (Zhang et al., 2025f; Anthropic, 2024), and deep research (OpenAI, 2025b; Google DeepMind, 2024).

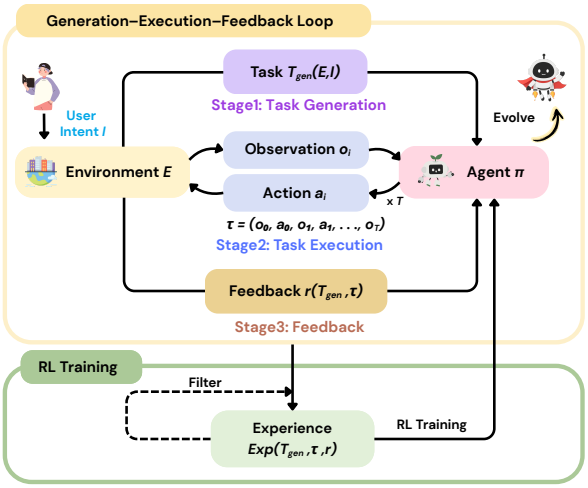

Figure 1: We define the *Generation-Execution-Feedback (GEF) loop*, where the environment plays a central role in generating tasks based on user intent, supporting interactive task execution, and delivering feedback on trajectories, to form valuable experience for RL training. This reframes environment design challenges from merely building passive containers for agent activity to active generators of adaptive, challenging tasks, realistic interactions, and providers of informative, robust feedback.

However, as agent capabilities continue to evolve, achieving intelligence beyond human-level merely through supervised fine-tuning (SFT) pre-trained models on static datasets (Li et al., 2025c; Lu et al., 2025a) becomes increasingly challenging. Such datasets are typically manually annotated or curated under human oversight, which makes them costly and labor-intensive to produce at scale, intrinsically bounded by human-level knowledge,

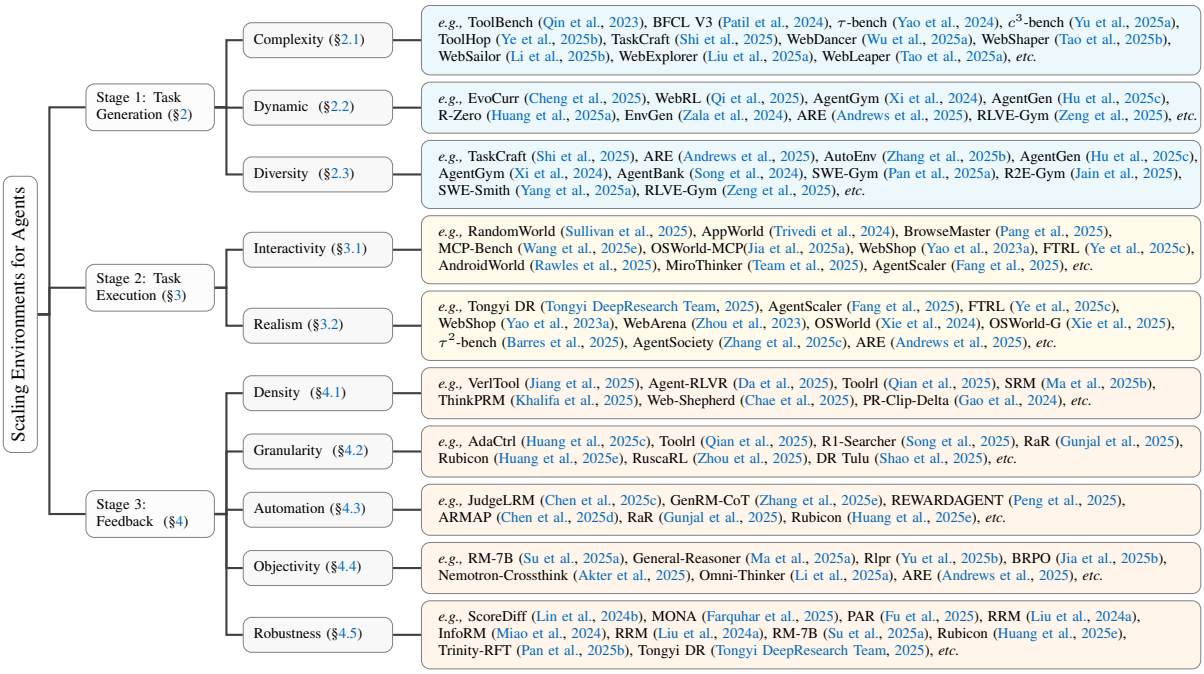

Figure 2: Taxonomy of environment scaling, with dimensions for *Task Generation*, *Task Execution*, and *Feedback* (GEF). Representative works are illustrated as leaves on the branches.

and lacking realism and adaptability. A growing consensus suggests reinforcement learning as a more aligned training paradigm (Tao et al., 2024; Zhang et al., 2025a), where, instead of relying on pre-curated data, agents are encouraged to explore directly within the environment, learn from their accumulated experience, and ultimately awaken new capabilities. In this process, the environment is no longer a mere container for the agent's activities but **an active producer of experience data**. We formalize this process as the *Generation-Execution-Feedback (GEF) loop*, illustrated in Figure 1. In each iteration, the environment generates diverse tasks, and the agent takes actions to obtain observations, forming an execution trajectory. The environment then evaluates these trajectories, providing valuable feedback that guides the agent's learning. Over repeated iterations, this loop refines the agent's policy and expands its capabilities, underscoring the growing need to design more **complex, realistic, and richly interactive environments** that can efficiently generate and collect qualitative experience (CAMEL-AI, 2025).

Recent advances recognize the environment's key role in scaling experience collection and have begun scaling environments from various angles. For instance, AgentGen (Hu et al., 2025c) and GEM (Liu et al., 2025c) design heterogeneous environments to enhance task diversity. R-Zero (Huang et al., 2025a) proposes a co-evolving challenger-solver framework to adaptively increase task difficulty, while ARE (Andrews et al., 2025) introduces an asynchronous event system and large-scale states to support dynamic and realistic exploration. Despite these advancements, a systematic framework that categorizes and analyzes these approaches in a unified way remains absent.

Therefore, we comprehensively investigate current methods and propose a unified taxonomy (Figure 2) aligned with the stages of the *GEF loop*, adopting a pioneering environment-centric perspective. In the **task generation** stage (§2), we emphasize *complexity*, *dynamic*, and *diversity*, which together characterize an environment's ability to generate challenging, adaptive, and diverse tasks continuously. Moving into the **task execution** stage (§3), we highlight *interactivity* and *realism*, since these properties determine the richness and reliability of the collected experience. Finally, in the **feedback** stage (§4), which plays a crucial role in shaping agent behavior and providing guidance, we categorize reward designs along *density*, *granularity*, *automation*, *objectivity*, and *robustness*. Beyond taxonomy, we highlight several recurring trade-offs in environment design, like diversity versus learnability, realism versus cost and controllability, and automation versus reliability. These tensions show that progress requires not only scaling individual stages, but also balancing competing design goals across them. We also discuss representative frame-

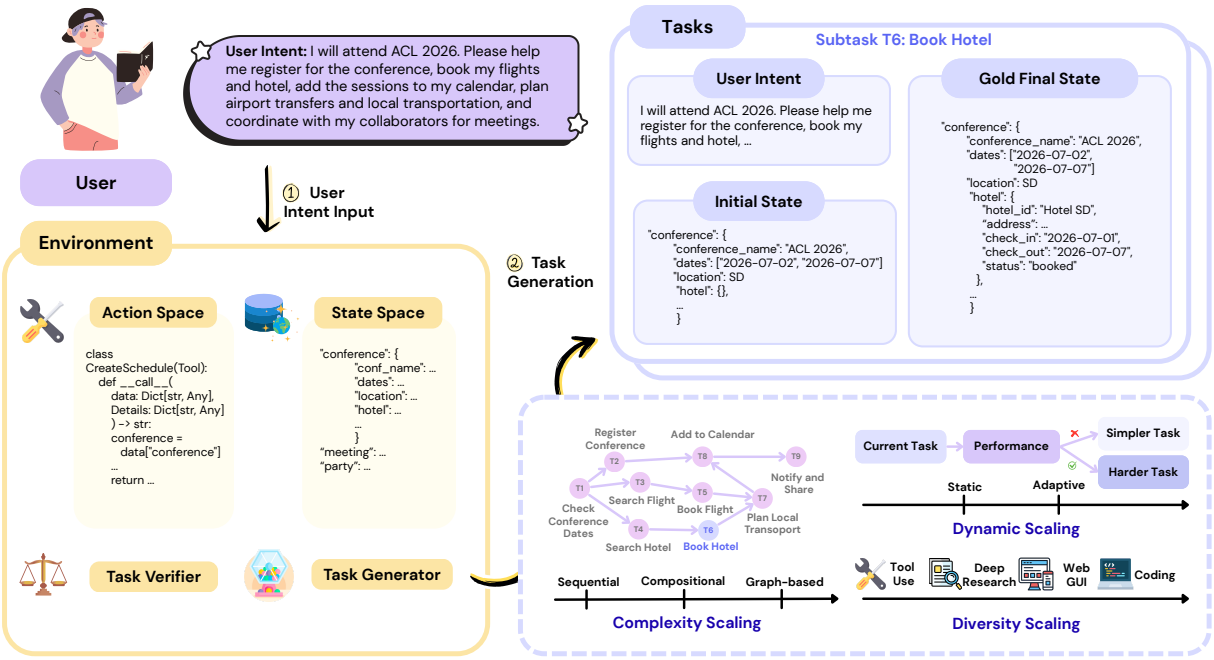

Figure 3: Illustration of scaling in the **task generation** stage. Given a user intent, the environment, equipped with infrastructure (e.g., tools, state space) and a task generator (generation mechanism), automatically creates tasks that are executable by agents. Scaling in this stage covers *complexity scaling*, *dynamic scaling*, and *diversity scaling*.

works across domains and the associated implementation challenges in §5. Overall, our survey emphasizes that environments are key to experience collection and offers a unified, environment-centric view of this emerging research area.

2 Stage 1: Task Generation

As illustrated by Figure 3, task generation encompasses the process where an environment provides infrastructure (e.g., tools, state space) and a generator (generation mechanism), enabling the automated creation of tasks based on intent, which are executable by agents within the environment. To create more challenging tasks that push the agent towards its capability boundary, scaling methods in this stage focus on three key areas: increasing task complexity[1] (§ 2.1), introducing dynamics (§ 2.2), and expanding diversity (§ 2.3).

2.1 Complexity Scaling

Static task complexity increases a task's inherent structural intricacy, moving beyond single-step commands to challenges defined by dependencies, logical flows, and hierarchical relationships. A typical scenario is tool use, from early single-step tasks to multi-turn, multi-step scenarios, where complexity scales up as the number of turns and steps increases (Qin et al., 2023; Patil et al., 2024; Yao et al., 2024; Ye et al., 2025b). More sophisticated tasks exhibit **hierarchical or compositional structure**, where high-level objectives are decomposed into nested sub-goals, requiring agents to solve novel problems by recombining acquired skills (Shao et al., 2023; Yu et al., 2025a; Shi et al., 2025; Wu et al., 2025b,a). Building on this, TaskCraft (Shi et al., 2025) expands tasks' structure both in depth (longer sequences of tool executions) and in width (multiple sub-goals per objective), thus enhancing hierarchical reasoning. Further escalating this complexity, **conditional and graph-based tasks** involve non-linear structures with branching logic, where planning must adapt dynamically to intermediate outcomes (Tao et al., 2025b; Li et al., 2025b; Tao et al., 2025a; Liu et al., 2025a; Geng et al., 2025). Such designs lead to significant performance gains, as shown in Table 1, highlighting the importance of scaling up tasks' complexity to foster robust and generalizable reasoning strategies.

2.2 Dynamic Scaling

A natural extension of inherent task complexity scaling is dynamic scaling, which involves creating an environment that adjusts task complexity based on the agent's performance, allowing agents to learn and adapt to new challenges and goals.

[1]For clarity, in *complexity scaling*, we only consider the intrinsic difficulty of a task (i.e., static complexity). The temporal evolution of task difficulty (i.e., dynamic complexity) is addressed in the *dynamic scaling* subsection.

This involves scheduling tasks of varying difficulty levels (curriculum learning) based on agent performance metrics, such as success rate (SR) or progress rate (PR), or targeting newly acquired or weaker skills for focused training (Zeng et al., 2025; Liang et al., 2024; Zala et al., 2024; Qi et al., 2025; Xi et al., 2024; Cheng et al., 2025; Zala et al., 2024). For instance, AgentGen (Hu et al., 2025c) introduces a bidirectional task variation method, adjusting task complexity upwards or downwards to match the agent's capabilities, while EnvGen (Zala et al., 2024) iteratively generates embodied environments that focus on the skills where agents are weak at. More recent advances introduce a challenger-solver co-evolving pipeline, where the challenger proposes near-boundary tasks based on the solver's uncertainty, and the solver improves by training on filtered task sets, resulting in progressively more difficult curricula and improved reasoning performance (Huang et al., 2025a). A similar conclusion is drawn by Zeng et al. (2025), where adaptively shifting a sliding window of difficulty (ensuring appropriately challenging problems throughout training) leads to superior performance gains and improved learning efficiency.

🔮 **Future Direction I** Despite the benefits of adaptively changing environments or task difficulties, most current methods are **limited to verifiable tasks and require manual intervention** to ensure high-quality task generation (Huang et al., 2025a; Zeng et al., 2025). Future designs should develop efficient pipelines for non-verifiable tasks while ensuring the reliability of automated task generation.

2.3 Diversity Scaling

Scaling the diversity of environments and tasks is crucial for preventing agents from overfitting to specific action patterns, thereby fostering more robust and generalizable performances (Hu et al., 2025c; Huang et al., 2025a). Although **Task-level Diversity Scaling** methods can generate tasks with different objectives and levels of complexity within a fixed environment (Huang et al., 2025a), enabling the agent to improve gradually, Andrews et al. (2025) argues that simple tasks in complex environments may be more effective than complex tasks in simple ones. This suggests that greater emphasis should be placed on **Environment-level Diversity**. As shown in Table 2, training on representative environments across domains (e.g., web, tool use, and coding) enables AgentGym (Xi et al., 2024) and AgentBank (Song et al., 2024) to achieve stronger performance under certain training method. Motivated by this, more recent work explores automatically constructing diverse environments from either pre-defined (Shi et al., 2025; Yang et al., 2025a; Jain et al., 2025) or continuously refined tool and application suites (Hu et al., 2025c; Zhang et al., 2025b). As heterogeneity continues to scale up, although no single learning strategy remains uniformly effective, the upper bound achievable through adaptively selecting among multiple strategies increase consistently (Zhang et al., 2025b), underscoring the promise of diversity scaling.

3 Stage 2: Task Execution

After task generation, the next crucial phase is task execution, where the agent engages in the interaction loop with the environment, receiving observations and taking actions iteratively. We organize works related into two dimensions: interactivity and realism (Figure 4). *Interactivity* (§ 3.1) refers to how the agent interacts with the environment, while *Realism* (§ 3.2) focuses on making observations more realistic to enhance interaction quality.

3.1 Interactivity

Interactivity concerns whether the environment is executable and whether the agent is blind to the returns of intermediate steps. In non-interactive settings, agents are evaluated against a single static ground-truth solution path, even though there may in fact exist diverse paths to successful task completion (Deng et al., 2023; Kapoor et al., 2024; Rawles et al., 2023; Qin et al., 2023). Consequently, such static supervision fails to credit alternative correct solutions and limits agents' ability to generalize to novel tasks (Sullivan et al., 2025; Xie et al., 2024; Rawles et al., 2025). Recent environment designs start to allow agents to interactively invoke real-world APIs, call functions, generate codes, or interact through GUI (Wang et al., 2024; Yao et al., 2023a; Trivedi et al., 2024; Sullivan et al., 2025) and to adapt subsequent actions based on intermediate results dynamically. **Width Scaling** methods focus on enabling parallel tool invocation (Pang et al., 2025) and broadening the interaction dimension (e.g., facilitating flexible switching between GUI operations and tool invocations (Jia et al., 2025a)), while **Depth Scaling** methods focus on efficient tool-use context management. For example, MiroThinker (Team et al., 2025) removes

weakly related tool calls from the context, thereby freeing up capacity to scale up tool-use depth and yielding consistent performance gains across various benchmarks. Importantly, a bottleneck for such scaling lies in the cost of APIs calls. To alleviate this issue, several recent advances implement an offline realistic database as the environment (Tongyi DeepResearch Team, 2025; Fang et al., 2025; Ye et al., 2025c), using function calls to read from and write to the database state, thereby keeping the cost of scaling up interactivity within a reasonable budget while preserving some realism.

Future Direction II While scaling interactivity enables richer tool use, it also introduces problems such as **overlong responses**, **diminishing marginal returns** from additional tool calls, and **escalating costs** (Team et al., 2025). Moreover, **efficacy diminishes** in scenarios that require combining multiple tools (Jia et al., 2025a). As the emerging paradigm of *thinking with images* (Su et al., 2025b) yields multimodal tool-call returns, fusing these outputs becomes substantially more challenging. Future environments should therefore prioritize improving the efficiency and quality of heterogeneous real-world tool invocation.

3.2 Realism

Realism aims to ensure that observations obtained from the environment remain consistent with the real world. In **Tool-Use** scenarios, despite the benefits brought by the Model Context Protocol (MCP) (Anthropic, 2024; Luo et al., 2025b; Wang et al., 2025e; Fan et al., 2025), which integrates heterogeneous tools into a unified context and greatly improves the efficiency of tool use, directly calling APIs in real environments still faces challenges of monetary cost and lack of robustness (Song et al., 2023; Wu et al., 2025b; Mastouri et al., 2025; Prabhakar et al., 2025). Previous **Model-based** environment designs use LLMs as a world model (Hao et al., 2023; Ge et al., 2024; Tang et al., 2024) or to simulate the results of tool calls (Qin et al., 2023; Lu et al., 2025b; Sun et al., 2025), reducing overhead and avoiding implementation errors but inevitably sacrificing realism. Facing this dilemma, **Offline-Database** methods (Tongyi DeepResearch Team, 2025; Fang et al., 2025; Ye et al., 2025c) make a trade-off by using a snapshot of a real-world database as the interaction environment, thereby preserving a relatively realistic simulation (e.g., tool-chain failures, asynchronous external events).

In **Computer-Use** scenarios, earlier works mainly construct on Q&A over static webpage screenshots (Mialon et al., 2023; Deng et al., 2023; Sun et al., 2022; Kapoor et al., 2024), rather than actually operating in real executable environments. This idealized setting makes agents brittle and prone to failure in real-world conditions (e.g. similar buttons, intrusive popup windows, and heterogeneous user interfaces) that demand context awareness and fine-grained control (Xie et al., 2025). To mitigate these, recent advances instead adopt real executable environments that involve coding (Yang et al., 2023), web browser navigation (Yao et al., 2023a; Zhou et al., 2023), and application control across operating systems (Xie et al., 2024).

Future Direction III Most existing environments follow a ReAct-style paradigm (Yao et al., 2023b), assuming that the environment remains static between an agent's observation and action. However, **information arrives as overlapping streams in real world** so perception and action should occur concurrently (Andrews et al., 2025). Future designs should place greater emphasis on such asynchronous settings, while also exploring ways to unlock richer scenarios and modalities.

4 Stage 3: Feedback

After the trajectories are collected during the execution stage, the environment evaluates them in the feedback stage. The task, trajectory, and feedback together form the experience for subsequent training. Scaling at this stage focuses on how feedback is provided, including its frequency and richness (*density* § 4.1 and *granularity* § 4.2), its level of automation (*automation* § 4.3), as well as how objectively and reliably it is delivered (*objectivity* § 4.4 and *robustness* § 4.5), as shown in Figure 4.

4.1 Density

The density of feedback refers to how frequently evaluative signals are provided. **Trajectory-level Outcome-based Rewards** (Jiang et al., 2025; Da et al., 2025; Qian et al., 2025; Wang et al., 2025b) are relatively sparse and contribute to more stable training, especially in tasks like mathematical reasoning and code generation (DeepSeek-AI et al., 2025). However, it is challenging to credit whether an intermediate step contributes to or hinders task completion in multi-step tasks. To alleviate this issue, **Step-level Process-based Rewards** (Khalifa et al., 2025; Chae et al., 2025; Gao et al., 2024;

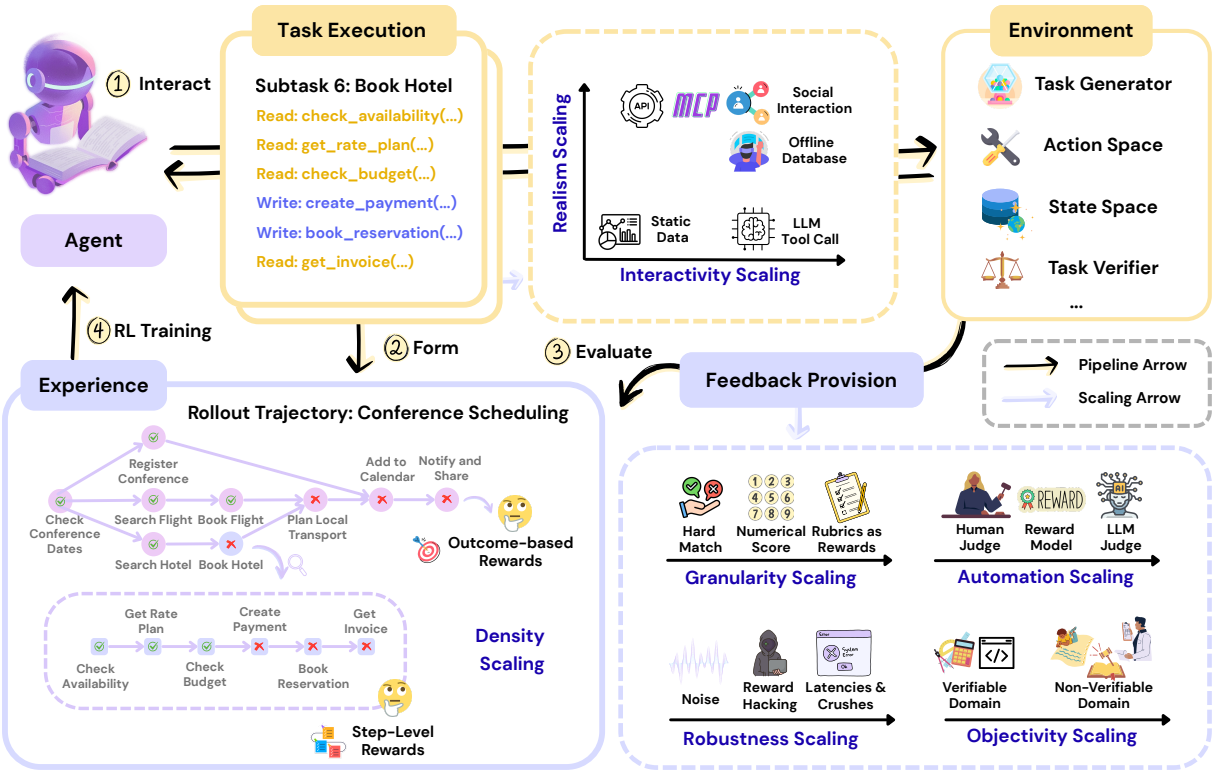

Figure 4: Illustration of scaling in the **task execution** and **feedback** stages. The agent interacts with the environment during task execution, producing action-observation trajectories, which are then evaluated by the environment, forming the experience for subsequent training. Scaling in the task execution stage involves *interactivity* and *realism*, while scaling in the feedback stage encompasses *density*, *granularity*, *automation*, *objectivity*, and *robustness*.

Ma et al., 2025b; Park et al., 2025) provide denser supervision and more detailed guidance. Nevertheless, simply scaling up feedback frequency does not necessarily translate into consistently improved performance. The gains are often smaller for natural language tasks (e.g., creative writing) than for logically coherent tasks (e.g., coding), and it may exacerbate reward hacking, where trivial patterns may obtain high rewards (Ma et al., 2025b; Gao et al., 2024). Efforts like PR-Clip-Delta (Gao et al., 2024) utilize reward differences between adjacent steps as rewards, clipping them if they exceed a predefined threshold, which helps mitigate repetitive behavior and the training instability associated with step-level rewards.

4.2 Granularity

Granularity scaling refers to increasing the level of detail in feedback as well as enriching the forms of feedback provided. In earlier stages, evaluative feedback typically consisted of binary signals (Christiano et al., 2017a; Ibarz et al., 2018) or a single numeric score (Stiennon et al., 2022; Ouyang et al., 2022). At finer granularities, the evaluative feedback on agents' performances is broken down into structured components, such as a set of scores across multiple criteria such as correctness and format, offering more informative guidance (Huang et al., 2025c; Qian et al., 2025; Song et al., 2025). The *Rubrics as Rewards* framework (Gunjal et al., 2025; Huang et al., 2025e; Zhou et al., 2025; Zhang et al., 2025d; Viswanathan et al., 2025) further decomposes task requirements into tangible, human-interpretable criteria. By designing rewards as checklist-style, instance-specific rubrics, it provides a middle ground between binary correctness signals and broad preference rankings.

Future Direction IV Despite rubrics providing more detailed information than a simple numeric reward, their predefined nature by humans and reliance on internal parametric knowledge may lead agents to **exploit internal patterns** rather than **explore external knowledge** (Shao et al., 2025). Future work should support dynamically adjusting rubrics as the boundaries of knowledge evolve.

4.3 Automation

Automation scaling involves the shift of the feedback mechanism from costly and labor-intensive human feedback to automated evaluations. Previous works rely heavily on human annotators, which poses a major scalability bottleneck (Sheng et al.,

2025; Hu et al., 2025a; Christiano et al., 2017b). Recent works adopt LLM-as-a-Judge, train generative reward models, or utilize agentic workflows with external tools to facilitate the feedback process. **LLM-as-a-Judge** (Chen et al., 2025c; Gunjal et al., 2025; Huang et al., 2025e) prompts off-the-shelf LLMs to provide preferences or numeric scores across multiple aspects. **Training-based** methods (Chen et al., 2025d; Zhang et al., 2025e) train a reward model with synthesized rationales or trajectories to judge whether user intent is fulfilled, significantly outperforming simple prompt engineering but at the cost of limited generalization and higher training costs. **Agentic** methods (Peng et al., 2025) further incorporate external searching tools to help verify factual accuracy and assess instruction-following ability, offering more reliable guidance, though there is still room for improvement in workflow efficiency and reward accuracy.

🔮 **Future Direction V** Automation magnifies risks such as **the propagation of biases** inherent in LLMs, like verbosity bias (favoring longer responses), position bias (favoring answers in certain positions), egocentric bias (preferring self-generated responses), and so on (Zheng et al., 2023). It also introduces the risk of **reward hacking**, where intelligent agents exploit loopholes in the reward model to achieve high scores, thereby deviating from the intended goals and even causing the model to crash. Future work should focus on balancing the critical trade-off between scalability and security, with an emphasis on developing robust risk mitigation strategies as automation scales.

4.4 Objectivity

Automated verification by LLMs may inevitably introduce biases and noise, while human evaluation is also subjective and limited by constrained knowledge. Therefore, it is necessary to eliminate subjectivity in environmental feedback designs. Objectivity scaling aims to reduce these biases and make automated verifiers fairer. Despite the *Reinforcement Learning with Verifiable Rewards (RLVR)* paradigm (Lambert et al., 2025) achieving great success in some easy-to-verify domains (e.g., math, coding (Shao et al., 2024; DeepSeek-AI et al., 2025)), it still falls short in creative domains (e.g., writing, medical consultation, and policy making), where ground truth is often missing, and verification remains open, making it difficult to reach a unified standard. Recent advances aim to extend RLVR to these hard-to-verify domains (Andrews et al., 2025; Ma et al., 2025a; Akter et al., 2025; Su et al., 2025a; Yu et al., 2025b; Liu et al., 2025b; Gunjal et al., 2025; Huang et al., 2025e; Li et al., 2025a). For instance, BRPO (Jia et al., 2025b) introduces a pairwise generative reward model designed to offer comparative quality scores, avoiding the direct scoring of creativity in writing materials. Works like ARE (Andrews et al., 2025) combine parameter-matching hard checks (e.g., verifying email id) with generative rubric-based soft checks to ensure relatively fair evaluation.

4.5 Robustness

Feedback robustness requires the environment to provide stable and reliable reward signals. **Reward-level Robustness** concerns the stability of the reward itself, since such signals may be inherently noisy or susceptible to hacking (agents learning undesirable and tricky behavioral patterns that obtain high rewards without achieving the intended goals). To mitigate noise, Lin et al. (2024b) and Su et al. (2025a) generate soft probabilistic rewards with generative verifiers. To prevent reward hacking, Farquhar et al. (2025) evaluates the future utility of actions through an overseer, constraining unstable behaviors while preserving explainability. Huang et al. (2025e) develops a defense rubric that penalizes sycophantic praise toward user prompts and overly flattering self-assessments in responses, encouraging the model to produce more substantive content. **Environment-level Robustness** is also crucial for agents, as environmental instabilities (e.g., delays, crashes, corrupted tool outputs) may also undermine feedback reliability and degrade the training process. To handle such failures, Trinity-RFT (Pan et al., 2025b) proposes asynchronous inference and retry mechanisms, while Tongyi DeepResearch Team (2025) employs caching, retrying failed calls, and switching to similar providers to prevent corrupted trajectories. These efforts take an encouraging step toward establishing the underlying frameworks that ensure stable feedback.

5 Implementation

In this section, we discuss environmental design choices across domains. In **Tool-Use** scenarios, environmental designs prioritize expanding the width and depth of *interactivity*. This involves supporting deeper tool call sequences to solve more complex tasks and incorporating more general, versatile

tools to handle tasks across a broader range of domains. Similarly, **Deep Research** scenarios focus on enabling agents to orchestrate *diverse* search and browsing APIs during task generation, as well as *robust* retrieval and reasoning through long contexts. For example, DR Tulu agent infrastructure (Shao et al., 2025) optimizes a unified MCP-based tool backend through global caching and asynchronous process lock, supporting high-concurrency operations. ARE (Andrews et al., 2025) further transforms tool-use benchmarks into separate applications, integrating mobile use and tool use into a unified environment.

In **Software Engineering (Coding)** scenarios, designs emphasize whether the agent can actually execute code (*Realism*) and whether the process can be reproduced (*Robustness*). Docker (Merkel et al., 2014) is commonly utilized as the basis of execution sandbox, as it ensures consistency across different machines through standard Dockerfiles while also enabling the safe execution of code within an isolated virtual environment, preventing potential safety issues (Yang et al., 2023; Jimenez et al., 2023; Yang et al., 2025a).

Web Navigation scenarios also focus on *realism* and *interactivity*. WebArena (Zhou et al., 2023) delivers websites in self-contained Docker images as well, avoiding unexpected content or configuration changes. WebShop (Yao et al., 2023a) offers a diverse range of semantic action space (searching queries and choosing buttons), with its modular architecture facilitating scaling to new web tasks and domains. VisualWebArena (Koh et al., 2024b) further introduces a novel Classifieds website built on OSClass, a robust open-source Content Management System (CMS), supporting visually grounded tasks such as posting, searching, and commenting, thereby offering a more interactive environment for user engagement.

In **Computer Use** scenarios, in addition to *interactivity* and *realism*, data collection efficiency and *diversity* integration (e.g., cross-OS tasks, heterogeneous tools) are also key concerns. OpenCUA (Wang et al., 2025d) and OSWorld (Xie et al., 2024) provide infrastructures that support efficient task annotation and the real-time capture of user interactions. UI-TARS-2 (Wang et al., 2025a) unifies GUI operations and SDK function calls into a versatile platform, supporting a variety of task kinds and maintaining long-lived states across intricate, multi-step interactions.

In **Embodied** scenarios, agents are required to ground objects in photo-realistic 3D spaces, answer questions, or perform multi-step actions (Weihs et al., 2021; Das et al., 2018). These tasks require environments to maintain *realism*, such as actual grounding and collision avoidance. Frameworks such as ALFWorld (Shridhar et al., 2020) provide the necessary infrastructure for abstract reasoning and concrete execution. More recently, Genie 3 (Parker-Holder and Fruchter, 2025) has further improved real-time *interactivity* and long-horizon consistency, providing a fertile foundation for the advancement of future LLM agents.

Implementation Challenges A key challenge in environment implementation is the *Generator-Verifier Asymmetry* (Wei, 2025), which refers to the mismatch between the intelligence required for the generator and that needed for the verifier. In **easy-to-verify** domains (e.g., math, coding (Wei et al., 2025; Jimenez et al., 2023; Phan et al., 2025)), task generation can be difficult (scaling up high-quality, non-trivial tasks is challenging), while verification is relatively easy and computationally inexpensive. In contrast, in **easy-to-generate** domains (e.g., creative writing, medical consultation (Lin et al., 2024a; Arora et al., 2025)), it is easy to propose open-ended and challenging tasks, but verification may involve subjectivity or require expert knowledge. Future environmental designs may enable the generator and verifier to co-evolve, tapping into the potential of using a powerful generator as a verifier to stimulate the development of even more powerful generators (Huang et al., 2025a; Hong et al., 2025; Lu et al., 2025d; Chen et al., 2025b; Wang et al., 2025c).

6 Conclusion

In the era of experience, environments, positioned as active experience generators, are central to the evolution of LLM agents. Scaling them toward more complex, dynamic, realistic, and richly interactive worlds is essential for high-quality experience collection. From an environment-centric perspective, our survey is the first to propose a unified taxonomy that organizes representative advances across the three-stage *GEF loop* (task generation, task execution, and feedback), together with implementation frameworks, evaluation benchmarks, and applications. Additionally, we surface key challenges and highlight future frontiers in environmental design, offering insights to guide future research toward advancing agent intelligence.

Limitations

As scaling environments remains an emerging research topic, relatively few studies have explicitly adopted this framing. Thus, we take a broad view of environment and organize representative studies along the *Generation-Execution-Feedback (GEF) loop* (task generation, task execution, and feedback) from a pioneering environment-centric perspective. This broader lens bring in some adjacent lines of work that may not have been explicitly designed from the environment side, but makes our taxonomy comprehensive and insightful. Finally, given the rapid pace of agentic research, some of the most recent papers may fall outside this snapshot. We will continue to update this survey as the literature evolves.

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A Background

A.1 Scaling Laws for LLM Agents

As large language models exhibit predictable performance scaling with increases in the number of parameters, the volume of training data, and the compute budget, agent systems likewise display scaling regularities along three axes: (i) expanding the agent population and identifying properties that emerge as interactions increase; (ii) increasing environmental complexity and assessing how realistic, dynamic settings shape learning and adaptation; and (iii) extending the horizons of evolution and memory to study how agents generalize and improve through accumulated experience (CAMEL-AI, 2025). While most existing surveys on LLM agents adopt an agent-centric view (Luo et al., 2025a; Xi et al., 2025; Yehudai et al., 2025; Gao et al., 2025), covering topics from multi-agent interaction (Qian et al., 2024; Tran et al., 2025) to self-evolution (Gao et al., 2025; Tao et al., 2024), environment scaling remains underexplored and has not been systematically organized. In this work, we take an environment-centric perspective on scaling environments and examine how dynamic, richly interactive, high-fidelity worlds can accelerate agent development and evolution.

A.2 Generator-Verifier Asymmetry

A fundamental characteristic in many real-world tasks is the inherent *Generator-Verifier Asymmetry* (Wei, 2025), namely the mismatch between the intelligence required for generator, which generates (§2) or executes (§3) tasks, and that required for verifier, which provides feedback (§4). These two kinds of intelligence naturally form two axes critical to next-generation Agentic AI, as illustrated in Figure 5. From this perspective, scaling up environments essentially corresponds to scaling intelligence along the x-axis and the y-axis. Current progress in RL largely exploits the regime on the easy-to-verify side of this asymmetry. These **Easy-to-Verify, Hard-to-Generate Domains** include fields such as mathematics and programming (Wei et al., 2025; Jimenez et al., 2023; Phan et al., 2025). For these domains, generating and solving a continual stream of high-quality, non-trivial tasks is challenging. In contrast, verification is objective and computationally inexpensive (e.g., via unit tests or exact match on mathematical results). This enables weak-to-strong supervision, where a simple verifier can provide accurate feedback to train a much stronger agent for solving hard tasks. On the contrary, the **Hard-to-Verify, Easy-to-Generate Domains** include areas such as creative writing, policy-making, or healthcare (Lin et al., 2024a; Arora et al., 2025). For these easy-to-propose, open-ended tasks, verification is subjective, requires substantial expert judgment, or unfolds over long horizons, making high-quality feedback scarce and expensive. This bottleneck, corresponding to the upper-left region of coordinate system, poses more difficulty in modeling the environment, and rendering environment scaling more challenging yet offering greater potential for advancing agent capabilities. Notably, the asymmetry also presents an opportunity: if the generator's stronger intelligence can be systematically leveraged to strengthen the verifier, so that it can supervise an even stronger generator, then such asymmetric property can be exploited to drive agents'

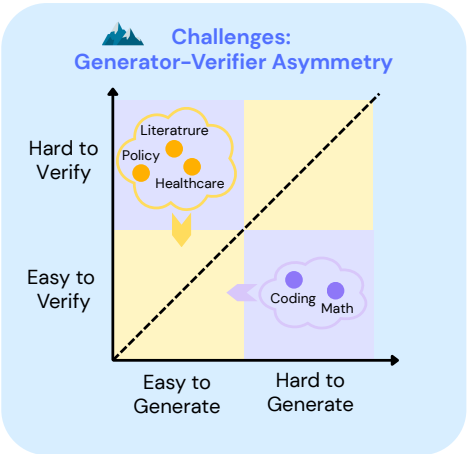

Figure 5: Generator-verifier asymmetry challenge.

self-evolution (Huang et al., 2025a; Hong et al., 2025; Lu et al., 2025d; Chen et al., 2025b; Wang et al., 2025c).

A.3 Conceptual Framework

Following the formalization by Gao et al. (2025), we model the environment E as a partially observable Markov decision process (POMDP)[2]. At the beginning of each episode, the environment generates a task $T_{\text{gen}} = (E, I)$, where $I \in \mathcal{I}$ represents user intention drawn from intention space $\mathcal{I}$. The agent π interacts with the environment over horizon $T \in \mathbb{N}$, producing an interleaved observation–action trajectory $\tau = (o_0, a_0, o_1, a_1, \ldots, o_T) \in (\mathcal{O} \times \mathcal{A})^{T+1}$, where $\mathcal{O}$ and $\mathcal{A}$ denote the observation and action spaces respectively. The environment then evaluates performance and provides feedback $r \in \mathbb{R}^k$, which may take the form of step-level signals $r_{\text{step}}^{(t)} = R_{\text{step}}(s_t, a_t, T_{\text{gen}}) \in \mathbb{R}$ for $t \in \{0, \ldots, T\}$, where $s_t \in \mathcal{S}$ denotes the state of the environment at step t, trajectory-level signals $r_{\text{traj}} = R_{\text{traj}}(\tau, T_{gen}) \in \mathbb{R}^m$, or a combination of both $r_{\text{comb}} = f(r_{\text{step}}^{(0:T)}, r_{\text{traj}})$ where $f : \mathbb{R}^{T+1} \times \mathbb{R}^m \to \mathbb{R}^k$. These signals need not be limited to sparse scalar rewards but can encode structured or adaptive assessments reflecting correctness, efficiency, reasoning depth, or long-term outcomes. This *Generation-Execution-Feedback (GEF) loop* encompasses task generation, task execution, and feedback. Repeated iterations drive the accumulation of experience, denoted as $Exp = (T_{\text{gen}}, \tau, r) : \mathcal{I} \to \mathcal{T} \times (\mathcal{O} \times \mathcal{A})^* \times \mathbb{R}^k$, and the progressive evolution of the agent π.

B Additional Discussions

B.1 Comparative Analysis

A comparative analysis of methods for scaling task complexity and task diversity is presented in Tables 1 and 2.

B.2 Multi-Agent Realism

When extending to the **multi-agent setting**, where agents may coordinate or compete, each agent's behavior naturally becomes part of others' environment (Tran et al., 2025; Qian et al., 2024; Li et al., 2024; Zhang et al., 2024; Barres et al., 2025). Realism in this regime therefore requires environment designs that support agent–agent interactions in addition to agent–tool interactions. This highlights the need to build robust underlying infrastructure and communication mechanisms, which provide the necessary foundation for complex social and economic phenomena (e.g., information diffusion, opinion polarization, and herding effects (Yang et al., 2025b; Zhang et al., 2025c)) to emerge and be meaningfully simulated as the number of agents scales. For instance, Zhang et al. (2025c) adopts the MQTT communication protocol to support asynchronous decision making among autonomous agents, while Andrews et al. (2025) decouples agent and environment clocks and treats other agents' activities as independent events, thereby allowing the world state to evolve asynchronously and supporting the collection of more realistic experiential data.

C Evaluation Benchmarks

Previous evaluation studies have typically focused on the intelligence of the agents themselves, but there is a lack of direct measurement indicators for aspects such as adaptability to the environment, interactivity, realism, and robustness. Therefore, most environmental assessments are conducted indirectly, usually by observing the performance of intelligent agents to reflect the quality of the environment. For instance, studies such as TaskCraft (Shi et al., 2025) and AgentScaler (Fang et al., 2025) train the agents through the trajectories generated by the interaction between the environment and the agents, thereby evaluating the environment. The stronger performance of the agents is regarded as an indirect indication of higher environmental quality. Initially, direct measurements of the environment are mainly limited to symbolic or textual environments. Bytesized32 (Wang et al., 2023) proposes specific-task text games and evaluates them using automated metrics in terms of fidelity, validity, specification adherence, and winnability. Text2World (Hu et al., 2025b) benchmarks the generation of symbolic world models, using structural similarity for overall evaluation, and capturing more granular features such as action dynamics through component-level F1 scores. Recent studies have begun to extend the direct assessment to more modalities. VidOSC (Xue et al., 2024) explores the dynamic characteristics of open-world environments. WorldScore (Duan et al., 2025) proposes a

[2]Unlike prior work (Gao et al., 2025), we adopt a broad view of the environment: everything external to the current agent, including the state space, the executable action space, the design of feedback for interaction and evaluation, and the activities of users and other agents, is considered part of it.

Method	Skill Dimension	Task Structure	Task Complexity		Multi-Turn	Performance
			Width	Depth		
ToolBench (Qin et al., 2023)	Tool Use	Sequential	1	-	×	-
τ-bench (Yao et al., 2024)	Tool Use	Sequential	1	-, 30	✓	-
BFCL V3 (Patil et al., 2024)	Tool Use	Sequential	1	-, 20	✓	-
c^3-bench (Yu et al., 2025a)	Tool Use	Compositional	1∼9	1∼4, 10	✓	-
TaskCraft (Shi et al., 2025)	Tool Use	Compositional	2	1∼4, 7	×	-
WebRL (Qi et al., 2025)	Web	Compositional	1∼4	-, >10	✓	-
WebDancer-32B (Wu et al., 2025a)	Web	Compositional	-	2∼4, 10	×	40.7
WebShaper-32B (Tao et al., 2025b)	Web	Graph-Based	-	3∼7, 30	×	52.4
WebSailor-32B (Li et al., 2025b)	Web	Graph-Based	-	2∼8, 30	×	53.2
WebExplorer-8B (Li et al., 2025b)	Web	Graph-Based	-	0∼6, 100	×	50.0

Table 1: Comparative Analysis of Task Complexity and Performance Across Methods. *Width* denotes the number of requirements that must be satisfied within a single task. *Depth* denotes the number of tool calls/steps per task, where the first value indicates the range of steps taken by the majority of tasks and the second value gives the maximum steps. *Performance* reports GAIA (Mialon et al., 2023) scores (if available). *Multi-Turn* indicates whether interaction between the user and the agent is multi-turn.

Method	Modality	Skill Dimension	# of Envs	# of Tasks	# of Trajs	Source	Performance		
							SWE	ALF	WS
SWE-Gym-32B (Pan et al., 2025a)	Text	Code;	-	2,438	491	Real	20.6	-	-
R2E-Gym-32B (Jain et al., 2025)	Text	Code;	-	8,135	3,321	Synth	34.4	-	-
SWE-Smith-32B (Yang et al., 2025a)	Text	Code;	-	50,137	5,016	Both	40.2	-	-
AgentLM-13B (Zeng et al., 2023)	Text + Visual	Web; Embodied; Code; Tool Use;	-	-	1,866	Both	-	55.2	65.0
AgentBank-13B (Song et al., 2024)	Text + Visual	Web; Embodied; Code; Tool Use;	16	-	51,287	Both	-	72.4	63.1
AgentGym-7B (Xi et al., 2024)	Text + Visual	Web; Embodied; Code; Tool Use;	14	89	6,130	Both	-	88.0	76.5

Table 2: Comparative Analysis of Environment and Task Diversity across Methods. *SWE* refers to SWE-bench (Jimenez et al., 2023). *ALF* refers to ALFWorld (Shridhar et al., 2020). *WS* refers to WebShop (Yao et al., 2023a).

unified framework for evaluating world generation. While WorldPrediction (Chen et al., 2025a) focuses on advanced visual reasoning, emphasizing long-term procedural planning and semantic-time abstraction capabilities. Despite these advancements, comprehensive and universal assessment protocols are still scarce, highlighting the need for more generalized and domain-independent methodologies to rigorously and directly evaluate environmental quality beyond the performance metrics of intelligent agents.

D Applications Across Domains

Driven by interactions with dynamic and diverse environments, recent agentic systems built on state-of-the-art LLM families such as GPT (OpenAI, 2025a), Claude (Anthropic, 2025), Gemini (Team et al., 2024), and Qwen (Bai et al., 2023) have become increasingly powerful and widely applicable.

Tool Use In tool-use scenarios, environments expose APIs and function calls as structured action spaces for agents, enabling them to reason with external tools through function calling or code generation (OpenAI, 2023; Anthropic, 2024; Wu et al., 2025b; Mastouri et al., 2025; Luo et al., 2025b; Wang et al., 2025e; Fan et al., 2025).

Software Engineering In code generation or software engineering scenarios, environments leverage repositories, test frameworks, and IDE integration to cultivate agents' long-horizon programming capabilities. Systems such as Qwen3-Coder (Qwen Team, 2024) and Claude 4 (Anthropic, 2025) demonstrate reliability in code editing and debugging. ReTool (Feng et al., 2025) novelly integrates code-interpreter execution into the reasoning loop, enabling agents to exhibit code self-correction and adaptive tool selection. SWE-smith (Yang et al., 2025a) and R2E-Gym (Jain et al., 2025) develop scalable, executable code environ-

ments based on GitHub repositories, enabling the further evolution of SWE agents.

Web Navigation In web navigation scenarios, environments are typically built on HTML/DOM structures to support tasks such as browsing, form filling, and transactions (Lai et al., 2024; Fosowl, 2024; Significant-Gravitas, 2023), requiring agents to click buttons and navigate between web pages. Graphical user interface (GUI) environments extend these tasks to desktops and mobile devices, further complicating task complexity (Qin et al., 2025; Ye et al., 2025a; Lu et al., 2025c; Liu et al., 2024b; Sun et al., 2022; Huang et al., 2025b).

Computer Use In more recent computer-use scenarios, environments integrate terminals, different operating systems, various applications, and APIs, making tasks much more interactive, open-ended, and realistic (Wang et al., 2025d,a; Xie et al., 2024; OpenAI, 2025; Jia et al., 2025a; Xie et al., 2025).

Deep Research In deep research scenarios, environments demand stronger long-context reasoning and more robust retrieval capabilities, as demonstrated by prominent long-form tasks such as AstaBench (Bragg et al., 2025), DeepResearchBench (Du et al., 2025), and ResearchQA (Yifei et al., 2025). By learning from the interactive experiences collected from these environments, agentic systems such as Tongyi DR (Tongyi DeepResearch Team, 2025), Gemini DR (Team et al., 2024), OpenAI DR (OpenAI, 2025b), and DR Tulu (Shao et al., 2025) are able to conduct sustained, in-depth analysis with mitigated context dilution.

E More Future Directions

Co-Evolution via Embedded External Tools As the complexity of task increases, feedback mechanisms must scale in order to avoid sparse, noisy, or misaligned learning signals. Future environments can achieve this by including external tools or modules to serve as verifiers, simulators, compilers, or executable systems into the learning loop. These tools would evolve together with the task generation, providing structured, verifiable feedback and enabling agents to interact with increasingly sophisticated challenges. By integrating embedded tools with automated evaluators such as LLM-based formative signals, environments can better support multi-step, open-ended, and creative problem solving, while also helping to mitigate the Generator-Verifier Asymmetry.

Scaling Through Generator-Verifier Synergy Future environments can encourage stronger generators to have the ability to decompose complex tasks into smaller subproblems with intermediate solutions, making them tractable for weaker verifiers. This enables scalable supervision in domains where holistic verification is difficult such as creative cultural production and policy-making. In contrast, weaker generators could provide diverse candidate solutions that could be filtered, ranked, or refined by stronger verifiers. By incorporating these dynamics into the environment, the asymmetry between generators and verifiers can serve as a catalyst for continuous self-improvement.

Open-Ended, Multi-Agent Environments Future environments can scale to support large-scale multi-agent interactions, emergent social dynamics, and economic or organizational level simulations, providing rich contexts for studying both collaborative and non-cooperative behaviors in complex environments. In particular, scaling to massively multi-cultural and multi-lingual settings requires scaling environment construction for agents to navigate the subtle semantics of concepts and values that vary across different societies, not only in the textual but also in the multi-modal domain (Koh et al., 2024a; Huang et al., 2025d). Such open-ended and interactive scenarios environments foster generalization and strategic planning abilities of agents, equipping LLM agents to better handle complex, real-world challenges beyond isolated task execution.

F Ethics and Safety Implications

Agent systems require robust ethical safeguards, interoperable standards, and alignment with emerging regulatory frameworks to enable responsible integration into the global technology ecosystem (Howell and Ifayemi, 2024). Some prior work focuses specifically on safety, such as mitigating inherent biases that produce discriminatory outputs or defending against malicious inputs that circumvent safety-alignment mechanisms (Zhao and Gómez Fariñas, 2023). However, new challenges are likely to emerge as agents accumulate experience through interactions with their environments and with other agents, and as their capabilities for autonomous task planning, external data access, and tool use continue to grow. For example, prompt injection or tool injection attacks on a single agent may lead to privacy breaches or system-

wide contamination, while agents empowered to autonomously operate on external data can, in the absence of strict safeguards, cause irreversible damage by initiating fund transfers or deleting critical files (Tang et al., 2025). Therefore, when developing scaled environments for future LLM-based agents, safety considerations must be treated as a central and indispensable element of system design.