AI Agents for Computer Use: A Review of Instruction-based Computer Control, GUI Automation, and Operator Assistants

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Abstract

Instruction-based computer control agents (CCAs) execute complex action sequences on personal computers or mobile devices to fulfill tasks using the same graphical user interfaces as a human user would, provided instructions in natural language. This review offers a comprehensive overview of the emerging field of instruction-based computer control, examining available agents – their taxonomy, development, and respective resources – and emphasizing the shift from manually designed, specialized agents to leveraging foundation models such as large language models (LLMs) and vision-language models (VLMs). We formalize the problem and establish a taxonomy of the field to analyze agents from three perspectives: (a) the environment perspective, analyzing computer environments; (b) the interaction perspective, describing observations spaces (e.g., screenshots, HTML) and action spaces (e.g., mouse and keyboard actions, executable code); and (c) the agent perspective, focusing on the core principle of how an agent acts and learns to act. Our framework encompasses both specialized and foundation agents, facilitating their comparative analysis and revealing how prior solutions in specialized agents, such as an environment learning step, can guide the development of more capable foundation agents. Additionally, we review current CCA datasets and CCA evaluation methods and outline the challenges to deploying such agents in a productive setting. In total, we review and classify **86** CCAs and **33** related datasets. By highlighting trends, limitations, and future research directions, this work presents a comprehensive foundation to obtain a broad understanding of the field and push its future development.

Keywords: AI agents, computer use, mobile control, GUI automation, LLM, VLM

Outline

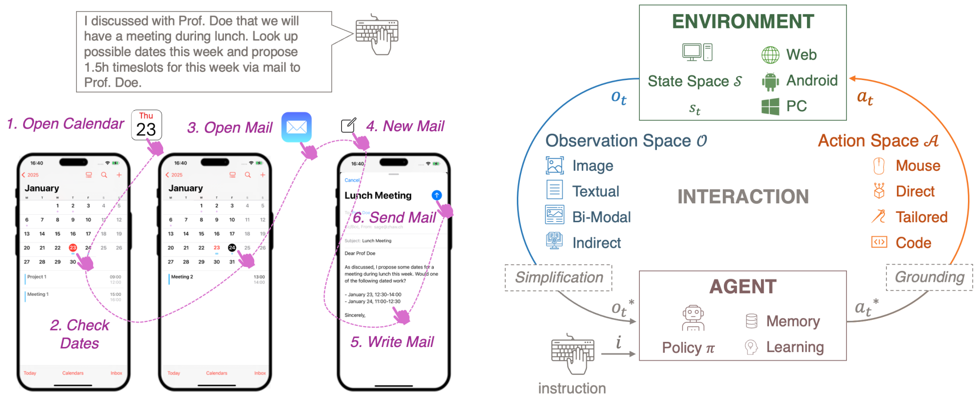
1 Introduction

In recent years, deep learning (Schmidhuber, 2015) has surpassed the point of enabling useful AI agents (Wei et al, 2022b; Zhuge et al, 2023) in several domains. Unlike other deep learning systems (LeCun et al, 2015; Stadelmann et al, 2019; Simmler et al, 2021), AI agents move beyond mere predictive functions to act within a certain environment (van Otterlo and Wiering, 2012; Humphreys et al, 2022). One important such environment is represented by computer systems (desktop or mobile) and the applications running on them. Consider the wealth of tasks humans today accomplish using their computing devices, and imagine the benefit if the same tasks could be approached by AI agents working through the same interfaces on the same kind of devices, just by being instructed to do so by a user in natural language. The opportunities are immense, and we witness now what will become known as the *early days* of AI agents for computer use with first commercial prototypes becoming available (e.g., Anthropic, 2024; Google Deepmind, 2024; David, 2025). This review gives a comprehensive overview of the research landscape and approaches behind such agents.

Specifically, *instruction-based computer control agents (CCAs)* receive instructions from a user, which they fulfill by using computers through their graphical user interfaces (GUIs). CCAs access screen information analogously to a human user, e.g., visually, and act through the same interfaces, i.e., a keyboard, mouse, or touchscreen. For instance, a user could instruct a smartphone agent to propose meeting dates via email. The agent would then operate the phone through simulated touch actions to fulfill the request, as illustrated in Fig. 1a. Unlike many other autonomous agents, CCAs are not limited to purely simulated environments, getting exposure to the complex dynamics of real-world applications and access to growing collections of sample trajectories by observing users operate the devices they are installed on. This makes them a particularly interesting form of AI agent both for research and commercial exploitation.

Early CCA research primarily explored reinforcement learning (RL) techniques (e.g., Branavan et al, 2009; Jia et al, 2019; Humphreys et al, 2022) that were successful in simplified scenarios (e.g., MiniWoB, Shi et al, 2017). The progress in more realistic scenarios (for instance Mind2Web, Deng et al, 2023) accelerated in 2023. This was mainly driven by the integration of foundation models in the decision-making process through leveraging their emerging properties (Wei et al, 2022a) for computer control (Kim et al, 2023). This fueled and facilitated research on foundation model-based CCAs, leading to a rapid increase in publications in the field (see Fig. 2).

This review organizes and analyzes the growing body of CCA research, providing an overview of *the field*. Therefore, it introduces a taxonomy (see Fig. 1b for an overview and Section 2.2 for a thorough introduction) to structure the landscape of the CCA field in an efficient way, effective to gain a deeper understanding of the following aspects of agent design: (i) What fundamental building blocks constitute computer domains like smartphones, personal computers, or the Web, and what are the conceptual similarities? For example, various computer domains provide an alternative textual screen representation, such as HTML (Web) or the Android View Hierarchy (Android). (ii) How do these building blocks shape the interaction between a CCA and the computer?



(a) Example Computer Control Task (b) Proposed Taxonomy

Fig. 1: Overview: (a) An example task for an instruction-based computer control agent: A user specifies a task (propose meeting dates), and the agent executes it. (b) We structure the literature on CCAs according to three *perspectives* corresponding to the main differentiating aspects: (1) The shared *environment* properties across computer domains (e.g., the Web, Android). (2) The means of *interaction* between the agent and the environment as manifested in the observation and action spaces. (3) The *agent* components: how an agent acts through a policy π while tracking the past in memory and how an agent learns to act.

For example, an agent may observe the environment through screenshots while acting through simulated mouse clicks. (iii) What essential components enable a CCA to effectively perceive, reason, and act within its environment? For example, employing a policy for decision-making with access to tracked information about the past. (iv) What learning frameworks are commonly employed by CCAs to acquire and refine their skills? For example, an agent may start with environment-agnostic pre-training and is subsequently refined to adapt to a specific environment.

The taxonomic structure developed for to this end is built around the foundational concepts of *intelligent agents*, namely the nature of environments (Russell et al, 2022, Chapter 2.3), policies (Sutton and Barto, 2018, Chapter 1.3), state, observation and action spaces (Sutton and Barto, 2018, Chapter 17.3), and the structure of agents (Russell et al, 2022, Chapter 2.4). This theoretical background provides the basis for understanding CCAs, highlighting essential components for effective agent design. Applying it to existing CCAs reveals critical gaps in the current literature that are rarely discussed. For example, despite the importance of tracking past information (Sutton and Barto, 2018, Chapter 17.3), some agents neglect it entirely (e.g., Niu et al, 2024) while many others only track past actions but *not* past observations (e.g., Li et al, 2024e). Furthermore, despite their general out-of-the-box competence, many foundation model-based agents lack a mechanism to *autonomously* adapt to a specific computer environment (e.g., Zheng et al, 2024a), condemning them to repeat

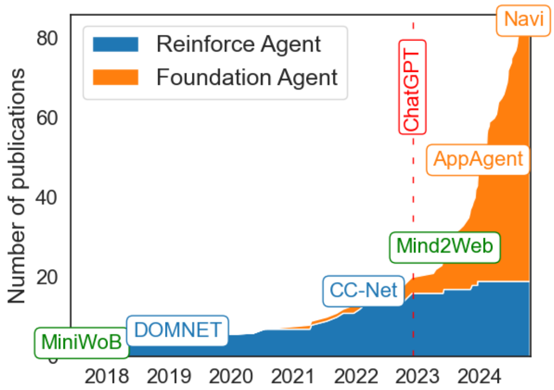


Fig. 2: CCA publications over time. Boxes highlight seminal milestones. The advent of ChatGPT marks a shift from RL-based agents to those primarily relying on foundation model reasoning.

identical errors. We aim our review at helping to identify such gaps, facilitating to more efficiently advance the current state-of-the-art.

Complementing our survey on agent design according to our taxonomy, we review existing CCA datasets and evaluation methods and discuss practical challenges for deploying CCAs in a productive setting to give a full picture of the field as a solid basis for future research and development.

1.1 Relation to Other Surveys

In contrast to existing surveys, our review examines the field of instruction-based computer control from a technology-agnostic perspective and introduces a unifying framework that bridges diverse domains, methodologies, and technologies. This allows us to summarize insights from a broader range of approaches, including different types of computer domains, such as personal computers and Android, different types of technologies, such as reinforcement learning and foundation models, and different kinds of modalities, such as text and vision-based input. This broad scope allows us to introduce a novel, unifying taxonomy for instruction-based computer control that is compatible across a wide range of agent types – something previous work could not realize due to their limited scope. Specifically, existing surveys have the following limitations:

Limited scope within computer control: Zhang et al (2024a) and Wang et al (2024c) review computer control only for foundation-model-based agents, not discussing other learning frameworks such as reinforcement learning as the core principle of design. Wu et al (2024a) discuss only mobile agents, neglecting other computer domains. While these surveys provide a comprehensive review of some aspects of computer control, they focus on a specific sub-part of the field. To have a unified taxonomy and to discuss future research directions comprehensively, it is important to analyze the field as a whole.

Lack of computer control specificity Some surveys (e.g., Arulkumaran et al, 2017; Moerland et al, 2023) focus on general, reinforcement learning-based agents. Other surveys (e.g., Wang et al, 2024b; Li et al, 2024a) review general, foundation-model-based agents. While these reviews provide a comprehensive overview of agents based on a specific technology, they do not focus on the domain of computer control and all its intricacies.

Adjacent research areas with limited relevance: Another set of surveys (e.g., Yu et al, 2023; Li, 2023) concentrate on related topics, such as GUI testing, but do not cover agent-based interactions. Other reviews (e.g., Syed et al, 2020; Chakraborti et al, 2020) focus on robotic process automation using software robots (agents) to automate predefined workflows.

In contrast, our review provides a technology-agnostic review that connects these disparate computer control subfields and technologies. This allows us to highlight synergies and introduce a unified taxonomy for instruction-based computer control, incorporating insights from reinforcement learning (RL), large language models (LLMs), vision language models (VLMs), and beyond. While Gao et al (2024b) provides a valuable overview with similar scope, our review goes deeper into key aspects, offering a more comprehensive analysis and novel insights, culminating in a taxonomy built upon existing intelligent agent theory.

1.2 Survey Methodology

The CCA field is fragmented and a unified terminology is not yet established. This prevents a classic systematic survey, and we proceeded as follows instead:

Initial collection: Using prior knowledge and combinations of keyword searches, we selected a preliminary list of publication candidates.

Publication selection: We selected publication candidates to be included in the survey after carefully reviewing their titles, abstracts, or additional parts of their content for fit using the criteria catalog described below.

Extension: We extended our selection by manually analyzing each selected publication's related work section and bibliography for additional candidates, following the same selection process. We repeated this phase for every selected publication. We ended the initial and extended collection phase in October 2024.

The selection criteria for the collection process of papers on both agents and datasets are defined as follows:

Deep learning focus: We only selected agents applying deep learning techniques to computer control, excluding traditional control algorithms.

Computer control focus: We exclude instruction-based agents (chatbots) that access external tools but do not control the computer through user interfaces (e.g., Yang et al, 2023b; Tang et al, 2023; Li et al, 2024f; Guo et al, 2024b; Qin et al, 2024). We also exclude pure tool-based datasets that do not require computer control interactions.

Focus on being instruction-based: We exclude task-specific, non-instruction-based agents, such as agents playing video games (e.g., Baker et al, 2022; Zhu et al, 2023), controlling server facilities (e.g., Ran et al, 2019; Fulpagare et al, 2022), agents for coding (e.g., Ross et al, 2023; Qian et al, 2024) or software testing (e.g., Koroglu et al, 2018; Degott et al, 2019; Pan et al, 2020). We only consider datasets that provide instructions and require agents to fulfill these instructions through computer interactions.

We ultimately selected 86 publications on instruction-based computer control agents and 33 computer control datasets (cp. lists in Appendix A.1–A.3).

1.3 Survey Structure

This review is structured in a way to provide a unified introduction to the *field of instruction-based computer control*. Due to the developing nature of this field, individual CCAs that stand for important strands do not yet stand out; rather, many agents only employ certain aspects of what contributes to the full picture of a CCA. Hence, most subsequent chapters of this review put individual elements of the taxonomy at the center rather than individual CCAs, giving representative exemplary (indicated by citations prefixed by "e.g.") or specific CCAs (no "e.g." before citations) as references for each aspect. A notable exception will be Section 5.2, where individual agents are most prominently portrayed, as it discusses their core development paradigm. Otherwise, a structuring of the field by agents can be found in the tables in the Appendix A.

Specifically, in Section 2, we formalize the problem of instruction-based computer control agents and introduce respective terminology as a precursor to introducing the perspectives of the proposed taxonomy. Then, we look into each perspective in detail in the three subsequent chapters: in Section 3, we discuss the composition of commonly used domains (*environment perspective*); in Section 4, we analyze the interaction between the agent and the environment through the observation and action space (*interaction perspective*); in Section 5, we dissect the components of an agent, how an agent acts, and how an agent learns to act (*agent perspective*). Then, in Section 6, we summarize existing datasets used to train or evaluate agents, and we examine metrics and methodologies used to evaluate an agent's performance in Section 7. Finally, we outline challenges for deploying these agents in a production environment in Section 8 before we conclude by summarizing our findings and providing directions for future research in Section 9.

2 The Field of Instruction-based Computer Control

2.1 Definitions

Human users instruct CCAs through a text-based instruction i, which must be achieved by the CCA through interacting with a computer environment. The nature of these environments is discussed in the *environment perspective* chapter (see Section 3).

The interaction process between an agent and environment is visualized in Fig. 1b. At each time t, the *environment* is in a particular *state* $s_t \in \mathcal{S}$, where $\mathcal{S}$ is the state space. An agent interacting with the environment does not perceive the entire environment state s_t, as computer environments are only partially observable. An agent instead sees a portion of the state called an *observation* $o_t \in \mathcal{O}$, where $\mathcal{O}$ is the observation space, which is a subspace of the state space $\mathcal{S}$. For example, o_t could be a screenshot of the current screen, only showing the foreground application, whereas s_t would encompass all running computer processes. Given an observation o_t, an agent must decide on an executable *action* $a_t \in \mathcal{A}$, where $\mathcal{A}$ is called the action space. $\mathcal{A}$ may contain general-purpose actions like mouse clicks, touch gestures, or keyboard inputs (e.g., Shi et al, 2017), or very task-specific actions like directly sending an email (Wang et al, 2024d). This interaction process is discussed in the *interaction perspective* chapter (see Section 4).

The agent's behavior defining which action a_t is selected is governed by a *stochastic policy* π. In its simplest case, π does not retain information about previous observations and instead samples the next action a_t based solely on the current observation o_t and the instruction i:

$$a_t \sim \pi(\ \cdot \mid o_t, \ i \ ) \tag{1}$$

However, for computer control, a policy π should remember (aspects of) past observations $(o_0, ..., o_{t-1})$ necessitating a *memory* component.The cyclic interaction within an episode (i.e., fulfilling one user instruction) leads to a sequence of observation-action pairs called *trajectory* $\tau = \big((o_0, a_0), (o_1, a_1), ...\big)$. A trajectory ends after reaching a terminal state, such as completing i or reaching a maximal number of steps. The inner workings of agents are discussed in the *agent perspective* chapter (see Section 5).

Due to practical concerns, CCAs often *simplify* an observation, denoted $o_t \rightarrow o_t^*$, to reduce the size of $\mathcal{O}$ and ease the learning of the policy π. For example, UI screenshots are often downscaled or cropped (e.g., Chen et al, 2024b). Meanwhile, for actions, the *grounding* process $a_t^* \rightarrow a_t$ converts an abstract action a_t^* into an executable action $a_t \in \mathcal{A}$. Grounding is typically required when a text foundation model is used for planning, requiring the agent to convert abstract descriptions such as `click submit button` into executable commands such as `click(x,y)`, where `x` and `y` are screen coordinates inside the submit button (e.g., Gao et al, 2024a).

2.2 A Comprehensive Taxonomy

We introduce a taxonomy for CCAs that distinguishes three perspectives: the *environment perspective*, the *interaction perspective*, and the *agent perspective*. Each perspective discusses CCAs with a different focus and classifies them according to the features visualized in Fig. 3, where the full taxonomy is given. We provide a brief overview of each perspective here, with detailed discussions in the subsequent sections.

Environment perspective: Here we discuss properties of computer environments and identify observation and action types shared across computer domains. This addresses question (i) from Section 1.

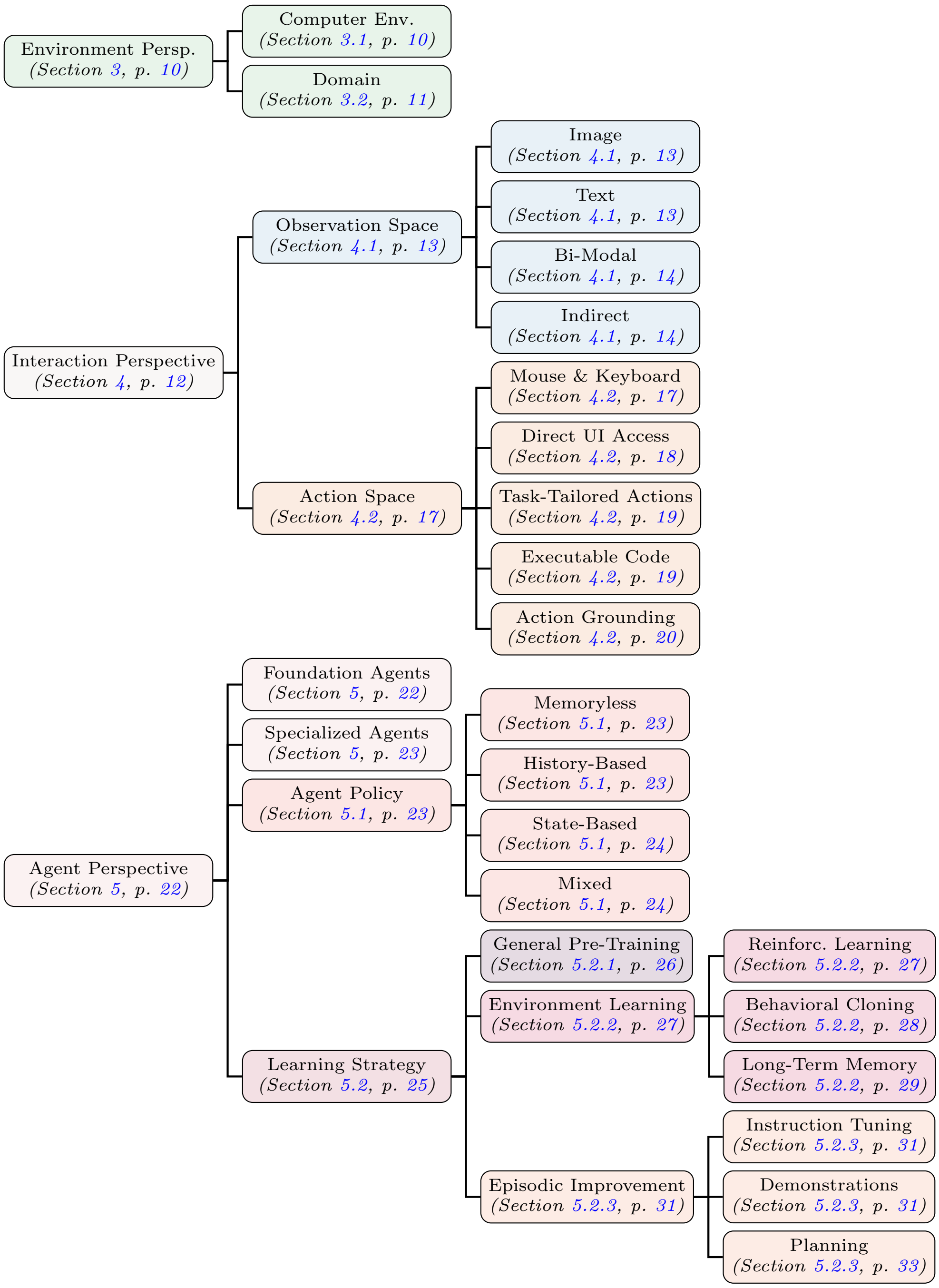


Fig. 3: The taxonomy introduced to structure the field of instruction-based CCAs by three main perspectives and their respective components. The respective colors will be used throughout this paper to help easily associate content with each component.

Interaction perspective (agent $\leftrightarrow$ environment): Observation spaces $\mathcal{O}$ and action spaces $\mathcal{A}$ are examined through which agents interact with their environments, and it is discussed how observation simplification and action grounding can simplify the computer control task. This addresses question (ii) from Section 1.

Agent perspective: We distinguish between *foundation agents* that are built on top of foundation models and more manually designed *specialized agents*. We also discuss the importance of tracking the past, how agents learn, and how agents leverage demonstrations and planning strategies. This addresses questions (iii) and (iv) from Section 1.

3 Environment Perspective

This perspective discusses the common properties of computer environments and shared concepts across computer domains.

3.1 The Nature of Computer Environments

In Table 1, we classify computer environments according to the framework established by Russell et al (2022, Chapter 2.3). Computer environments are typically partially observable and single-agent. In the literature, they are mostly assumed to be deterministic, meaning that for a state s_t and action a_t only one possible outcome s_{t+1} exists. While this assumption holds in many cases, real-world environments can have stochastic elements such as a shuffle button in a music app. Additionally, the literature assumes that computer environments are episodic, meaning that each episode is independent of the previous ones. In reality, however, computer environments are sequential: The environment is not reset after each trajectory, and prior actions can influence future states across episodes. Another simplifying assumption is that the environment is static, meaning that the environment's state s_t only changes in response

Property	**Research computer environment**	**Actual computer environment**
Observability	Partially observable	Partially observable
Number of agents	Single-agent	Single-agent[a]
Determinism	Deterministic	Primarily deterministic[b]
Episodicity	Episodic	Sequential
Dynamism	Static[c]	Dynamic
Stationarity	Stationary	Non-stationary
Environment knowledge	Initially unknown	Initially unknown

[a] Assuming the user hands control to the agent and does not intervene.
[b] Computer control is primarily deterministic due to user-friendly design principles but can be stochastic.
[c] Toyama et al (2021) is an exception providing a dynamic Android environment.

Table 1: Properties of common computer environments, assembled from Russell et al (2022, Chapter 2) and Sutton and Barto (2018, Chapter 2.3). The middle and right columns compare common assumptions in research to actual computer environments.

to the agent's actions a_t. However, background processes can affect s_t at any time, independent of the agent's actions. A further simplification is the more unrealistic assumption that the environment is stationary, implying that the environment does not change over time. In practical settings, however, applications and systems are continuously updated (Humble and Farley, 2011), altering the environment's behavior. Finally, computer environments are typically assumed to have unknown dynamics, meaning an agent does not initially know the effect of an action. While technically true, some agents leverage pre-training to learn conventions and begin with anticipatory knowledge (see Section 5.2.1). For example, they might learn that clicking a 'submit' button typically submits a form.

3.2 Domains

In the existing literature, we identify the Web, Android, and personal computers as the most commonly utilized domains. Each domain provides a unique set of possible observations and actions, yet we establish shared types of observation and action types across these domains.

Observation types shared across domains:

Image screen representation: A screenshot capturing the current screen, parts of the screen, or an extended view of the screen as a pixel image (e.g., Niu et al, 2024; Song et al, 2024a; Zhang et al, 2024b).

Textual screen representation: A textual representation of the screen, such as HTML in the Web domain (e.g., Kim et al, 2023; Wen et al, 2024a; Zhang et al, 2024b).

Indirect: Indirect observations that do not describe the current screen but information of the computer state $s_t \in \mathcal{S}$, for example, by accessing stored files (e.g., Song et al, 2023b; Wu et al, 2024c; Guo et al, 2024a).

Action types shared across domains:

Mouse/touch and keyboard: Screen coordinate-based actions like mouse clicks or touch taps and keyboard actions for typing text into a previously selected element (e.g., Humphreys et al, 2022; Wang et al, 2024a; Rahman et al, 2024).

Direct UI access: UI element-based actions like clicking a specific HTML element based on its `id` (e.g., Gur et al, 2023; Zhang et al, 2023; Branavan et al, 2009).

Task-tailored actions: Task- or domain-specific actions to solve a sequence of steps in a single action (e.g., Nakano et al, 2022; Bonatti et al, 2024; Wang et al, 2024d).

Executable code: Allowing the agent to generate executable code to interact with the environment through a programmatic interface (e.g., Sun et al, 2023; Gur et al, 2024; Deng et al, 2024a).

	Web	**Android**	**Personal computer**
Image screen representation	Only website, entire web browser	Phone screen	Only foreground application, entire computer screen
Textual screen representation	HTML, accessibility tree	Android View Hierarchy, accessibility tree	UI Automation Tree
Indirect	Network traffic	-	Read files

(a) Observation types

	Web	**Android**	**Personal computer**
Mouse/touch and keyboard	Mouse/touch and keyboard	Touch and keyboard	Mouse and keyboard
Direct UI access	HTML elements	Android elements	UI Automation Tree elements
Task-tailored	Find on page, go to URL	Go back, go to home screen	Switch application, send email
Executable code	Selenium WebDriver	Android Debug Bridge	UI Automation API, Bash

(b) Action types

Table 2: Our classification of observation types and action types across the different computer domains. The table provides examples for each domain from the literature (see citations in the main text).

Linking observations and actions through shared types across different computer domains allows the transfer of methods across domains. Table 2a presents an overview of the specific instantiations of observation types across the Web, Android, and personal computer domains, while Table 2b describes the action types across these domains.

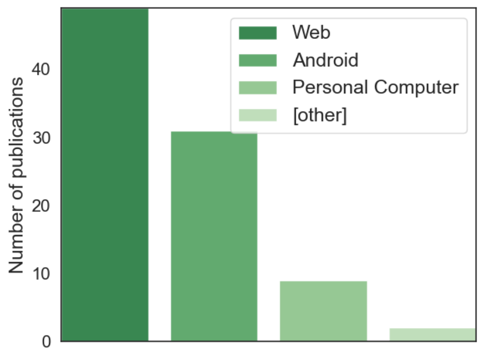


Fig. 4: Publication counts by domain.

Fig. 4 shows that the most often used domains are so far the Web and Android, likely because these are open platforms and the first benchmarks in the field focused on these types of domains (see Section 6).

4 Interaction Perspective (Agent $\leftrightarrow$ Environment)

This section discusses the interaction between the agent and the environment through the observation and action types established in Section 3.

4.1 Observation Spaces

In the previous section, we introduced three observation types: image screen representation, textual screen representation, and indirect. Most computer environments contain only observations of one type in their observation space $\mathcal{O}$. However, some utilize both image and textual observations, termed bi-modal screen representation.

Fig. 5 illustrates the distribution of these observation spaces across the 86 agents analyzed in this survey (see Table A1 in the appendix for a detailed list of each agent's utilized observation types). The distribution shown reflects the increased attention CCAs received after the rise of large language models (LLM) (cp. Fig. 2), which are text-based. However, as we will discuss, each observation type has its own merits, and while textual screen representations are the most commonly used, they are not inherently superior to other types.

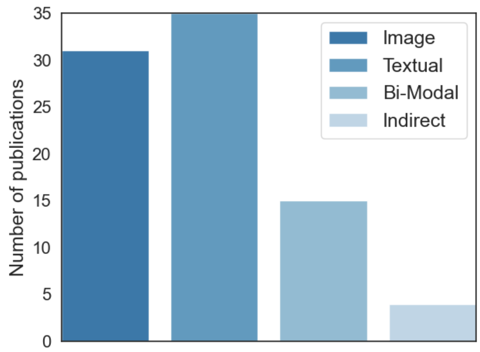


Fig. 5: Frequencies of observation spaces.

Image Screen Representation

Agents processing image screen representations (screenshots) have been successfully employed in the Web (e.g., Zheng et al, 2024a), Android (e.g., Zhang et al, 2023) and personal computer (e.g., Gao et al, 2024a) domains. An agent using screenshots closely aligns with human visual perception, differing primarily in capturing one static image o_t at a single moment t instead of having a continuous input stream. Also, an agent's image representation may only show parts of the screen like the foreground application (Gao et al, 2024a) or extend beyond the typical field of view observed by humans. For example, Chen et al (2024b) render the entire website as an image, while humans need scrolling to perceive the whole page. The alignment with human perception makes screenshots widely applicable, as most applications provide a visual user interface.

Due to practical concerns, screenshot observations o_t are typically simplified $o_t \rightarrow o_t^*$ by downsampling their resolution (e.g., Toyama et al, 2021; Chen et al, 2024b). Rahman et al (2024) even combine a high resolution 1120×1120 and low resolution 224×224 screenshot to have a compact view but still access image details if needed. To feed the text-based instruction i into vision-only agents, the instruction is either encoded separately and added in the embedding space (e.g., Baechler et al, 2024) or visually rendered atop of each screenshot (e.g., Shaw et al, 2023).

Textual Screen Representation

Agents processing textual screen representations have been successfully employed in the Web domain using HTML (e.g., Kim et al, 2023), the Android domain using the Android Hierarchy View (e.g., Shvo et al, 2021), and the personal computer domain using the Windows UI Automation Tree (e.g., Zhang et al, 2024b).

Textual screen representations can be extensive, especially HTML as it carries additional design information. Therefore, processing raw HTML (e.g., Kim et al, 2023; Assouel et al, 2023) is only feasible in artificial environments where the HTML is minimal, such as the MiniWoB++ benchmark (see Section 6). In real-world applications, HTML is typically simplified through a combination of the following strategies:

Heuristic pruning: Select only the most essential attributes such as `id`, `class` or `name` for each element while removing others (e.g., Li et al, 2023; Tao et al, 2023).

Filter elements: Only keep specific elements, for example, leaf elements (e.g., Gur et al, 2019) or the ones judged most relevant to fulfill a given instruction i (e.g., Deng et al, 2023; Zheng et al, 2024c).

Embed : Use an embedding model to compress HTML into a vector representation (e.g., Jia et al, 2019; Gur et al, 2019; Liu et al, 2018).

Summarize : Use an auxiliary model to compress the HTML into an abstract text summary (e.g., Zheng et al, 2024c).

One advantage of using HTML as a textual screen representation is that LLMs are typically pre-trained on HTML, enabling them to exhibit a general understanding of it. To enable agents in the Android domain to benefit from this advantage as well, Wang et al (2023) propose to map the Android View Hierarchy to simplified HTML, an approach later adopted by subsequent works (e.g., Deng et al, 2024a). This mapping approach has also been explored for agents that process image-based observations. In these cases, a screenshot is translated into a textual representation to allow the agent to benefit from the pre-training of text-only foundation models. The translation is commonly done in two steps: first, object detection is used to detect UI elements, and then an additional model is used to extract an element's properties, such as its text and type. Screenshot translation has been applied in the Web (e.g., Cho et al, 2024), Android (e.g., Li et al, 2024d) and personal computer (e.g., Gao et al, 2024a) domains.

Bi-Modal Screen Representation

Bi-modal means an agent observes both a screenshot and the corresponding textual screen representation. Bi-modal screen representations have been applied in the Web domain (e.g., He et al, 2024), the Android domain (e.g., Sun et al, 2022) and the personal computer domain (e.g., Zhang et al, 2024b). Typically, the two modalities have modality-specific encoders embed the two types of observations before they are combined in the embedding space (e.g., Furuta et al, 2024). Whether bi-modal agents can leverage the advantages of both modalities is an open research question, as more information can also lead to distracting information overload.

Indirect Observation

There exist agents that do not observe any screen representation but have dedicated actions or routines to collect information (observations) about the current computer state s_t (e.g., Qin et al, 2024; Kong et al, 2023; Guo et al, 2024b). For example, Guo et al (2024a) use a content reader routine that at each time step t reads information from a PowerPoint file as observation o_t. Song et al (2023b) execute a REST-API call as an action a_t, and use the API *response* as the next observation o_{t+1}. Similarly, Wang et al (2024d) use task-tailored actions to directly read information from files, e.g., `read_excel_file`, or use application-specific actions, e.g., an action `list_emails` in an email application.

Image vs. Textual Screen Representation

As illustrated in Fig. 6, textual screen representations provide certain advantages but also come with drawbacks when compared to image screen representations. Although other theoretical advantages and disadvantages may exist, we limit our discussion to those observed in practice, as described in the works of He et al (2021); Wang et al (2023); Li et al (2023); Zheng et al (2024a); Cheng et al (2024).

Advantages of textual screen representations are:

Revealing visually hidden information: Textual representations can explicitly show information that may be visually hidden in images, such as items within a collapsed drop-down menu.

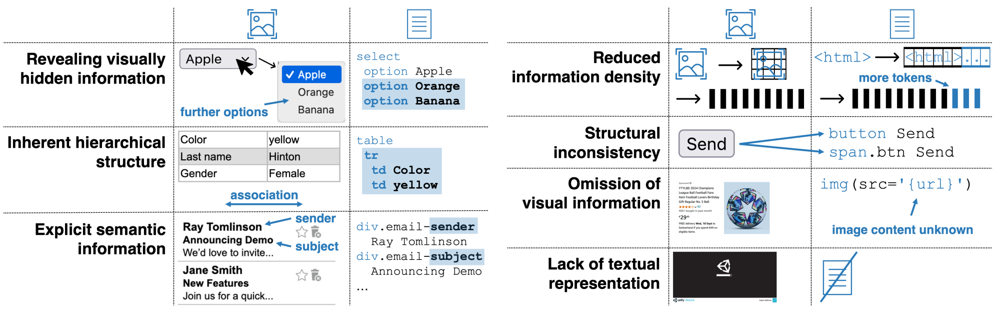
Inherent hierarchical structure: Textual representations, like the Document Object Model (DOM) tree, are structured in a hierarchical tree, facilitating a clearer understanding of relationships between elements (e.g., Jia et al, 2019).

Explicit semantic information: Textual representations often include semantic information in element attributes that are not visible in images, such as `id` tags. For example, the `id` attribute in `<input id="flight-from">` indicates that the input field corresponds to the flight departure location (example taken from the MiniWoB++ benchmark (Shi et al, 2017)).

Disadvantages of textual screen representations are:

Reduced information density: Some text formats, particularly raw HTML, can introduce verbosity that reduces the overall information density.

Structural inconsistency: Visually similar content can be rendered using different underlying structures. For example, a button might be implemented with either a `<button>` or a `<span>` tag. Similarly, visually similar components can



(a) Advantages (b) Disadvantages

Fig. 6: Illustrations of the advantages and disadvantages of textual screen representations. The textual representation is HTML code using concise PUG syntax.

have vastly different underlying code due to different implementation choices, such as the selected styling framework (e.g., Bootstrap[1] vs. Tailwind CSS[2]) and HTML-generating framework (e.g., Angular[3] vs. React[4]).

Omission of visual information: Textual representations often lack information about spatial relationships and positioning that can be critical in understanding the screen's layout.

Lack of textual representation: Some screen components, such as embedded plugins, may not have an alternative textual screen representation. Certain applications may entirely lack any alternative textual screen representation.

Some of these disadvantages can be mitigated through engineering solutions. For instance, the absence of visual positioning can be addressed by incorporating absolute or relative screen coordinates into the textual screen representation (e.g., Shi et al, 2017; Liu et al, 2018), or by embedding elements with information from nearby neighboring elements (Liu et al, 2018). Additionally, the verbosity inherent in raw text can be reduced by simplifying the observations $o_t \rightarrow o_t^*$.

Discussion

Historically, the advantages of textual screen representations were crucial for performance on the popular web benchmark MiniWoB++ (Shi et al, 2017; Liu et al, 2018) and most leading agents used a textual (Tao et al, 2023; Gur et al, 2024; Li et al, 2023; Kim et al, 2023; Jia et al, 2019; Liu et al, 2018) or bi-modal screen representation (Furuta et al, 2024; Humphreys et al, 2022). Humphreys et al (2022) even found their bi-modal agent to drop 75% in performance when disregarding the textual screen representation and only 25% when disregarding the image screen representation. This is because clean and unified HTML makes the advantages of textual screen representation more pronounced by minimizing disadvantages like reduced information density and structural inconsistency. However, the performance of such text-based agents dropped dramatically with a task success rate below 10% (Deng et al, 2023; Gur et al, 2024; Furuta et al, 2024) when applied to more realistic website benchmarks like Mind2Web (Deng et al, 2023). Recent work (Hong et al, 2024; Zheng et al, 2024a) using new visual foundation models has demonstrated superior results on Mind2Web using only image screen representations. Zheng et al (2024a) found that agents utilizing GPT-4 with solely an image screen representation achieved a task success rate of 38%, whereas utilizing GPT-4 with a textual screen representation reached 12%. The reason for this is that HTML is often more verbose and inconsistent on actual websites, whereas the human-aligned visual representation has a lot of structure through common design principles. A similar trend is evident in the Android domain. While textual screen representations have historically performed best (Wen et al, 2024a; Wang et al, 2023; Shvo et al, 2021), recent work with only image screen representations shows superior results (Zhang et al, 2023; Hong et al, 2024). However, the lack of a unified benchmark across those studies hinders direct comparison in the Android domain.

[1] https://getbootstrap.com/
[2] https://tailwindcss.com/
[3] https://angular.dev/
[4] https://react.dev/

Given this development, we suspect the advantage of textual representations (like semantic identifiers) to have provided a general shortcut for better performance in less verbose environments, but due to their disadvantages (like inconsistency in their structure), hitting a barrier in more realistic settings. Therefore, we suggest that state-of-the-art agents on actual tasks require image screen representations (or bi-modal representations) due to the contained structure through common design principles. This is supported by Fig. 7, highlighting that there has been a trend in research toward vision-based agents, especially in 2024.

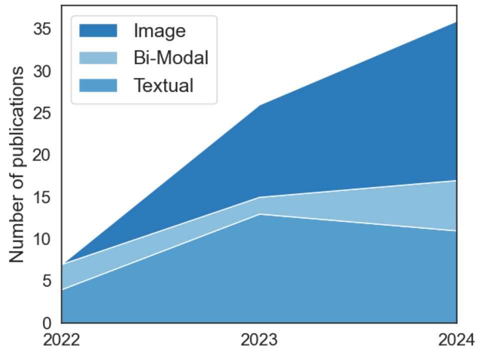


Fig. 7: Number of publications by observation space over the last three years.

4.2 Action Space

In Section 3, we introduced four action types: mouse/touch and keyboard actions, direct UI access actions, task-tailored actions, and executable code. Computer environments typically provide only actions of one type in their action space $\mathcal{A}$. Fig. 8 illustrates the distribution of these action spaces across the surveyed agents[5], while Table A1 provides a detailed list of utilized action types for each CCA. Most agents rely on mouse/touch and keyboard actions (`click(x,y)`) or direct UI access actions (`click(e)`). To solve a task, those general-purpose actions are combined into more complex action sequences.

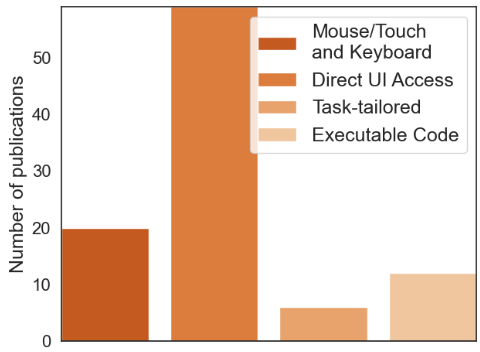


Fig. 8: Frequencies of action spaces.

Mouse / Touch and Keyboard

Mouse, touch, and keyboard actions are general-purpose actions, aligning with human (inter-)actions, making them straightforward to collect and use as training data for CCAs (Humphreys et al, 2022). Both mouse actions, such as `click(x,y)`, and touch actions, such as `tap(x,y)`, require *absolute* screen coordinates `(x,y)`, making them conceptually identical for CCAs[6]. Fig. 9a illustrates various approaches for predicting screen coordinates. Some methods make discrete predictions, such as predicting a position on a low-resolution coordinate grid (e.g., Shi et al, 2017; Toyama et al, 2021), predicting two interdependent discrete values for the `x` and `y` coordinates (e.g.,

[5]Publications featuring agents that support multiple action types are counted once for each action space.
[6]For humans, mouse actions are relative (to the current cursor position) and touch actions are absolute.

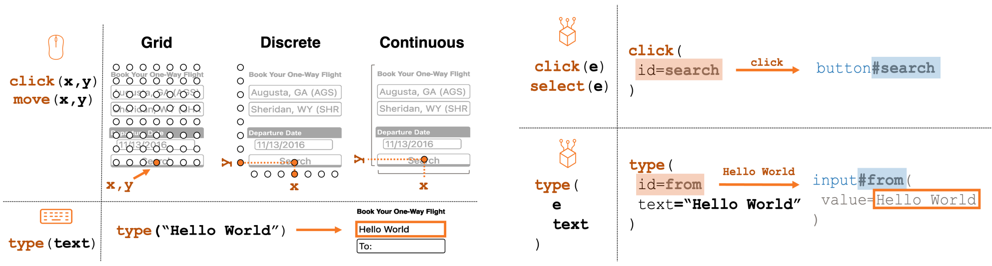
Humphreys et al, 2022), or generating discrete tokens through a text generation model (e.g., Hong et al, 2024). Other approaches use continuous values by predicting two interdependent continuous coordinate values (e.g., Toyama et al, 2021).

Keyboard actions such as `type(text)` are typically used to input text into a previously selected UI element. In most cases, the agent generates the text using a language model (e.g., Hong et al, 2024). Earlier methods also used predefined text fragments (e.g., Humphreys et al, 2022) or extracted text from the instruction i (e.g., Gur et al, 2019), which only works if the instruction contains the necessary text. In addition to typing text, keyboard actions are frequently used for special commands, such as pressing arrow keys (e.g., Li et al, 2023) or using shortcuts such as `select all`, `copy` or `paste` (e.g., Cho et al, 2024).

Direct UI Access

Direct UI access actions such as `click(e)` or `type(e, text)` involve interacting directly with a UI element `e` observed by the agent. To apply such actions, the application domain must provide an accessible interface, and the agent must be able to identify referenceable UI elements. There are two primary approaches for referencing an element `e`. The first approach allows the agent to directly reference the element by predicting a unique identifier, such as the element's `id` attribute (e.g., Li et al, 2023). For instance, clicking a perceived element `<button id="search">` is done by predicting the action `click(id=search)` (see Fig. 9b). Similarly, Kim et al (2023) utilizes the element's XPath[7] as a unique identifier instead of the `id` attribute. The second approach involves the agent scoring each element and selecting the one with the highest score (e.g., Jia et al, 2019). This can include predicting a probability score for each element (e.g., Li et al, 2024d), enabling the agent to select the most relevant UI element. To simplify the action space, the set of referenceable elements can be reduced. A common strategy is to focus only on leaf nodes in the user interface tree (e.g., Liu et al, 2018). Alternatively, an auxiliary model can preselect potential candidate elements (e.g., Deng et al, 2023). For specific tasks such as web navigation, Zaheer et al (2022) and Chen et al (2024b) limit the referenceable set to only hyperlink elements.

[7]https://www.w3.org/TR/xpath-31/



(a) Common mouse and keyboard actions, highlighting coordinate prediction.

(b) Common direct UI access actions, referencing the HTML element by its id attribute.

Fig. 9: Examples of common mouse, keyboard, and direct UI access actions.

A text output action, denoted as `type(e, text)`, fills a UI element `e` (e.g., an input field) with text. The text generation process follows similar approaches to those used in keyboard actions, including generating free text (e.g., Li et al, 2023), selecting predefined text fragments (e.g., Shvo et al, 2021), or extracting text directly from the instruction i (e.g., Jia et al, 2019).

Task-Tailored Actions

Task-tailored actions are typically *not* general purpose and are specifically designed to fulfill specific sub-tasks. For instance, Wang et al (2024d) define application-specific actions such as `create_event` for a calendar application and `send_email` for an email client. Task-tailored actions are easier to use and learn than a trajectory of corresponding general-purpose actions and, thus, provide a shortcut to the agent. However, the use of task-tailored actions comes with certain limitations: they require additional engineering effort to implement, as the environment must explicitly support these actions, and they cannot be easily generalized across different tasks.

In contrast, there also exists domain-specific actions that have a higher degree of generality. For example, Bonatti et al (2024) define the action `open_application`, which enables an agent to open and switch between applications on a Windows operating system. Similarly, Nakano et al (2022) define a `search` action, which allows the agent to navigate to specific text positions within a website. These domain-specific actions strike a balance between general-purpose functionality and task-specific relevance.

Executable Code

Another approach to control computers is to generate code that performs actions within the environment when being executed. While actions generated by an agent such as `click(x,y)` can be seen as interpretable code, we define executable code here as generating program code that a common interpreter can execute, such as the Python or the Bash interpreter. Executable code varies in its structure and the level of abstraction provided by its application programming interface (API):

Structure of generated code:

Straight-line code consists of a sequence of statements without control flow (e.g., Tao et al, 2023). It is akin to predicting a single or multiple actions.

Control-flow code includes control flow mechanisms such as conditional statements (e.g., `if`), loops (e.g., `for`), and function definitions. Complex code can represent the agent's entire execution plan, as seen in Sun et al (2023), where the agent dynamically adjusts its plan based on precondition checks failing.

API abstraction level utilized by generated code:

General-purpose API: Some agents use an API with functions akin to general-purpose actions like clicking elements or screen coordinates. For example, Gur et al (2024) use the Selenium WebDriver API[8] providing such low-level actions.

[8] https://www.selenium.dev/documentation/webdriver/

Task-tailored API: Some agents use an API of hand-engineered functions akin to task-tailored actions. For example, Guo et al (2024a) define functions like `def insert_rounded_rectangle(...)` for their PowerPoint agent.

Fig. 10 shows executable code as action space examples. Executable code is generated using either general foundation models (e.g., Guo et al, 2024a) or specialized models (e.g., Gur et al, 2024). Foundation models often come pre-trained on well-established APIs like Selenium WebDriver, while hand-engineered functions are typically introduced through contextual prompts or, additionally, using an API selector to first retrieve relevant functions (Song et al, 2023b). An open question is the benefits of using executable code over other action types. Chen et al (2023) and Gao et al (2023) found that using straight-line code can reduce hallucinations in GPT-3 compared to task-tailored actions. However, Assouel et al (2023) suggest that this advantage disappears when using GPT-4, indicating that the benefits of executable code over other action types diminish with more advanced models.

Straight-line code using a **task-tailored API**

```python
# task-tailored API
def create_rectangle():
    ...

# straight-line code
rect = create_rectangle()
set_fill_color(rect, "red")
```

Control-flow code using a **general-purpose API**

```python
# general-purpose API
from selenium import webdriver as driver

# control-flow code
e = driver.find_element(By.NAME, "from")
if e.getText() != "":
    e.clear()
e.sendKeys("BAS")
```

Fig. 10: Two examples for executable Python code as action space. Two different levels of structure (straight-line or with control flow) and API abstraction level (task-tailored or general-purpose) are shown.

Action Grounding

Action grounding, denoted as $a_t^* \rightarrow a_t$, refers to the process of converting an abstract action, such as `click submit button`, into an executable action, $a_t \in \mathcal{A}$, such as `click(e)`, where `e` represents the specific UI element. Grounding is essential when a text foundation model generates an abstract, text-based plan that must be transformed into a sequence of executable actions (Gao et al, 2024a; Kim et al, 2023). Several approaches have been proposed for grounding actions:

Prediction-based grounding: A grounding model predicts the corresponding UI element for an ungrounded action. For example, Li et al (2020b) predict `click(e)` where `e` refers to the Settings App icon, based on the abstract action `navigate to settings`.

Rule-based grounding: A rule-based module matches an abstract action a_t^* to the actionable UI element. For example, Song et al (2024a) use text matching rules to achieve this mapping, whereas Lee et al (2023b) first predict abstract *template* actions containing placeholders (e.g., `click(text="[contact_name]")`), followed by rule-based grounding substituting the placeholders with context-specific values derived from the user instruction i.

Grounding is not limited to textual models but is also used in vision-based agents. These agents, particularly those using multi-modal foundation models, require grounding due to the current inability of VLMs to precisely predict screen coordinates. Several strategies for grounding in vision models have been explored and discussed by Zheng et al (2024a). The most successful one is *set-of-mark* prompting (Yang et al, 2023a), where actionable elements are annotated with bounding boxes and unique identifiers, enabling the agent to access them directly using the identifier instead of relying on coordinate prediction. There exist two approaches for identifying the actionable elements: Either using an additional textual screen representation with positional data (e.g., Zheng et al, 2024a; Li et al, 2024e; Zhang et al, 2023) or extracting them from the screenshot via a specialized model (e.g., Lu et al, 2024). While the latter approach offers flexibility, it is often imprecise, leading to suboptimal performance (Bonatti et al, 2024).

Despite the success of set-of-mark prompting, we posit that this grounding step may be a temporary solution driven by the current limitations of foundation models, which have not yet been trained sufficiently to predict screen coordinates directly. However, recent studies suggest that learning visual grounding via coordinate prediction is feasible and straightforward (Dardouri et al, 2024; Cheng et al, 2024), which may eventually render the need for set-of-mark prompting unnecessary.

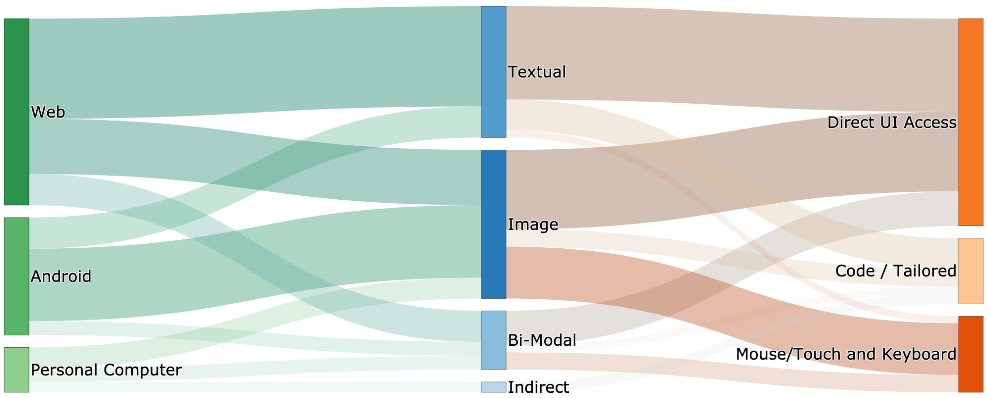


Fig. 11: Sankey diagram showing the connections in the reviewed literature between the domains (left) and observation spaces (middle) and between the observation and action spaces (right).

Discussion

Fig. 11 illustrates the relationships between the domain, the observation space, and the action space as present in the reviewed literature. The connection between observation and action spaces is particularly important, as the structure of the action space is often closely tied to the nature of the observation space. This gives rise to a general rule: vision-based agents typically rely on mouse/touch and keyboard actions, while text-based agents tend to use direct UI access actions. However, there are notable exceptions. For instance, some agents (e.g., Song et al, 2024a; Wen et al, 2024a) first translate screenshots into textual screen representations, which are then used to perform direct UI access actions. Bishop et al (2024) and Li et al (2024c) predict mouse actions based on HTML observations, where necessary spatial information is automatically extracted and encoded into additional attributes via a web browser API. Furthermore, Cho et al (2024) combine both mouse/touch and keyboard actions and direct UI access actions, though they do not provide a detailed analysis or explanation of this hybrid approach.

The choice of action space depends largely on the specific application and domain of the agent. Tailored actions, while more efficient for particular tasks, are often less generalizable. In contrast, general-purpose actions are more flexible but typically harder to learn to use well (i.e., to combine) for an agent, as they require complex orchestration to perform a wide variety of tasks. For most real-world applications, we argue that a combination of general-purpose actions with domain-specific tailored actions, such as a subroutine for switching between applications, represents the most practical and effective compromise in the literature at the moment. This combination offers broad task applicability while maintaining task efficiency. Moreover, we anticipate that future models will favor coordinate-based general-purpose actions over direct UI access actions, with future foundation models being trained to predict screen coordinates directly as coordinate-based actions align naturally with image screen representations.

5 Agent Perspective

Section 3 detailed the computer environments and Section 4 the agent-environment interactions, describing the exterior of an agent. This section extends the taxonomy to the interior of CCAs by first introducing the two most common agent types *foundation agents* (based on foundation models) and *specialized agents* (based on domain-specific design). We analyze each design aspect separately while showcasing connections, nuances, and exceptions across and beyond these agent types.

Foundation Agents: A foundation agent (e.g., Zheng et al, 2024a) uses a *general pre-trained* foundation model (such as an LLM or VLM) as its policy π by employing the model's broad knowledge and in-context learning capabilities for *episodic improvement* (see Sections 5.2.1 and 5.2.3). For example, a text-based foundation model receives the HTML observation o_t alongside a prompt specifying its role as a web agent, a description of available UI actions $\mathcal{A}$, and the instruction i. The model then *generates* an action a_t, such as `click(id=search)`. During each episode, the agent typically accumulates a *history* of past observations and actions to provide additional contextual information to the foundation model as needed (see Section 5.1).

Specialized Agents: A specialized agent (e.g., Humphreys et al, 2022) employs a *custom* deep learning architecture as its policy π, which *predicts* actions $a_t \in \mathcal{A}$ based on a given observation o_t and instruction i, using predefined output possibilities. For example, the architecture might process an image o_t and a text instruction i as inputs, generating logits for each action type such as `clicking` alongside additional outputs for screen coordinates `(x,y)`. To track the past, observations are continuously aggregated in an internal Markov *state*. Learning involves *environment learning* techniques such as reinforcement learning (see Section 5.2.2).

Table 3 summarizes the key characteristics of the two common agent designs.

	Architecture	Action	Memory	Learning Strategy
Foundation agent	LLM / VLM	Generation	history-based	General + Episodic
Specialized agent	Custom	Prediction	state-based	Environment learning

Table 3: Properties of the two common CCA types (see main text for details).

5.1 Policy - How to Act

A policy is the decision-making component of an agent (Sutton and Barto, 2018, Chapter 1.3). In the context of computer control, we distinguish three types of policies: Memoryless policies, history-based policies, and state-based policies.

Memoryless Policies

The simplest form of a policy is a memoryless policy (e.g., Chen et al, 2024b), meaning it does not utilize any memory to track past observations or actions and predicts the next action a_t solely based on the current observation o_t. Such policies are defined as (see also Eq. (1)):

$$a_t \sim \pi(\ \cdot \mid o_t,\ i\ ) \tag{2}$$

Memoryless policies are sufficient for simple tasks but are generally inadequate for computer control, where selecting an appropriate next action a_t at time-step t often depends on aspects of past observations $o_0, o_1, ..., o_{t-1}$ rather than solely on the current observation o_t. For example, in the context of purchasing multiple items from an online store, an agent must remember which items were already added to the shopping cart. Consequently, while memoryless policies can be utilized to simplify model architectures (e.g., Shvo et al, 2021), more sophisticated policies with memory capabilities are typically required for computer control tasks.

History-based Policies

A simple strategy to track the past is to accumulate observations and actions in a continuously growing sequence, called history $h_t = (o_0, \ldots, o_{t-1}, a_0, \ldots, a_{t-1})$ (e.g., Zheng et al, 2024a). For example, a vision-only agent's history consists of all the screenshots it perceived and the actions it performed during an episode. When predicting the next action a_t, the agent retrieves relevant information from its history h_t. We define such policies as *history-based policy*:

$$a_t \sim \pi(\ \cdot \mid o_t,\ i,\ h_t\ ) \tag{3}$$

Foundation agents typically use history-based policies as their foundation model lacks an internal state. Due to the limited context length of foundation models, a simplified history $h_t \rightarrow h_t^*$, is often used. A common simplification is to only keep the past actions $h_t^* = (a_0, \ldots, a_{t-1})$ (e.g., Zheng et al, 2024a) and to discard past observations. In extreme cases, only the last action $h_t^* = (a_{t-1})$ is retained (e.g., Gao et al, 2024a). Other approaches retain certain previous observations $o_{<t}$. For example, Furuta et al (2024) keep the last two screenshots with all actions as $h_t^* = (o_{t-2}, o_{t-1}, a_0, \ldots, a_{t-1})$. Some approaches compress previous observations, e.g., Lu et al (2024) use embeddings of the last four observations as part of the history $h_t^* = (\tilde{o}_{t-4}, \ldots, \tilde{o}_{t-1}, a_0, \ldots, a_{t-1})$. Similarly, Zheng et al (2024c) summarize past observations into text, enabling to keep the entire summarized observation history alongside raw actions $h_t^* = (\tilde{o}_0, \ldots, \tilde{o}_{t-1}, a_0, \ldots, a_{t-1})$.

State-based Policies

Alternatively, *state-based policies* track the past by continuously aggregating observations into an internal state, called the Markov state m_t (e.g., Humphreys et al, 2022). For example, a vision-only agent updates m_t iteratively for each observed screenshot. The agent learns to track the relevant aspects of the past observations in m_t to better predict future actions. Formally, state-based agents are defined as:

$$a_t \sim \pi(\ \cdot \mid o_t,\ i,\ m_t\ ) \tag{4}$$

The state m_t is updated at each time-step using a state-update function $m_{t+1} = f(o_t, m_t)$. Specialized agents commonly use state-based policies, incorporating m_t and f into deep learning models such as recurrent neural networks (e.g., Humphreys et al, 2022).

A notable exception is Zhang et al (2023), who propose a foundation agent with a state-based policy using an external *text-based* state m_t. The foundation model not only generates the next action a_t but also the next state m_{t+1} given the current state m_t and observation o_t, effectively operating as both policy and state-update function.

Mixed Policies

History-based and state-based approaches are also mixed. For example, Bonatti et al (2024) prompt their internal foundation model with the past actions and the last observation $h_t^* = (o_{t-1}, a_0, \ldots, a_{t-1})$ and in addition keep an external text-based state m_t. Similarly, Iki and Aizawa (2022) feed the current observation o_t, the last action $h_t^* = (a_{t-1})$, and an external text-based state m_t into a fine-tuned model to predict the next action a_t as well as state m_{t+1}.

Discussion

Computer control agents utilize three types of policies: memoryless, history-based, and state-based (Eqs. (2) to (4)). The distribution of these policies across agents analyzed in this review is shown in Fig. 12 (for a detailed association to publications, refer to Table A2). History-based policies dominate, particularly among foundation agents, reflecting the prevalence of foundation models in computer control. In contrast, memoryless and state-based policies are more common in specialized agents, with memoryless policies used for simpler agents and state-based policies for more advanced ones.

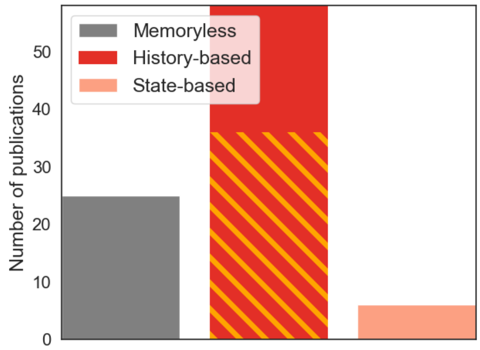


Fig. 12: Frequencies of policy types. Orange strips indicate agents that only track past actions, neglecting observations.

A problem with history-based policies is that the observations o_t are typically large, e.g., high-dimensional images, meaning they don't fit into the context window of a foundation model. A simple yet effective strategy to cope with this issue is only to track past actions a_t, ignoring observations o_t. We suspect this to be effective because a user-friendly GUI does not require a user to remember information about past screens. However, ignoring observations o_t has inherent limitations, especially as tasks become more complex, requiring agents to recall observed information, thus making better history simplification strategies necessary. Currently, history simplifications are hand-engineered (e.g., Cho et al, 2024) or rely on environment-agnostic summarization models (e.g., Zheng et al, 2024c). A promising future research direction might be to make history simplification learnable, enabling adaptation to specific environments. Interestingly, the learnable state-update function f in specialized agents already implements a sequential history simplification. While directly applying this concept to foundation models is non-trivial, it offers valuable insights for designing adaptive history-simplification mechanisms.

5.2 Learning Strategy - How to Learn to Act

Each agent's learning strategy can be conceptualized as implementing the following three steps (not every CCA uses all three steps):

General pre-training: The agent acquires broad, environment-agnostic knowledge. Examples include foundation models learning general-purpose capabilities or vision backbones learning image representations.

Environment learning: The agent learns to adapt to a specific computer environment. This involves explicit parameter (weight) updates or implicit methods, such as storing environment experiences for later retrieval.

Episodic improvement: The agent refines its performance within the current episode through methods such as instruction tuning or few-shot learning (Brown

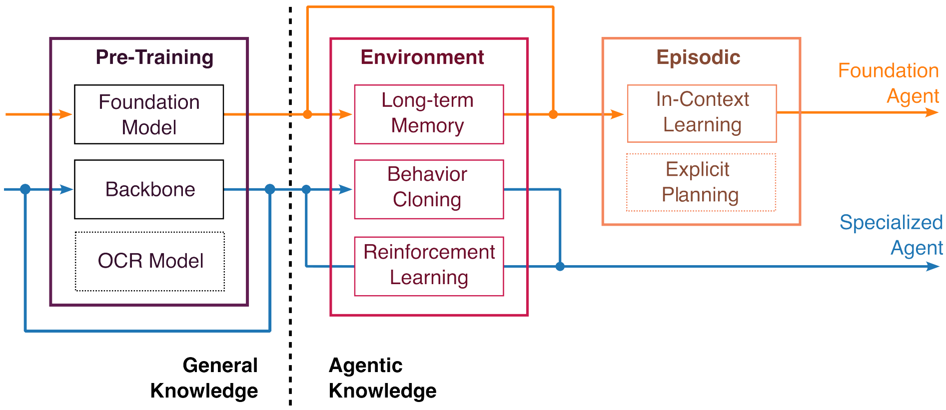


Fig. 14: Overview of learning steps and strategies: *Pre-training* involves acquiring broad, environment-agnostic knowledge. *Environment learning* and *episodic improvement* hone a CCAs agentic skills. A combination of these steps defines a learning strategy. CCAs typically follow one of two strategies: (1) *Specialized agents* start from scratch or use a pre-trained backbone, learn to act in a specific environment through behavioral cloning (BC) or reinforcement learning (RL) (blue); (2) *foundation agents* begin with a general-purpose foundation model, optionally storing successful episodes for future demonstration retrieval, and employ in-context learning (orange).

et al, 2020). Unlike the previous steps, episodic improvement is temporary, as intermediate outcomes are discarded once the episode ends, and no long-term learning occurs.

Fig. 13 provides an overview of the distribution of these learning steps observed among agents analyzed in this review, while Table A2 details the strategies employed by specific publications. Fig. 14 illustrates the sequential nature of the three learning steps and their role in the learning strategies of foundation agents and specialized agents. The following sections explore each learning step in detail, emphasizing current practices and highlighting exceptions.

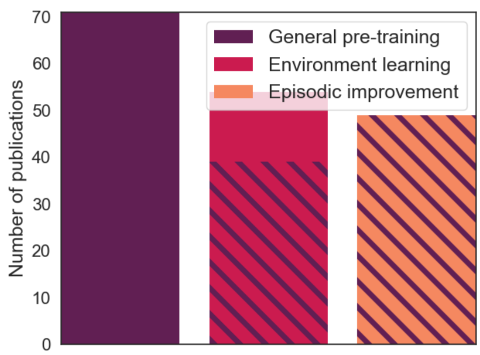


Fig. 13: Frequencies of learning steps. Purple stripes indicate initial pre-trained.

5.2.1 Leveraging General Pre-Training

Foundation agents leverage foundation models with broad knowledge and in-context learning capabilities (Brown et al, 2020). These capabilities can eliminate the need for environment-specific fine-tuning, allowing agents to operate in computer environments using only the foundation model's broad knowledge and instructions provided through prompts to adapt to specific environments (e.g., Kim et al, 2023).

For example, GPT-4 (OpenAI et al, 2024), when prompted as a web agent, can complete tasks such as filling out forms or navigating website links (Zheng et al, 2024a). In contrast, specialized agents are either trained from scratch (e.g., Humphreys et al, 2022) or initialized with a pre-trained backbone (e.g., an image encoder) to accelerate learning the observation space (Li et al, 2024b). These agents typically require additional fine-tuning to adapt to computer environments (see Section 5.2.2). The foundation model or backbone choice depends on the observation space, action space, and specific task requirements. For example, Zheng et al (2024a) use GPT-4 (OpenAI et al, 2024) as a multi-modal foundation model for their bi-modal agent. Gur et al (2024) employ a coding-proficient foundation model (Chung et al, 2024) to generate executable code. Shaw et al (2023) fine-tune a vision backbone for their vision-based agent. Iki and Aizawa (2022) fine-tune a text backbone for their text-based agent. Song et al (2024a) use pre-trained object detection and OCR models to convert screenshots into text-based observations for direct UI access actions. Gur et al (2024) pre-train an LLM from scratch on only HTML data while utilizing an HTML-specific local and global attention mechanism.

5.2.2 Environment Learning

Environment learning is about learning to act in a computer environment through experiences in the same or a similar computer environment. This process typically follows one of three main strategies: *Reinforcement learning*, *behavioral cloning*, or leveraging *long-term memory*.

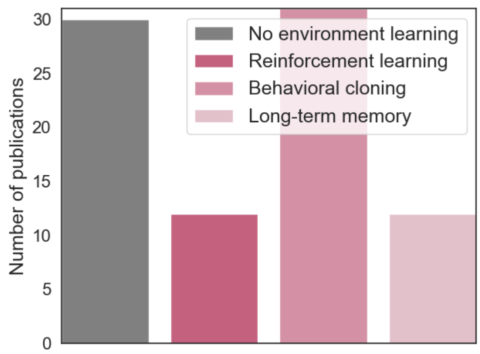


Fig. 15: Frequencies of environment learning strategies.

Fig. 15 illustrates the distribution of these strategies across the surveyed publications, with detailed information provided in Table A2. Many foundation agents bypass the environment learning step, relying solely on their pre-trained, out-of-the-box capabilities. While these capabilities can be remarkably effective (e.g., Zheng et al, 2024a), the absence of environment learning limits these agents, as they lack mechanisms to adapt or improve their performance within specific computer environments.

Reinforcement Learning

In reinforcement learning, an agent acts in an environment and learns to maximize a cumulative reward by trial and error (Sutton and Barto, 2018). For computer control tasks, such environments are hand-crafted simulations, called *controlled environments*, designed to mimic real-world computer settings while providing a reward signal for guidance. RL has been implemented with various algorithms, including approximate policy iteration (Humphreys et al, 2022), policy gradients (Shi et al, 2017), and bootstrapping with tree search (Shaw et al, 2023).

Agents in simpler environments may rely on brute-force exploration to learn directly from random behavior (e.g., Toyama et al, 2021; Shvo et al, 2021). However, in most computer environments, rewards are sparse as they are only given upon completing the assigned instruction i (e.g., Shi et al, 2017), such as submitting a flight booking form with *all* correct details. Sparse rewards make learning from an initial random behavior often unsuccessful, as an agent is unlikely to predict a long action sequence by random chance (Humphreys et al, 2022). One strategy to mitigate sparse rewards is to begin by training an agent on human-labeled demonstrations (behavioral cloning, see below), providing it with enough competence to start finding and learning from rewards (e.g., Shi et al, 2017; Humphreys et al, 2022). Relatedly, Liu et al (2018) use human-labeled demonstrations to constrain the action space by defining sets of valid actions based on similarity to demonstrated actions, increasing the likelihood of reward discovery. Without demonstrations, reward shaping (Ng et al, 1999) can artificially reduce sparsity by providing intermediate guidance, as shown by Gur et al (2019) and Li and Riva (2021). Alternatively, the task complexity can be adaptively adjusted. Gur et al (2021), for instance, introduce a controlled environment that enables autonomous curriculum learning (Bengio et al, 2009) by automatically changing a task's complexity. Similarly, Gur et al (2019) employ curriculum learning by gradually moving an agent's starting point away from the goal state as it gains competence.

The key advantage of RL is its ability to autonomously explore environments, effectively navigating a dynamic dataset of all possible experiences. However, RL's reliance on controlled environments limits its application to broad computer control tasks, as rewards must be defined and consequences suppressed, such as making purchases. AndroidEnv (Toyama et al, 2021) is an exciting approach to combat this. They simulate a complete, virtual Android environment on top of which tasks can be configured by defining instructions and rewards.

Behavioral Cloning

In behavioral cloning (BC) (Pomerleau, 1988), an agent learns to mimic a shown behavior through supervised learning. The shown behavior is usually a sequence of recorded observations and actions of a human controlling a computer to achieve an instruction i. As mentioned, BC can be used to first train a somewhat competent agent as initialization to RL in a controlled environment. Typically, RL further enhances the agent by exploring aspects missing from the behavioral data. For instance, Humphreys et al (2022) demonstrate that after training their agent on 2.4 million human-labeled actions, RL increased the task success rate from approximately 30% to over 95%. Nonetheless, some agents rely entirely on BC, which can suffice for simpler tasks (e.g., Gur et al, 2023).

Unlike RL, BC does not require the agent to execute actions in the environment, making it applicable in *uncontrolled* environments. For example, Zhang and Zhang (2024) fine-tune a model on Android demonstrations from Rawles et al (2023), while Hong et al (2024) combine Android demonstrations from Rawles et al (2023) with

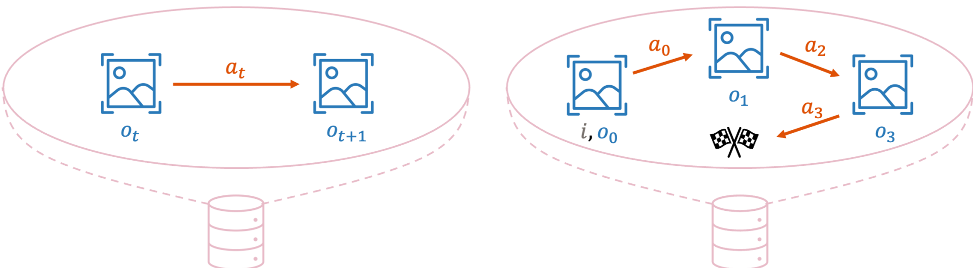
Web demonstrations from Deng et al (2023). BC methods vary in training strategies and data collection. For example, Gur et al (2023) train the entire model, Hong et al (2024) only update specific components, while Li et al (2024c) use low-rank adaption (Hu et al, 2021) to fine-tune a foundation model. Datasets are typically human-labeled (e.g., Humphreys et al, 2022), but autonomous data collection methods also exist. For instance, Furuta et al (2024) use rejection sampling to identify successful trajectories from another agent's actions in a controlled environment, leveraging the environment's rewards for validation. Similarly, Lai et al (2024) iteratively collect successful demonstrations using their improving agent.

Long-Term Memory

Foundation models exhibit strong few-shot learning capabilities (Brown et al, 2020), enabling foundation agents to enhance action prediction by incorporating successful demonstrations directly into their context (see Section 5.2.3). This paradigm, known as in-context learning, allows agents to *autonomously* adapt to an environment by collecting experiences for later retrieval. Fig. 16 illustrates the two main types of experiences:

Environment transitions: The agent memorizes environment transitions as triples $(o_t,\ a_t,\ o_{t+1})$, where a_t represents the action taken, and o_t, o_{t+1} capture the pre- and post-action observations, respectively. For example, the agent might store that when it clicks on the calculator app (a_t) on the home screen (o_t), the calculator app opens (o_{t+1}). Wen et al (2024a) collect such transitions for Android apps in an offline phase by random exploration. They describe and summarize these transitions using a large language model, enabling the agent to enrich actionable elements with outcome information. For example, a `More options` button could be annotated to reveal specific hidden menu items, informing the agent what to expect if this button is clicked. Autonomous transition memories can also be combined with human demonstrations, as shown by Zhang et al (2023) and Li et al (2024e).

Task demonstrations: The agent memorizes task demonstrations by storing a tuple $(i,\ \tau_i)$ containing the instruction i and a successful demonstration $\tau_i = (o_0, a_0, \ldots, o_t, a_t)$ of solving i. Since only successful attempts are informative for



(a) Memorize transitions (o_t, a_t, o_{t+1}) (b) Memorize task demonstrations (i, τ)

Fig. 16: Two kinds of experiences an agent can store in its long-term memory.

the agent, the agent must have a mechanism to filter *successful* trajectories. A common approach is to use a controlled environment's reward (e.g., Tao et al, 2023). To manage memory constraints, trajectories are typically simplified to $\tau_i^* = (\tilde{o}_0, a_0, \ldots, \tilde{o}_t, a_t)$ before being stored. For instance, Deng et al (2024b) store only the actions $\tau_i^* = (a_0, \ldots, a_t)$, while Sun et al (2023) store the complete executable program that solves i. These simplifications mirror history simplifications ($h_t \to h_t^*$), as the history h_t is a (partial) trajectory. An alternative approach to discovering successful trajectories is programming by demonstration. Here, a human supervises the agent, intervenes if necessary, and demonstrates the correct solution for i, enabling online learning. Song et al (2024a) propose this method to summarize the corrected behavior for future retrieval.

A critical perspective on long-term memory emphasizes its focus on storing specific experiences rather than learning abstract concepts from them, akin to early reinforcement learning approaches that memorize tabular state values instead of learning approximations. To mitigate this, Lee et al (2023b) organize memories into a graph where observations are nodes, actions are edges, and both are generalized to unify related experiences. For example, an action $a =$ `click(text=Bob)` is generalized to $a^* =$ `click(text=[contact name])`. When retrieving memories, the graph is searched, and parameterized actions are instantiated based on the current state (o_t, i), grounding parameters like `[contact name]` to specific values.

Discussion

Recently, foundation agents have achieved significant progress without any environment learning technique (e.g., Zheng et al, 2024a), and probably will improve further with future foundation models. However, agents without environment learning are prone to repeat errors in an identical scenario. They fail to autonomously adapt and, thus, fail to exhibit rational behavior as defined by Russell et al (2022, Chapter 2.2). Thus, rational agents require some form of environment learning.

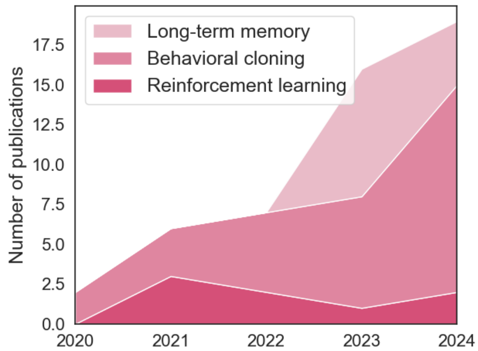


Fig. 17: Number of publications by kind of environment learning over the last 5 years.

Fig. 17 illustrates the evolution of environment learning approaches over the last five years. A few years ago, reinforcement learning with initial behavior cloning dominated (e.g., Humphreys et al, 2022). In the last two years, the focus shifted to foundation agents, relying solely on behavior cloning (Lù et al, 2024) or long-term memory (Zhang et al, 2023).

However, reinforcement learning remains a high-potential paradigm and can be utilized to fine-tune foundation models to adapt to a specific computer environment. For example, Fereidouni and Siddique (2024) demonstrate that reinforcement learning applied to a smaller foundation model (780M parameters) outperforms in-context learning on larger models (3B parameters). Adapting foundation models effectively remains an open research challenge. In Section 8, we discuss this further from a more practical perspective.

5.2.3 Episodic Improvement

Episodic improvement refers to an agent's ability to "think" about its current situation to enhance performance within a single episode without retaining any knowledge for future episodes. This approach effectively trades *test-time compute* for better task execution during the ongoing episode.

Foundation agents commonly achieve episodic improvement through in-context learning (Brown et al, 2020), encompassing techniques such as *instruction tuning*, where guidance is provided to the model through the prompt, and few-shot learning, which gives examples of successful trajectories as *demonstrations* to the agent. In contrast, current specialized agents typically do not employ episodic improvement. However, analogous practices exist in other domains, such as agents that "think ahead" by searching through the simulated consequences of predicted actions, as demonstrated by game-playing agents (Silver et al, 2017).

In-Context Learning through Instruction Tuning

Foundation models can be optimized by *prompt engineering*. Table 4 exemplifies some snippets taken from the (much longer) prompts in the literature. Typically, these prompts are designed by humans to adapt a foundation model to specific environmental conditions (e.g., Zheng et al, 2024a). However, there are exceptions. For example, Sun et al (2023) uses a second model as a planner to autonomously generate prompts for the agent. This strategy, known as *self-prompting*, involves using multiple instances of the foundation model, each fulfilling different roles and interacting with one another through iterative prompting (e.g., Song et al, 2024b). The rise of vision-based foundation models has led to the development of visual prompt engineering. This includes techniques such as extending screenshots to incorporate user instructions (Lee et al, 2023a), overlaying bounding boxes on actionable UI elements (e.g., Bonatti et al, 2024), and adding unique identifiers for visual grounding (e.g., Zhang et al, 2024b).

In-Context Learning through Demonstrations

Fig. 18 illustrates four common techniques for collecting and providing demonstrations to the agent:

Human-crafted: For a given class of tasks, a fixed set of human-crafted demonstrations $\{\tau_1, \tau_2, \ldots\}$ is provided to the foundation model (e.g., Kim et al, 2023).

Semantic search: Based on the semantic similarity of the instruction i compared to previous instructions, an agent retrieves human-crafted demonstrations from a database (e.g., Cho et al, 2024).

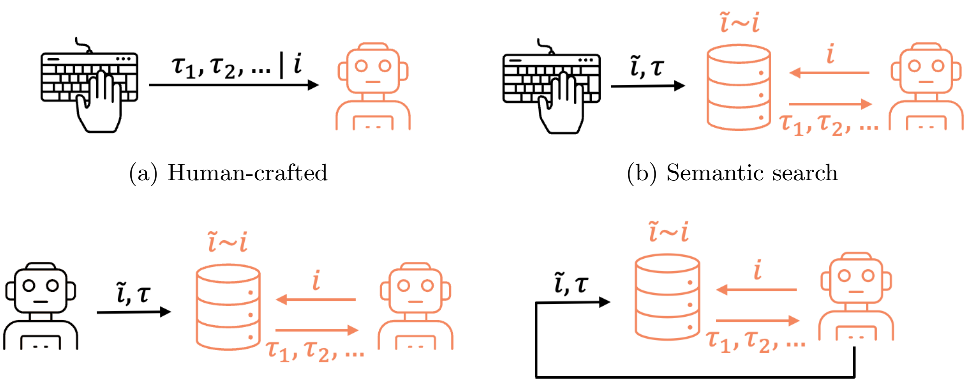
Auxiliary model: A secondary agent is first used to generate a large set of demonstrations, after which the agent retrieves those demonstrations that are semantically relevant to the current instruction i.

Category	Prompt Snippet
Action Generation	`[...] you can click an object by referring to its id, such as 'click id=..., [...]'` (Li et al, 2023)
Provide history h_t	`Previous Actions: {PREVIOUS ACTIONS}` (Zheng et al, 2024a)
Prescribe a role	`Imagine that you are imitating humans doing web navigation [...]` (Zheng et al, 2024a)
Elicit intermediate, structured thoughts	`[...] think about what the current webpage is [...] analyze each step of the previous action history [...] based on your analysis [...] decide on the following action [...]` (Zheng et al, 2024a)
Provide general guidelines	`To be successful [...] only issue a valid action [...] only issue one action [...]` (Zheng et al, 2024a)

Table 4: Example snippets of actual prompts. See Table 6 in (Zheng et al, 2024a) for a full example of a prompt.

Agent-collected: The agent autonomously collects its own demonstrations, referred to as *long-term memory*, by searching through its past experiences (see Section 5.2.2).

Given the limitations of context length, a provided trajectory $\tau = \big((o_0, a_0), (o_1, a_1), ...\big)$ is typically simplified $\tau \to \tau^*$, similar to how a history h_t is simplified $h_t \to h_t^*$ (see Section 5.1). In addition to the trajectory, a demonstration may include rationales for each action taken (e.g., Cho et al, 2024). These rationales, inspired by chain-of-thought prompting (Liu et al, 2023a), can aid the agent when making similar decisions. Such reasoning can be written by humans (e.g., Wang et al, 2023) or generated autonomously by another model (e.g., Cho et al, 2024; Sodhi et al, 2023).



(a) Human-crafted

(b) Semantic search

(c) Auxiliary model

(d) Agent collected

Fig. 18: The four most common few-shot learning strategies for CCAs (see main text for details).

Episodic Improvement through Planning

CCAs are goal-directed, meaning they must plan to achieve a non-trivial instruction i (Russell et al, 2022, Chapter 2.4). Most agents perform implicit planning in their latent space, a process Li et al (2023) term *iterative planning*, where future states or action consequences are not explicitly constructed. However, some foundation models generate explicit plans in text form: One common method is *chain-of-thought* prompting (Liu et al, 2023a), which guides the model to produce intermediate reasoning steps before deciding on an action, improving performance (e.g., Rawles et al, 2023; Zhang et al, 2024d). Another method involves decomposing an instruction into sequential sub-tasks, such as breaking down the task `Book an economy class flight from Hangzhou to Beijing` into steps like `Open the Alipay app` and `Input 'Hangzhou' as the departure city` (Guan et al, 2023). Generated plans can be iteratively improved. For instance, Kim et al (2023) prompt their foundation model to critique and refine its generated plans recursively. While this can yield minor improvements, (Kambhampati, 2024) suggests that the benefits of self-critiquing may be limited. After initial prompting, agents may either follow their initial plan rigidly (e.g., Kim et al, 2023) or adapt it based on new observations (e.g., Sun et al, 2023). In contrast to these prompt-based planning strategies, Koh et al (2024b) use a formal planning approach that involves a search algorithm. They simulate actions in a controlled environment and search through potential future states (observations) to better decide on the next action. This approach shows significant performance gains, with task success rates improving by 50% at a search depth of 5. Building on this, Chae et al (2024) fine-tune a model to predict the effects of actions on current observations, allowing for better decision-making without relying on an external simulator. Those ideas are similar to recent test-time compute techniques using agentic workflows (Snell et al, 2024; Singh et al, 2024).

We suspect that current computer control benchmarks likely do not require extensive planning, as many tasks can be completed with a few independent actions (e.g., filling out a web form). However, more complex tasks with sequentially dependent steps, such as looking up different, dependent information, will require planning (Russell et al, 2022, Chapter 11).

5.2.4 Discussion

General pre-training focuses on acquiring knowledge independent of any specific environment and is largely disconnected from agent theory. Environment learning and episodic improvement are both about adapting a CCA to a computer environment. Environment learning techniques are about an agent *autonomously* learning a specific environment. In contrast, episodic improvement refers to *manually* adapting an agent's existing capability to a specific environment. In this context, we predict that planning will become a crucial component for computer control agents to tackle more challenging tasks.

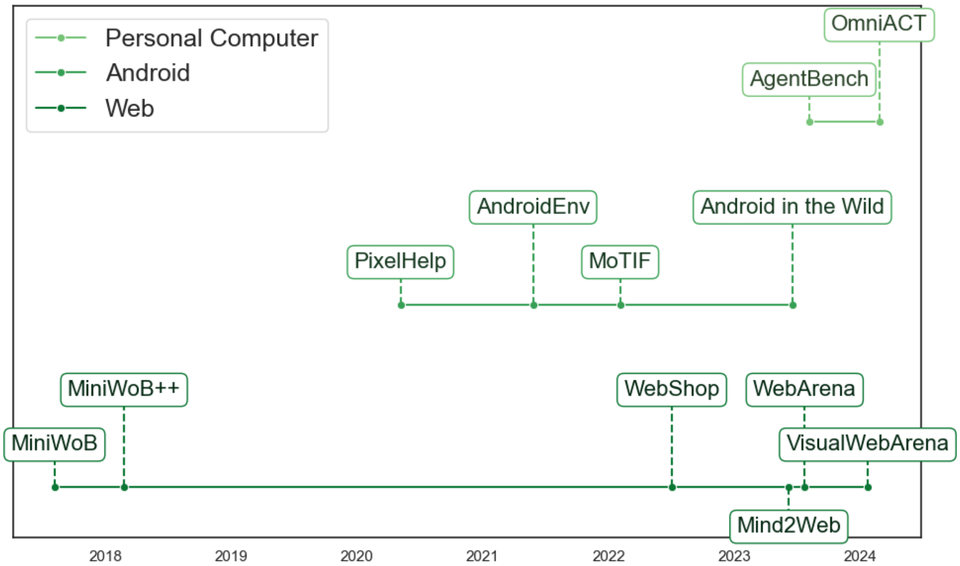


Fig. 19: Datasets over time by domain. In general, complexity increases over time. For the *Web domain*: MiniWoB and MiniWoB++ contain 100 tasks on a simplified UI. WebShop is a more realistic single web shop application focusing on realistic product diversity. Mind2Web contains 2350 demonstrations across 137 actual websites. WebArena is a controlled environment of 4 realistic web applications. VisualWebArena extends WebArena with 910 more visual tasks and an additional application. For the *Android domain*: PixelHelp contains step-by-step instructions across 4 applications. AndroidEnv provides a framework to define custom tasks in Android applications. MoTIF contains 756 demonstrations across 125 applications. Android in the Wild provides over 700, 000 demonstrations across 357 applications. For the *personal computer domain*: AgentBench is a benchmark framework that spans operating systems, databases, web, and gaming tasks, including existing benchmarks like WebShop or Mind2Web. OmniACT contains 9802 tasks labeled with straight-line code actions spanning 57 applications on Windows, MacOS, Linux, and the Web.

6 Computer Control Datasets

This section discusses computer control datasets. We limit the discussion to the most prominent datasets based on recency and citations. Fig. 19 highlights their chronological development, while Table A3 provides an overview of all considered computer control datasets and their key properties. In the following, we discuss different dataset types, relate them to our taxonomy, discuss their complexity, and describe the usage of datasets as benchmarks to compare agent capabilities across publications. We do not cover datasets used for general pre-training of foundation models or those only partially relevant for computer control, such as question answering (e.g., Hudson and Manning, 2019) and tool usage datasets (e.g., Patil et al, 2023).

6.1 Dataset Types

CCAs leverage two types of computer control datasets:

Controlled Environments: A controlled environment is simulated, meaning an agent can act freely without consequences, as the simulation can always be reset. Thus, they can be utilized for reinforcement learning given they provide an additional reward signal (e.g., Humphreys et al, 2022). Furthermore, they can be utilized to collect long-term memories in a safe simulation phase (e.g., Wen et al, 2024a) and to plan at inference time by simulating potential actions (Koh et al, 2024b).

Offline Dataset: An offline dataset is collected by instructing, e.g., humans on a computer task while recording observations and executed actions. The agent only sees the recorded interaction during training, meaning it never acts in the underlying environment, making training safe from consequences. Offline datasets can be utilized for few-shot learning (e.g., Deng et al, 2023) or fine-tuning an agent (e.g., Rahman et al, 2024) in an uncontrolled environment like a productive website. Furthermore, an offline dataset of a controlled environment can be used for initial behavioral cloning to combat sparse rewards (Humphreys et al, 2022).

Both dataset types have distinct characteristics. Controlled environments are costly to create because they involve engineering simulations that mimic real-world behaviors, but the agent can explore all aspects of the environment autonomously. In contrast, offline datasets can be recorded in any environment but are incomplete as not every possible interaction can be captured. Furthermore, offline datasets only show a single trajectory to achieve an instruction, but maybe multiple ones exist.

6.2 Domains, Observation and Action Spaces

Both controlled environments and offline datasets are typically domain-specific. As shown in Fig. 20, the majority of existing datasets are from the Web domain (e.g., Zhou et al, 2024), followed by the Android domain (e.g., Rawles et al, 2023) and the personal computer domain (e.g., Hong et al, 2024).

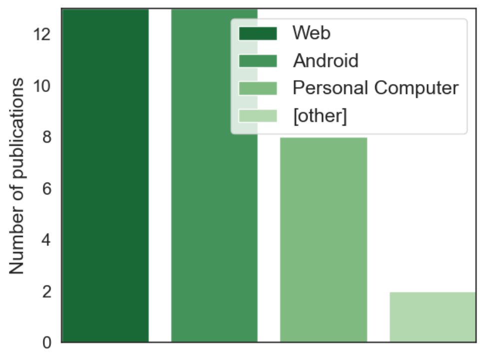


Fig. 20: Dataset counts by domain.

The types of observations and actions available in these datasets vary depending on the domain and data collection method. For observations, some datasets provide only image screen representations (e.g., Rawles et al, 2023), some only textual screen representations (e.g., Pasupat et al, 2018), while others offer both (e.g., Chen et al, 2021). Regarding actions, some datasets focus solely on mouse/touch and keyboard actions (e.g., Kapoor et al, 2024), some provide direct UI actions (e.g., Chen et al, 2024b), while others focus on task-tailored actions (e.g., Liu et al, 2024). Table A3 shows an overview. In many cases, additional observation and action types can be generated through post-processing efforts. For instance, HTML representations can be rendered through a web browser to provide image-based screen representations.

6.3 Dataset Complexity

Several factors, including the size of the state, observation, and action spaces and the diversity of the tasks, influence the complexity of a computer control dataset. Controlled environments are often simplified and less diverse compared to offline datasets. For instance, in MiniWoB++ (Shi et al, 2017), all tasks are performed within a uniform, simplified website design with minimal graphical user interface (GUI) elements and clean HTML. Similarly, WebShop (Yao et al, 2022) is limited to a single, simplified webshop application. While WebArena (Zhou et al, 2024) offers more realistic web environments, it is limited to four tasks. Offline datasets tend to feature more realistic observations, with the diversity depending on the variety of scenarios, such as how many websites were included. For example, Mind2Web (Deng et al, 2023) records tasks from 137 websites across 31 categories, providing substantial diversity. Similarly, Android in the Wild (Zhang et al, 2024d) records tasks spanning 357 Android apps or websites. The complexity of tasks varies greatly across datasets. For example, MiniWoB++ (Shi et al, 2017) includes 100 tasks with randomized text and an average of 3.6 actions per task, ranging from simple actions like clicking a button to more complex tasks like filling out a form to book a flight. WebShop (Yao et al, 2022) offers 12,000 crowd-sourced instructions, all related to shopping, with an average of 11.3 actions per task. Mind2Web (Deng et al, 2023) provides 2,000 tasks averaging 7.3 actions, while WebArena (Zhou et al, 2024) features 812 tasks, some requiring actions across applications, such as the task to create a Reddit account mirroring a GitLab profile.

Generally, the complexity of newer datasets increases as agents become more capable. A straightforward way to do this is to make observations and tasks more diverse and challenging. For example, WebArena (Zhou et al, 2024) has a more realistic observation space than MiniWoB++ (Shi et al, 2017), and tasks require more actions to be achieved. However, there are many other ways to increase complexity: VisualWebArena (Koh et al, 2024a) adds images as part of the instruction, such as asking an agent to create a post selling a product shown in an image. AgentStudio (Zheng et al, 2024b) provides video-based observations, requiring agents to process dynamic, time-dependent information. MT-Mind2Web (Deng et al, 2024b) extends Mind2Web by introducing multi-turn tasks, where users give sequential instructions to the agent, requiring a more nuanced agent behavior. MoTIF (Burns et al, 2022) introduces infeasible instructions in its offline dataset, challenging agents to recognize unachievable tasks.

6.4 Datasets as Benchmarks

A benchmark refers to a controlled environment or offline dataset used to evaluate and compare the performance of agents across different publications. To enable meaningful comparisons, it is crucial that the same environment configuration and metric are used across studies. However, this standardization is often lacking in the literature.

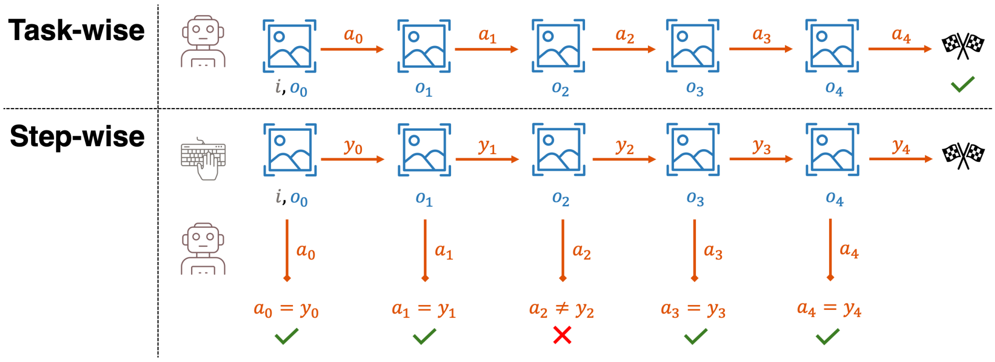


Fig. 21: Task-level metrics measure performance across individual tasks (instructions). Step-level metrics measure performance across individual steps (actions).

For example, in the MiniWoB++ benchmark (Shi et al, 2017; Liu et al, 2018), various studies selected different subsets of the 100 available tasks, complicating cross-study comparisons. For example, Humphreys et al (2022) used all 100 tasks, while Zheng et al (2024c) focused on only 64 tasks.

Offline datasets have inherent challenges in serving as proper benchmarks. Multiple paths may exist to achieve a given instruction, but only one path (taken by the human) was recorded in the dataset. For instance, Zheng et al (2024a) observed that their agent's task success rate increased significantly—from 12% to 36%—simply by switching to online evaluation with a human evaluating the end state. However, online evaluation introduces its own issues, such as high costs and a lack of consistent reproducibility, which limits its broader applicability in benchmark comparisons.

One problem we found when reviewing the current CCA literature is that agent capabilities are difficult to compare across publications. This is because many publications introduce a custom benchmark or simplify existing benchmarks, often to highlight specific aspects of their method. Thus, we advocate that publications evaluate their proposed agent on established, reproducible, and complete benchmarks.

7 Agent Evaluation

Various evaluation metrics are used in the current literature. We identify three groups of evaluation metrics (see also Fig. 21): *Task-level metrics*, *step-level metrics*, and *other metrics*.

7.1 Task-Level Metrics

Task-level metrics focus on the overall effectiveness of an agent in achieving an instruction i. *Task success rate* is the most common task-level metric, which measures the overall success rate of completing an entire task (Deng et al, 2023; Zhang et al, 2024d). For controlled environments, the environment indicates successful task completion. For offline datasets, an agent predicting the full trajectory correctly counts as a successful task completion. However, as discussed in Section 6.4, this underestimates the real task success rate, as other trajectories than the recorded trajectory may be viable. To estimate an agent's actual performance in an uncontrolled environment, an agent must be deployed in an online setting, and a human evaluator judges if an agent completes the task (Zheng et al, 2024a; Song et al, 2023b; Li et al, 2017). Ideally, agents must also predict a final `end` action as part of completing a task to stop themselves in, e.g., a productive setting (e.g., Wang et al, 2024a). In the literature, task success rate is also called *complete match* (e.g., Li et al, 2020b).

Other less common task-level metrics exist, often providing a more nuanced assessment of the agent's capabilities. *Task progress* measures the average task completion progress, meaning how far the agent, on average, is to complete a task (e.g., Sodhi et al, 2023; Zhang et al, 2024d). *Average reward*, captures the average reward obtained across episodes within a controlled environment (e.g., Jia et al, 2019). This metric helps compare agents during development but not for comparing agents across different environments, as they may define different reward functions.

7.2 Step-Level Metrics

Step-level metrics focus on the overall effectiveness of an agent in predicting actions (steps) across tasks. *Step success rate* is the most common step-level metric, which assesses the accuracy of action prediction (e.g., Deng et al, 2023). In the literature, step success rate is also called *partial match* (e.g., Li et al, 2020b) or *action accuracy* (e.g., Wen et al, 2024a).

Each step (action) is part of a trajectory (a sequence of multiple actions), which in turn represents a single task in the dataset (comprising multiple tasks). Consequently, step-level metrics must define how to average step scores both within their trajectory and across tasks, similar to other fields like multi-class classification, where metrics are averaged within classes and across samples (Grandini et al, 2020). Two natural approaches for averaging exist:

Macro averaging: Step scores are averaged first within their respective trajectory and then across tasks. As a result, each step score is weighted by the inverse of its corresponding trajectory's length.

Micro averaging: Step scores are averaged across all steps (of all trajectories). This assigns equal weight to each step score regardless of trajectory length.

For computer control, *macro averaging* seems to be the prevailing approach, established by Mind2Web (Deng et al, 2023) and adopted by subsequent work (e.g., Zheng et al, 2024c).

Other less common step-level metrics include the *action F1* score (e.g., Li et al, 2024b), *action recall* (e.g., Li and Riva, 2021), or measuring only if parts of the action are correct like the *element accuracy* for direct UI access actions (e.g., Deng et al, 2023). Finally, all step-level metrics only exist for offline datasets, as controlled environments' rewards do not indicate the correctness of individual actions.

7.3 Other Metrics

Other metrics in the literature measure performance indicators other than an agent's capabilities. Song et al (2023b) evaluate agent *efficiency* by measuring the number of API calls required to execute an instruction successfully, emphasizing minimal resource usage during task execution. Zhang et al (2024b) incorporate a safeguard mechanism to seek user confirmation before executing critical actions (e.g., delete) to build a safer and more trustworthy agent. The *safeguard rate* measures how accurately the agent identifies sensitive actions and requests user confirmation.

7.4 Discussion

The task success rate measures an agent's effective performance, focusing on the proportion of tasks completed from start to finish. This metric is distinct from alternatives such as task progress, which measures how far an agent progresses on average, or step success rate, which tracks the accuracy of individual action predictions. While the task success rate can be measured reliably and reproducibly in a controlled environment, it is more challenging for an offline dataset. Measuring the *offline* task success rate, based on strict trajectory matching, underestimates the actual performance, providing a *lower bound*. This limitation arises because any deviation from the recorded trajectory, even if the deviation is a viable alternative, renders the entire trajectory incorrect. For instance, solving a task may require filling out form fields not only correctly but also in the exact (and potentially arbitrary) order captured in the dataset[9]. Online evaluation with human assessors offers a more accurate measure of the *true* task success rate, as only the task outcome is evaluated (Zheng et al, 2024a). However, this approach introduces reproducibility challenges. First, human evaluators are prone to human error (Reason, 1990). Second, the involvement of human evaluators incurs additional costs. Third, online evaluation may have to run on live systems, which could result in adverse consequences such as irreversible changes (e.g., data deletion). Despite these challenges, we suggest to use the task success rate as the primary metric for comparing agent performance on specific benchmarks. For offline datasets, it is essential to clarify whether the reported task success rate is derived from offline (trajectory matching) or online evaluation. When using online evaluation, the process should be thoroughly documented to ensure reproducibility.

8 Challenges for Deployment and Application

Current research in computer control agents focuses on enhancing their autonomous capabilities across various domains and benchmarks. However, deploying these agents in production introduces several additional challenges.

[9] Step-level metrics face similar issues, but the impact is less severe since alternative viable actions affect only specific action predictions without invalidating the entire trajectory.

8.1 Technical Challenges and Considerations

Challenges of a Production Setting

A production setting entails a specific environment, such as a business application, that the agent must be able to control. Thus, a CCA must be adapted to that production environment either through environment learning (see Section 5.2.2) or prompting (see Section 5.2.3). Foundation agents with prompting start with impressive out-of-the-box performance (e.g., Zheng et al (2024a) achieve 51.1% task success rate on Mind2Web (Deng et al, 2023)) but lack a practical way to improve performance to become production-ready. Environment learning techniques provide a path for such improvements but are often too costly, depending on many labeled demonstrations or a controlled environment. Effectively adapting an agent to a comprehensive production environment remains an open research question. Next to the specific environment, a production setting provides additional challenges like diverse user hardware, such as different screen resolutions or a multi-monitor setup, as well as different device configurations, including a wide range of Android distributions, home screen setups, or color schemes (Lee et al, 2024). Finally, a production environment is *non-stationary* as applications undergo continuous enhancement (Humble and Farley, 2011), changing their interfaces and behavior. A production-ready agent must be able to handle those everchanging circumstances, either autonomously or through continuous updates implemented by its developers.

Speed, Cost, and Availability

While current research primarily focuses on an agent's autonomous capabilities, practical deployment demands careful consideration of *prediction speed*, *operational costs*, and *availability*. Faster prediction time leads to less latency and a better user experience. Costs can be monetary through API calls to third-party foundation models or hardware considerations for local agents. In terms of potential monetary costs, solving a single task costs roughly $0.28 when assuming to use a state-of-the-art foundation model, processing 765 image tokens (high-resolution screenshot), 600 text tokens (agent prompt and user instruction), 1000 text output tokens (reasoning and action prediction), and 7 actions per task (as in Deng et al, 2023) and current API pricing (December 2024). Furthermore, reliance on external resources introduces dependencies that can impact availability, such as requiring a stable internet connection and the reliable operation of third-party services.

Privacy

While LLMs can run on local machines (Tuggener et al, 2024), many state-of-the-art models such as GPT-4V OpenAI et al (2024) are only available through an API. Agents relying on external resources, such as proprietary foundation models, introduce privacy concerns. Individuals and companies may be reluctant to send screenshots to an external server streamed over the internet. This raises similar data privacy challenges observed in other foundation model applications (Neel and Chang, 2024). However, a crucial difference emerges with agents: traditional user education on data-sharing practices becomes insufficient, as users cannot fully control an agent's access to information when it operates autonomously on their devices. For example, an agent in financial reporting might inadvertently open, observe, and thus transmit sensitive financial documents without the user's explicit consent and in contradiction to contractual or legal requirements.

8.2 Safety Considerations

Despite advances in autonomous agent development, current systems often lack the reliability and comprehensiveness required for safe real-world deployment. The consequences of an agent's unintentional, erroneous actions can differ depending on the domain, ranging from minor disruptions, such as playing the wrong music video, to more severe issues, like the unauthorized disclosure of confidential medical records. For production, the risk of erroneous actions must be balanced with the agent's capabilities and the benefits of automation. This balance can be achieved by adjusting design parameters: The agent's *level of autonomy* and the *scope of its deployment*.

Reducing Automation

Most CCA research is about *full automation*, meaning the agent is in control, and it is assumed no human is in the loop. To decrease the risk of erroneous actions, agents can operate in *conditional automation*, meaning the agent is in control, but it can hand back control to the user for critical actions. For example, Li et al (2024e) let their agent determine critical actions, such as validating payments. However, this approach still risks the agent overlooking critical actions, which can be avoided in use cases like payment by requiring external validation through a separate payment processing system inaccessible to the agent. In contrast, Wang et al (2023) also allows agent-initiated conversations, allowing them to solicit information. A further restriction would be running the agent in *partial automation*, meaning the human is in control and hands it to an agent only to fulfill a straightforward sub-task. For example, web browsers providing auto-fill functions for typical web forms can be considered partial, non-instruction-based computer control agents. An even further automation restriction is agents only *assisting* users, meaning the human stays in control the whole time while the agent provides only suggestions. This design is typical for non-instruction-based computer control agents like GitHub CoPilot[10] or Grammarly[11].

Managing the Scope of the Production Environment

To decrease the risk of erroneous actions, the scope of the production environment can be constrained. For a given use case, the action space $\mathcal{A}$ can be restricted by removing high-risk actions, such as disabling critical deletion operations. This can be achieved, for instance, by limiting the agent's file system permissions. Additionally, safety checks can be implemented to autonomously verify the feasibility and safety of actions prior to execution, effectively providing guardrails for the agent (Liang, 2023). Similarly, the state space $\mathcal{S}$ can be reduced to simplify the operational environment. For example, a web agent's access could be restricted to a predefined set of curated websites instead of

[10] https://github.com/features/copilot
[11] https://grammarly.com/

granting access to the entire web. In the context of personal computers, the operational domain could be narrowed to specific applications, such as those within an office productivity suite. These constraints not only limit the agent's potential behaviors but also simplify environment learning and enable more accurate assessments of the agent's capabilities.

8.3 Adapting Generally Capable Agents

Leading AI companies, such as Anthropic, have begun advancing into the realm of CCAs, offering generally capable, out-of-the-box solutions (Hu et al, 2024). However, we anticipate that truly *general* autonomous instruction-based CCAs – defined as those with capabilities, resilience, and safety comparable to highly skilled human computer users across most domains – are unlikely to emerge in the next two years, given the current state-of-the-art, for example, the unavailability of massive and challenging training data.

This projection highlights a critical research question: *How can generally capable agents be effectively adapted to address specific organizational use cases?* For example, enabling an agent to autonomously, safely, and reliably control a unique business application currently requires comprehensive customization. It involves tailoring pre-trained, capable agents to meet the precise needs of a given use case, warranting exposition to a lot of on-task training experience.

For pure text-based agents, the parallel challenge of adopting a generalist model to organizational needs and know-how is currently approached using retrieval-augmented generation (RAG) strategies, where foundation models are equipped with use-case-specific knowledge by grounding them in internal documents (Lewis et al, 2020). Similarly, the focus in adapting computer control agents would lie in achieving robust, organization-specific adaptation starting from a general-purpose, pre-trained agent – yet a similar process or framework has yet to be developed.

9 Conclusions

9.1 Summary

We provided a structured guide to the field of instruction-based computer control, categorizing 86 concrete CCAs along the way as examples for specific aspects of their design. Therefore, we provided a simple and effective taxonomy that enabled the first comprehensive overview of the whole field. Throughout our analysis, we identified several open research challenges and made key predictions for future advancements in the field that we summarize below:

Open Research Challenges

Efficient environment learning : In Section 5.2.2, we discussed strategies enabling agents to adapt to specific environments, such as reinforcement learning, behavioral cloning, and long-term memory. Each method has crucial challenges to overcome for efficient and safe deployment of agents in real-world scenarios, as we have pointed out in Section 8.

Planning : As discussed in Section 5.2.3, *explicit* planning remains underdeveloped in current CCAs despite its theoretical importance for achieving goal-oriented behavior. This gap represents a significant area for future research.

Optimal interaction interfaces : In Section 4, we examined observation and action spaces, pointing to the open questions whether bi-modal observations and execution through code provide tangible advantages.

Predictions for Future Development

Human-aligned observations and actions: We anticipate that image screen representations will emerge as the predominant form for observations due to their closer alignment with human perception and hence GUIs designed for humans. Furthermore, we foresee this will lead to screen coordinate-based mouse/touch actions becoming the predominant general-purpose interaction for CCAs, as these actions operate in pixel space.

Temporary role of set-of-mark prompting: We expect the reliance on set-of-mark prompting for grounding actions to diminish with advancements in foundation models. Training these models for direct coordinate prediction will likely render such approaches obsolete.

Recommendations on Evaluation and Benchmarking

We also examined 33 existing datasets and benchmarks used for training and evaluating CCAs. Current evaluation practices often rely on custom benchmarks or subsets of established ones, hindering reproducibility and cross-publication comparisons. To address this, we advocate for:

Standardized evaluation practices: The community should prioritize evaluating agents on all tasks of established, reproducible benchmarks to enable more robust comparisons of agent performance across studies. In the near future, more complex and standardized benchmarks will be needed, making room for an ImageNet moment (Krizhevsky et al, 2012) of the field.

Task success rate as a measure for agent capabilities: The task success rate quantifies the effectiveness of agents in solving tasks. It is critical to differentiate between offline and online task success rates, as these metrics respectively represent a lower bound of the agent's performance and its true capabilities. While supplementary metrics may provide insights into other aspects of agent behavior, they should be considered auxiliary and used in conjunction with the task success rate to ensure comparability between agents.

9.2 Discussion

CCAs are highly relevant both as an academic topic for research as well as industrially as emerging products. The task of automating computer control offers a challenging benchmark for AI progress beyond traditional simulated environments and holds the potential to automate various real-world computer tasks. The rise of foundation models has significantly advanced the capabilities of such agents, attracting increasing attention from researchers.

We anticipate the emergence of CCAs that deserve a designation as "personal AI assistants" by using the user's device starting from 2027. For their development, the huge potential of individual training experience by monitoring the user's own interaction with the device could be tapped into. This brings interesting challenges of privacy and, in privacy's service, distributed learning and trusted business models. This way, the CCA field could prove transformative for the tech industry itself as well as for regulatory approaches.

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A Structured Overview of Existing Work

For this review, we identified 86 CCAs and 33 datasets and categorized them according to the introduced taxonomy. Here, we present a detailed list of the identified literature and their classification.

A.1 Environment and Interaction Perspective

Table A1: Literature overview: Domain and interaction types. ✓ indicates the full presence of an aspect; (✓) indicates the presence of an aspect with variations; empty means the aspect is absent.

Paper	**Domain**	**Observation Space**							**Action Space**			
				Textual								
		Image	**Image to Textual**	**HTML**	**Android View Hierarchy**	**UI Automation Tree**	**Accessibility Tree**	**Indirect**	**Mouse Keyboard**	**Direct UI Access**	**Tailored**	**Executable Code**
Shaw et al (2023); Niu et al (2024); He et al (2024)	Web	✓							✓			
Pan et al (2024); Koh et al (2024b)	Web	✓								✓		
Iki and Aizawa (2022)	Web		✓						✓			
Lo et al (2023); Fereidouni and Siddique (2024); Guan et al (2023)	Web		✓							✓		
Cho et al (2024)	Web		✓						✓	✓		

Table A1 – continued from previous page

Paper	Domain	Observation Space							Action Space			
				Textual								
		Image	Image to Textual	HTML	Android View Hierarchy	UI Automation Tree	Accessibility Tree	Indirect	Mouse Keyboard	Direct UI Access	Tailored	Executable Code
Kim et al (2023); Li et al (2023); Liu et al (2018); Deng et al (2024b); Sodhi et al (2023); Gur et al (2019); Ma et al (2024a); Gur et al (2021); Jia et al (2019); Zheng et al (2024c); Li and Riva (2021); Murty et al (2024); Deng et al (2023); Gur et al (2023); Lutz et al (2024); Lai et al (2024)	Web			✓						✓		
Putta et al (2024); Xu et al (2021)	Web			✓							✓	
Furuta et al (2023); Sun et al (2023); Tao et al (2023); Gur et al (2024)	Web			✓								✓
Nakano et al (2022)	Web			✓						✓	✓	
Zaheer et al (2022)	Web			(✓)						✓		
Zhou et al (2024)	Web						✓			✓		
Zhang et al (2024e)	Web						✓			✓		✓
Humphreys et al (2022); Lin et al (2021); Shi et al (2017)	Web	✓		✓					✓			
Furuta et al (2024); Mazumder and Riva (2021); Lù et al (2024); Kil et al (2024); Zheng et al (2024a)	Web	✓		✓						✓		
Chae et al (2024)	Web			✓			✓			✓		

Table A1 – continued from previous page

Paper	Domain	Observation Space							Action Space			
				Textual								
		Image	Image to Textual	HTML	Android View Hierarchy	UI Automation Tree	Accessibility Tree	Indirect	Mouse Keyboard	Direct UI Access	Tailored	Executable Code
Wang et al (2024a); Zhang and Zhang (2024); Zhang et al (2024d); Lu et al (2024)	Android	✓							✓			
Wen et al (2024a); Sun et al (2022); Wu et al (2024b); Ding (2024); Li et al (2020a); Nong et al (2024)	Android	✓								✓		
Dorka et al (2024)	Android	✓							✓	✓		
Abukadah et al (2024); Song et al (2023a, 2024a); Li (2021); Ma et al (2024b)	Android		✓							✓		
Rawles et al (2023)	Android		✓						✓	✓		
Wen et al (2024b); Li et al (2020b)	Android				✓					✓		
Bishop et al (2024); Li et al (2024c)	Android						✓		✓			
Li et al (2024d); Lee et al (2023b)	Android						✓			✓		
Zhang et al (2023); Li et al (2024e)	Android	✓			✓					✓		
Wang et al (2023)	Android			(✓)	✓					✓		
Deng et al (2024a)	Android			(✓)	✓					✓		✓
Cheng et al (2024); Hong et al (2024)	Web, Android	✓							✓			
Lu et al (2024)	Web, Android		✓							✓		

Table A1 – continued from previous page

Paper	Domain	Observation Space							Action Space			
			Textual									
		Image	Image to Textual	HTML	Android View Hierarchy	UI Automation Tree	Accessibility Tree	Indirect	Mouse Keyboard	Direct UI Access	Tailored	Executable Code
Rahman et al (2024)	PC	✓							✓			
Gao et al (2024a)	PC	✓							✓			✓
Song et al (2024b)	PC	✓								✓		✓
Wang et al (2024d)	PC							✓			✓	
Wu et al (2024c); Guo et al (2024a)	PC							✓				✓
Zhang et al (2024b)	PC	✓				✓				✓	✓	
Bonatti et al (2024)	Web, PC	✓		✓		✓				✓	✓	✓
Yan et al (2023)	Android, iOS	✓								✓		
Song et al (2023b)	API							✓				✓

A.2 Agent Perspective

Table A2: Literature overview: Core agent design principles. PT = general pre-training; EL = environment learning; EI = episodic improvement; BC = behavioral cloning; RL = reinforcement learning; LTM = long-term memory; ✓ indicates the full presence of an aspect; (✓) indicates the presence of an aspect with variations; empty means the aspect is absent.

Paper	**Type**		**Policy**			**PT**		**EL**			**EI**		
	Foundation agent	**Specialized agent**	**Memoryless**	**History-based**	**State-based**	**Foundation model**	**Backbone**	**BC**	**RL**	**LTM**	**Instruction tuning**	**Few-shot**	**Planning**
Wang et al (2023)	✓		✓			✓					✓	✓	
Niu et al (2024)	✓		✓			✓					✓		✓
Ding (2024)	✓		✓			✓					✓		
Sun et al (2023); Lee et al (2023b)	✓		✓			✓				✓	✓	✓	✓
Tao et al (2023)	✓		✓			✓				✓	✓	✓	
Wu et al (2024c)	✓		✓			✓				✓	✓		
Nong et al (2024)	✓		✓			✓	✓				✓		✓
Kim et al (2023); Zhang et al (2024e); Zhou et al (2024); Sodhi et al (2023); Cho et al (2024); Koh et al (2024b); Deng et al (2024a)	✓			✓		✓					✓	✓	✓
Zheng et al (2024c); Bishop et al (2024)	✓			✓		✓					✓	✓	
Chae et al (2024); Song et al (2023b)	✓			✓		✓					✓		✓
Li et al (2023); Ma et al (2024a); Zheng et al (2024a); Wang et al (2024a); Wen et al (2024b); Cheng et al (2024); Wang et al (2024d); Guo et al (2024a)	✓			✓		✓					✓		

Table A2 – continued from previous page

Paper	Type		Policy			PT		EL			EI		
	Foundation agent	Specialized agent	Memoryless	History-based	State-based	Foundation model	Backbone	BC	RL	LTM	Instruction tuning	Demonstrations	Planning
Murty et al (2024); Deng et al (2023); Lù et al (2024); Zhang et al (2024d); Li et al (2024c)	✓			✓		✓		✓			✓	✓	
Lai et al (2024); Ma et al (2024b)	✓			✓		✓		✓			✓		
Deng et al (2024b); Lutz et al (2024); Wen et al (2024a); Li et al (2024e)	✓			✓		✓				✓	✓	✓	
Gao et al (2024a)	✓			✓		✓	✓				✓	✓	✓
Furuta et al (2023); Gur et al (2024)	✓			✓		✓	✓				✓	✓	
Guan et al (2023)	✓			✓		✓	✓				✓		✓
Song et al (2023a); Lu et al (2024)	✓			✓		✓	✓				✓		
Rawles et al (2023)	✓			✓		✓	✓	✓			✓	✓	✓
Song et al (2024a)	✓			✓		✓	✓			✓	✓	✓	
Pan et al (2024)	✓				✓	✓		✓			✓		
Zhang et al (2023)	✓				✓	✓				✓	✓	✓	
Zhang et al (2024b)	✓			✓	✓	✓					✓	✓	✓
Bonatti et al (2024)	✓			✓	✓	✓					✓		
Xu et al (2021)	(✓)		✓			✓							
Song et al (2024b)	(✓)		✓			✓		✓					✓
Abukadah et al (2024)	(✓)		✓			✓	✓	✓					
Zhang and Zhang (2024)	(✓)			✓		✓		✓					✓
Gur et al (2023); He et al (2024); Wu et al (2024b); Lu et al (2024); Hong et al (2024); Rahman et al (2024)	(✓)			✓		✓		✓					
Putta et al (2024)	(✓)			✓		✓			✓				✓

Table A2 – continued from previous page

Paper	Type		Policy			PT		EL			EI		
	Foundation agent	Specialized agent	Memoryless	History-based	State-based	Foundation model	Backbone	BC	RL	LTM	Instruction tuning	Demonstrations	Planning
Lo et al (2023)	(✓)			✓		✓				✓			
Nakano et al (2022); Fereidouni and Siddique (2024)	(✓)			✓		✓		✓	✓				
Furuta et al (2024); Kil et al (2024); Dorka et al (2024)	(✓)			✓		✓	✓	✓					
Liu et al (2018)		✓	✓										
Zaheer et al (2022); Li et al (2020a,b)		✓	✓					✓					
Gur et al (2019, 2021); Jia et al (2019); Li and Riva (2021)		✓	✓						✓				
Shi et al (2017); Li (2021)		✓	✓					✓	✓				
Mazumder and Riva (2021)		✓	✓				✓						
Li et al (2024d)		✓	✓				✓	✓					
Shaw et al (2023)		✓	✓				✓	✓	✓				
Lin et al (2021); Sun et al (2022)		✓		✓				✓					
Yan et al (2023)		✓		✓				✓		✓			
Humphreys et al (2022)		✓			✓			✓	✓				
Iki and Aizawa (2022)		✓		✓	✓		✓	✓					

A.3 Datasets

Table A3: Literature overview: datasets

Paper	**Domain**	**Type**		**OS**		**AS**			
		Controlled Environment	**Offline Dataset**	**Image**	**Textual**	**Mouse**	**Direct**	**Tailored**	**Code**
Established benchmarks									
MiniWoB (Shi et al, 2017)	Web	✓		✓	✓	✓			
MiniWoB++ (Liu et al, 2018)	Web	✓			✓		✓		
WebShop (Yao et al, 2022)	Web	✓	✓		✓		✓	✓	
Mind2Web (Deng et al, 2023)	Web		✓		✓	✓			
WebArena (Zhou et al, 2024)	Web		✓	✓	✓	✓			
VisualWebArena (Koh et al, 2024a)	Web		✓	✓	✓		✓		
PixelHelp (Li et al, 2020b)	Android		✓	✓	✓	✓	✓		
AndroidEnv (Toyama et al, 2021)	Android	✓			✓		✓		
MoTIF (Burns et al, 2022)	Android		✓	✓	✓	✓			
Android in the Wild (Rawles et al, 2023)	Android		✓	✓		✓			
AgentBench (Liu et al, 2023b)	PC	✓						✓	
OmniACT (Kapoor et al, 2024)	PC		✓	✓	✓	✓			
Other datasets									
RUSS (Xu et al, 2021)	Web	✓	✓		✓		✓		
gMiniWoB (Gur et al, 2021)	Web	✓		✓	✓		✓		
WebVLN (Chen et al, 2024b)	Web		✓	✓	✓		✓		
MT-Mind2Web (Deng et al, 2024b)	Web	✓			✓		✓		
WorkArena (Drouin et al, 2024)	Web		✓	✓	✓	✓	✓		
AutoWebBench (Lai et al, 2024)	Web		✓	✓	✓		✓		
QBE-F-Droid (Koroglu et al, 2018)	Android		✓		✓		✓		

Table A3 – continued from previous page

Paper	Domain	Type		OS		AS			
		Controlled Environment	Offline Dataset	Image	Textual	Mouse	Direct	Tailored	Code
AppBuddy (Shvo et al, 2021)	Android	✓			✓		✓		
Meta-GUI (Sun et al, 2022)	Android		✓	✓	✓		✓		
UGIF (Venkatesh et al, 2023)	Android		✓	✓	✓		✓		
Mobile-Env (Zhang et al, 2024c)	Android		✓	✓	✓	✓			
DroidTask (Wen et al, 2023)	Android		✓	✓			✓		
Android in the zoo (Zhang et al, 2024d)	Android		✓	✓			✓		
GUIAct (Chen et al, 2024c)	Android		✓	✓			✓		
AssistGUI (Gao et al, 2024a)	PC		✓	✓	✓	✓			
ScreenAgent (Niu et al, 2024)	PC	✓		✓		✓			
OSWorld (Xie et al, 2024)	PC		✓	✓	✓	✓			
AgentStudio (Zheng et al, 2024b)	PC		✓			✓			✓
PPTC (Guo et al, 2024a)	PC		✓		✓				✓
RestBench (Song et al, 2023b)	API		✓						✓
GUI-World (Chen et al, 2024a)	Multi		✓	✓		✓			