

# Explore, Select, Derive, and Recall: Augmenting LLM with Human-like Memory for Mobile Task Automation

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## Abstract

The advent of large language models (LLMs) has opened up new opportunities in the field of mobile task automation. Their superior language understanding and reasoning capabilities allow users to automate complex and repetitive tasks. However, due to the inherent unreliability and high operational cost of LLMs, their practical applicability is quite limited. To address these issues, this paper introduces MobileGPT<sup>1</sup>, an innovative LLM-based mobile task automator equipped with a human-like app memory. MobileGPT emulates the cognitive process of humans interacting with a mobile app—explore, select, derive, and recall. This approach allows for a more precise and efficient learning of a task’s procedure by breaking it down into smaller, modular sub-tasks that can be re-used, re-arranged, and adapted for various objectives. We implement MobileGPT using online LLMs services (GPT-3.5 and GPT-4) and evaluate its performance on a dataset of 160 user instructions across 8 widely used mobile apps. The results indicate that MobileGPT can automate and learn *new* tasks with 82.5% accuracy, and is able to adapt them to different contexts with near perfect (98.75%) accuracy while reducing both latency and cost by 62.5% and 68.8%, respectively, compared to the GPT-4 powered baseline.

## 1 Introduction

Today, we rely on a whole universe of mobile apps to handle tasks integral to our daily lives, ranging from communication to home security. Consequently, the demand for efficient task automation in the mobile environment has intensified, seeking to alleviate digital fatigue stemming from repetitive

and complex digital interactions that often overwhelm many users today [9, 14].

Unsurprisingly, numerous methods have been explored to achieve task automation. API-based approaches like Siri [2] and Google Assistant [12] allow users to interact with a mobile app’s specific functionality through natural language conversation. However, these approaches demand significant coding efforts from developers, who must manually create new logic for each task. Demonstration-based methods [22, 26, 27, 29] empower end-users to program custom automation scripts. Yet, due to their heavy reliance on human demonstrations, they face scalability challenges. Similarly, learning-based approaches [17, 25, 30, 59, 60] require extensive collections of human-annotated datasets, hampering the widespread application.

Recently, LLM-based task automators [39, 44, 55, 66, 69], equipped with high reasoning and generalization abilities [1, 37, 41], have been a game-changer. They enable task automation to be fully autonomous and generally applicable, sidestepping the labor-intensive manual development, demonstration, and training that previous methods required. However, this approach also comes with its own limitations. First, the inherent non-deterministic and unpredictable nature of LLMs can undermine the reliability and consistency of task automation. This is critical in mobile environments as many mobile tasks nowadays involve sensitive and private information. Second, LLMs are costly, both in terms of budget and time. We observed that tasks that would take just over 30 seconds for a human could take more than two minutes for an LLM, and cost over a dollar each time they are performed.

<sup>1</sup>The system is available at: <https://mobile-gpt.github.io/>

To overcome the limitations of previous approaches, we introduce MobileGPT, an innovative LLM-based mobile task automator augmented with an app memory capable of learning and recalling mobile tasks. MobileGPT is designed to accomplish following design goals: *i) Accurate and Consistent*: it should perform tasks with high accuracy and consistency, ensuring that once a task is learned, it can be faithfully reproduced. *ii) Adaptability*: When revisiting a task, it should dynamically adjust its execution in response to varying contexts, rather than blindly replicating the previous executions. *iii) Efficiency*: MobileGPT seeks to significantly reduce the cost and time involved in task automation, especially for tasks that are performed repeatedly.

In designing MobileGPT, we drew inspiration from how humans decompose complex tasks into smaller sub-tasks to effectively learn and recall tasks [7, 8, 19, 35]. Specifically, consider how humans learn new tasks using mobile apps: given an app screen, we first **1) explore** the candidate sub-tasks by analyzing screen interfaces and identifying their functionalities. Then, we **2) select** the most promising sub-task that can bring closer to the goal. Lastly, we **3) derive** and execute the primitive actions required to complete the chosen sub-task—low-level actions such as clicking, inputting text, or scrolling. Once we have completed the task by repeating these 3 steps, it becomes part of our memory, allowing for easy **4) recall** and repetition of not only the task itself but also its involved *sub-tasks*. For example, assume you have learned how to *"Send a message to Bob."* Having learned this, not only can you easily adapt this knowledge to similar instructions like *"Send a message to Alice,"* but also can apply it to execute new tasks such as *"Open chat with John."* This inherent human ability stems from our tendency to break down tasks into smaller *sub-tasks* and encapsulate them in a modular, reusable format.

This human capacity to learn and recall memories at the unit of sub-tasks is what we aim to replicate with MobileGPT. To achieve this, we address three key challenges: *i) Accurate and reliable task execution*: To ensure accurate task execution and memory construction, we employ several prompting techniques to improve LLMs' accuracy and provide mechanisms for users to correct errors in case LLMs make mistakes. *ii) Efficient memory storage*: To facilitate the reuse of sub-tasks, MobileGPT efficiently stores task information in a hierarchical memory structure, in which tasks are decomposed into multiple sub-tasks and each sub-task is further decomposed into a sequence of primitive actions. *iii) Flexible memory retrieval*: To ensure robust and cost-effective task automation in the dynamic landscape of mobile interfaces, MobileGPT leverages pattern matching and in-context learning techniques to flexibly adapt past executions to varying contexts and interface changes.

We have implemented a prototype of MobileGPT using online LLM services (GPT-3.5 and GPT-4). To evaluate its performance, we build a new benchmark dataset. The dataset covers 80 high-level tasks across 8 popular mobile apps, with each task accompanied by two different user instructions—totaling *160 user instructions*. The evaluation shows that MobileGPT achieves a task completion rate of 82.5% when executing new tasks and a near-perfect (98.75%) success rate in applying learned tasks to a new instruction. Moreover, it achieves a 62.5% reduction in task completion time and a 68.8% decrease in LLM query costs when recalling learned tasks, compared to the GPT-4 powered baseline. A usability study with 23 participants demonstrates that MobileGPT's human-in-the-loop memory repair system enables users to interact intuitively with the task automator, allowing them to repair and collaboratively build upon the task automation process.

## 2 System Overview

### 2.1 System Workflow

MobileGPT operates on a cycle of *Explore-Select-Derive* phases, akin to human cognitive learning processes, to execute and learn new mobile tasks. This section gives a high-level overview of the system's workflow (Figure 1).

**Explore.** Prior to performing any tasks, MobileGPT undertakes multiple *explore* operations offline to pre-emptively collect and organize the functionalities of the app. To achieve this, MobileGPT employs two software tools—random explorer [60] and user trace monitor [11]—to visit and analyze as many app screens as it can during the offline stage. For each screen it visits, MobileGPT asks the LLM to generate a list of sub-tasks available on the screen. This generated list is cached into memory to be used during the select phase upon receiving user instructions. App screens that have not been explored offline are analyzed on demand during the task execution.

**Select.** When a user issues a voice instruction, MobileGPT retrieves the list of sub-tasks associated with the current screen from the memory. Then, it asks LLM which sub-task to perform in order to complete the user instruction. The selected sub-task is carried on to the Derive phase to be translated into a sequence of low-level actions.

**Derive.** In the Derive phase, MobileGPT prompts the LLM with a pre-defined set of low-level action (e.g., click, input, or scroll), and asks it to pick an action needed to accomplish the chosen sub-task. The action is then dispatched to the mobile device to be executed within the app. This phase is repeated until the app navigates to the next page, or the LLM explicitly indicates that the sub-task is completed.

Upon finishing a sub-task, the system returns to the Select phase and selects the next sub-task to execute. This iterative

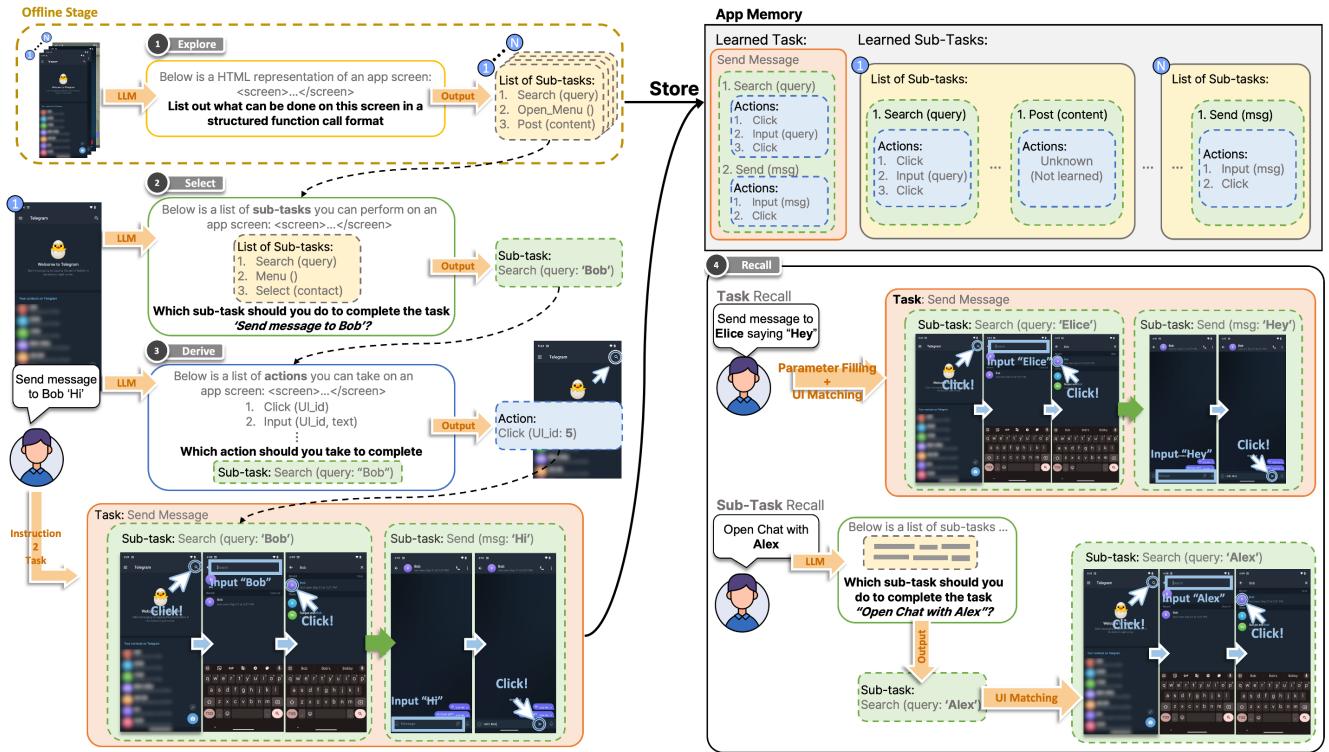


Figure 1: MobileGPT workflow and system overview

process is continued until the Select phase indicates that the user's instruction has been fully executed. Then, the instruction is translated into a high-level task (e.g., *"send a message to Bob"* to *"send message"*) and saved in the memory in a hierarchical format, as illustrated in Figure 1.

**Recall.** When the system is given an instruction while its memory is not empty, it checks if the instruction matches any previously learned task by comparing the instruction's high-level task representation with those stored in its memory. If a match is found, it executes the instruction directly from the memory. If no match is found, MobileGPT cycles through Explore, Select, Derive to learn the new task. However, if the new task involves any known *sub-tasks*, MobileGPT can still reproduce them, akin to how humans transfer knowledge from one task to another. This facilitates faster execution and learning of new tasks.

## 2.2 System Design

To enable the workflow above, MobileGPT addresses the following challenges:

- C1. How to *accurately and reliably execute* a task in the first try?
- C2. How to *efficiently store* task executions?
- C3. How to *flexibly recall* past task execution?

**C1.** The first step towards learning a task is to correctly execute it the first time. MobileGPT executes unknown tasks by leveraging multiple LLM queries to iterate through phases of Explore, Select, and Derive. However, given the complexity of mobile tasks and the unpredictability of LLMs, we cannot guarantee the complete accuracy of these executions. For instance, when instructed to *"find 5-star hotels,"* LLMs may simply type *"5-star hotel"* in the search field, whereas the expected behavior is to click the *'5-star'* filter option. Therefore, to address this inherent non-determinism and the unreliability of LLMs, MobileGPT employs a dual-strategy correction mechanism which allows both the LLM and the user to fix errors in the execution process.

**C2.** In many cases, tasks are not entirely independent of each other; many tasks share common sub-tasks. For instance, *'Send a message to Bob'* and *'Open chat with Bob'* both involve the sub-task of locating Bob's contact information. If the execution procedures of the two tasks are stored separately at the task level, the sub-task they perform in common should be trained redundantly. This causes unnecessary costs in terms of training budget and latency. To minimize such inefficiency, MobileGPT employs a three-level hierarchical memory structure: *tasks, sub-tasks, and actions*. This hierarchy enables MobileGPT to access memory at the

sub-task level, facilitating the sharing of past execution experience across different tasks (more details in Section 4.1).

**C3.** Even when repeating the same task or sub-task, the specifics of each step may vary depending on the context of execution. For example, searching for a contact in the context of "Send a message to Bob" involves entering and clicking "Bob" in the search page, whereas "Send a message to John" requires searching for "John" instead. Therefore, instead of blindly replicating past actions, MobileGPT flexibly adapts its past executions to accommodate not only the intricate parameters of the task but also changes in screen content. In addition, in case direct adaptation falls short, MobileGPT leverages the few-shot learning capability of LLMs to guide them in generating responses that are both consistent and deterministic throughout multiple trials of the task (more details in Section 5).

### 3 Accurate and Reliable Task Execution

LLMs have been reported to solve complex tasks more accurately by breaking them down into smaller sub-tasks [63, 65]. MobileGPT adopts this strategy by hierarchically decomposing tasks into sub-tasks according to the Explore-Select-Derive phases. This section outlines how MobileGPT effectively navigates each of these phases, while also addressing the challenges posed by the inherent unreliability of LLMs. For clarity, this section describes each phase under the assumption that MobileGPT's memory is empty.

#### 3.1 Prompting Mobile Screen to LLM

The initial step in applying LLMs for mobile tasks involves converting mobile screens into text representation. Drawing upon previous research [61] showing that LLMs comprehend Graphical User Interfaces (GUIs) better when presented in HTML format, we convert mobile screens into a simplified HTML representation.

We begin by extracting the screen's layout information using Android Accessibility Service [11]. This information includes a hierarchical relationship between UI elements and various attributes (e.g., class\_name, text, descriptions) and properties (e.g., clickable, editable) that describe the functionality and appearance of the UI. Then, to make the layout succinct, we prune UI elements that are neither interactive nor carry significant semantic attributes (e.g., empty layout container). Next, we map each remaining UI element into an HTML element, where the UI's text and description attributes serve as the content of the HTML element, and the UI's interactive property is translated into the corresponding HTML tag. For instance, the '`<button>`' tag is used for clickable UIs, '`<input>`' for editable UIs, '`<scroll>`' for scrollable UIs, and so on. Lastly, we assign each HTML element with a unique index number, which serves as a communication link between MobileGPT and LLMs to specifically refer to and

interact with each element on the screen. This process not only ensures a cleaner, more relevant representation of app screens but also significantly reduces the number of tokens by an average of 84.6%. Throughout this paper, we will refer to this HTML representation of an app screen as the "*screen representation*".

#### 3.2 Explore, Select, and Derive

We generate the screen representation every time there is a change in the screen. This screen representation is then used throughout the process of the Explore, Select, and Derive phases.

**Explore.** The goal of the *explore* phase is to generate a list of actionable sub-tasks for a given screen. Each sub-task represents an individual operation or functionality that the screen provides. To accomplish this, MobileGPT prompts the LLM with the screen representation and asks it to enumerate sub-tasks in a structured function call format with the following information included: 1) sub-task name and description, 2) parameter names and descriptions, and 3) index of relevant UI elements. For example, possible sub-tasks for Telegram's initial app screen (Figure 1) include:

- 
1. { name: "Search", desc: "Search for a contact", params: { "query": "who are you looking for?" }, UI\_index: 3 }
  2. { name: "Open\_Menu", desc: "Open menu", params: {}, UI\_index: 7 }
- 

Note that, unlike other phases, the explore phase operates independently of user instructions. Hence, we conduct this phase *offline*, before performing the user's designated task. We use tools like autonomous random explorer [60], which performs random UI actions to navigate through app screens, and user trace monitor [11], which tracks users' app usage in the background. These tools allow for the proactive collection of sub-tasks related to each app screen. While the current implementation of MobileGPT conducts this offline phase locally on the user's device, it could be offloaded to a server to enhance efficiency.

**Select.** During the *select* phase, MobileGPT's select agent prompts the LLM with *i*) the user instruction, *ii*) the current screen representation, and *iii*) a list of available sub-tasks. The list includes both the sub-tasks identified during the *explore* phase and a predefined set of global sub-tasks common to all screens such as 'Read\_Screen' for answering the user's question based on the current screen content and 'Finish' for indicating task completion. The LLM then picks the sub-task most pertinent to the instruction and fills in its required parameters. For instance, given the instruction "Send a message to Bob", the output of the first select phase would be:

- 
- { name: "Search", description: "Search for a contact", parameters: { "query": "Bob" }, UI\_index: 3 }
- 

When parameter values are unknown, MobileGPT asks the user for the missing information. This allows for interactive

communication between the user and the system, enabling task automation even when the user’s instruction is not entirely clear.

After a sub-task has been selected and its parameters filled, MobileGPT checks if the sub-task has already been learned (i.e., present in the memory) in the context of another task. If the sub-task is known, MobileGPT executes the sub-task directly from the memory, bypassing the Derive phase. Otherwise, it proceeds to the Derive phase.

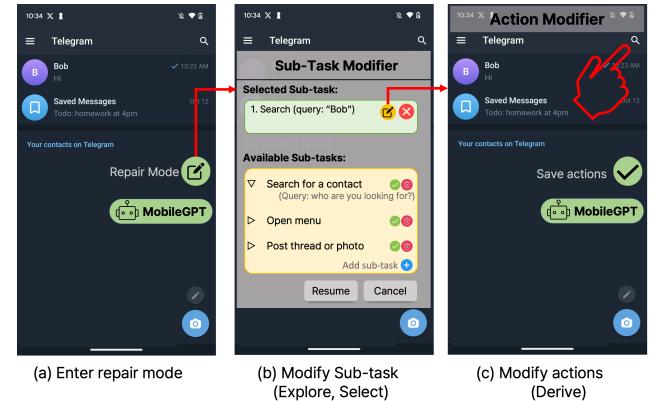
**Derive.** During the *derive* phase, MobileGPT incrementally derives and executes low-level actions to accomplish the sub-task selected during the *select* phase. Specifically, MobileGPT prompts the LLM with *i*) the sub-task to execute, *ii*) the current screen representation, and *iii*) a pre-defined list of low-level actions—click, input, scroll, long-click—. Then, the LLM selects one of the actions from the list along with the index of the target UI element on which the action needs to be performed. For instance, if the index of the search button is 5, the output of the first *derive* action for the sub-task ‘Search’ would be *click(ui\_index=5)*. The action is then dispatched to the mobile device to be executed within the app. MobileGPT repeats this process until there is a transition in the app screen or the LLM explicitly indicates that the sub-task is completed. Afterward, MobileGPT returns to the Select phase to choose the next sub-task, and alternates between the Select and Derive phases until it fulfills the user’s instruction.

### 3.3 Dual Strategy Failure Handling

Despite their high reasoning abilities, LLMs sometimes show inconsistent and erroneous behavior. To address this, MobileGPT employs a dual-strategy correction mechanism.

**Self-Correcting through feedback generation.** Previous studies [13, 36] indicate that language models can self-correct when given appropriate feedback. To facilitate this in MobileGPT, we have heuristically identified two main types of commonly occurring errors and developed a rule-based self-feedback generation module. Upon detecting an error, MobileGPT generates appropriate feedback and appends it at the end of the next prompt to guide LLMs in refining its approach and self-correcting the ongoing execution.

The first type of error occurs when the LLM incorrectly attempts to interact with the UIs. Feedback for this error includes: “*There is no UI with index i*” and “*The UI is not (clickable)*.” These errors can be easily detected as they result in a failure when executing the action. The second type of error is when LLM gets stuck in a loop. For example, endlessly scrolling through a YouTube video list or trying to scroll when already at the bottom of a list. Feedback for this error include: “*There is no change in the screen. Try another approach*” and “*You have looped the same screens X times*.



**Figure 2: Illustration of HITL task repair mechanism**

*Consider trying another approach.* These errors can be detected by monitoring the screen changes and tracking the visited app screens.

**Human-in-the-loop (HITL) task repair.** In case self-correction falls short, MobileGPT provides mechanisms for users to correct the LLMs’ mistakes themselves. In MobileGPT, there are three major points of potential LLM failure: Explore, Select, and Derive. *i*) *Explore* fails when sub-tasks are missing from the list of available sub-tasks, *ii*) *Select* fails when the LLM chooses incorrect sub-tasks or inputs wrong parameters, and *iii*) *Derive* fails when incorrect actions are derived and executed. MobileGPT provides specific repair mechanisms for each failure type<sup>2</sup>.

As illustrated in Figure 2, users can enter the repair mode anytime during the task execution by clicking on the MobileGPT’s floating button. Upon entering the repair mode, MobileGPT pauses its execution and hands control over to the user. The user can then perform repairs directly on the current screen or navigate back to previous screens to re-do mistakes made by MobileGPT. Note that certain critical actions, such as sending a message or deleting a contact, cannot be undone. In such cases, users would have to manually restore the app to its original state. Upon identifying the screen needing repair, users can *i*) add or remove sub-tasks from the list of available sub-tasks (Explore), *ii*) change the selected sub-task and its parameters (Select), or *iii*) edit the actions involved in the sub-task by demonstrating a sequence of actions, similar to the programming by demonstration techniques (Derive). Additionally, MobileGPT assists users in locating the point of repair by providing a detailed visual summary of the task execution both in terms of sub-tasks and actions. This allows users to pinpoint the failure point even if they were not closely monitoring the execution.

<sup>2</sup>see <https://youtu.be/Q-mg4ocpZy0> for demo video.

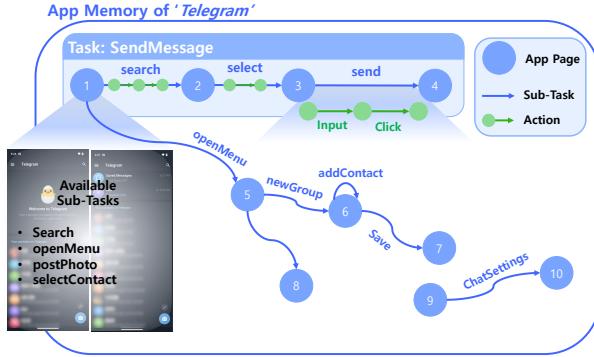


Figure 3: Transition graph of the app ‘Telegram’

A key advantage of MobileGPT’s HITAL repair is that users can return control back to the MobileGPT after fixing an error. This seamless transition requires a mutual understanding between the users and the LLMs, so that LLMs can recognize the corrections made and refine their approach accordingly. MobileGPT’s design—organizing tasks as a sequence of sub-tasks rather than low-level actions—plays a pivotal role. The natural language descriptions of sub-tasks not only help in delivering the LLM’s current progress to the user but also effectively capture the users’ intentions behind their repair. For example, when the user corrects actions involved the sub-task ‘Search’, the correction is encapsulated in a feedback “User repaired how to: Search for a contact” and delivered to the LLM. This feedback enables the LLM to grasp the intent behind the user’s demonstration and proceed accordingly. Without such contextual information, LLMs could repeat the same error or actions already performed by the user.

## 4 Hierarchical App Memory

MobileGPT’s memory architecture is designed to accumulate knowledge about the app as a whole, not just the tasks themselves. This resembles how humans get familiar with an app—the more a person uses the app, the more familiar they become with it. This section outlines how MobileGPT systematically archives the results of the Explore, Select, and Derive phases, and utilizes them for future task executions.

### 4.1 Memory Structure

MobileGPT organizes its memory in the form of a transition graph that encapsulates the following key information: i) available sub-tasks for each app screen(*Explore*), ii) sequence of sub-tasks involved in each task (*Select*), and iii) how to perform each sub-task (*Derive*). Figure 3 illustrates an example of this graph for the app ‘Telegram’.

**Node.** Each node in the transition graph symbolizes an app page—a particular state within an app that offers a unique set of functionalities (i.e., sub-tasks). Figure 4 illustrates examples of app pages; Screens with different visual appearances

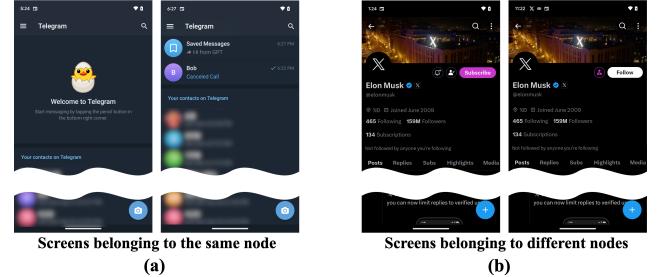


Figure 4: Examples of app pages: Screens in (a) belong to the same app page because they provide the same functionalities. Screens in (b) belong to different app pages because they provide different functionalities (the left is for ‘Subscribe’ but the right is for ‘Follow’).

can belong to the same page (Figure 4 a), while screens that look similar (Figure 4 b) could belong to different pages, depending on their functionalities.

To this end, MobileGPT uses a list of sub-tasks to represent each page node, categorizing screens that share the same list of sub-tasks as the same node (e.g., node 1 in Figure 3). This facilitates the sharing of sub-task knowledge across a wider variation of app screens, ensuring that a sub-task learned on one screen can be applied to another, even if the two screens do not look exactly alike. For example, once MobileGPT learns how to ‘Follow’ in Elon Musk’s profile page, it can use the same knowledge to ‘Follow’ Mark Zuckerberg.

**Edge.** Transitions between nodes are defined by sub-tasks, where each sub-task consists of a sequence of primitive actions that outline the steps for executing the sub-task. This hierarchical structure enables MobileGPT to efficiently reproduce learned sub-tasks by following the sequence of actions involved. MobileGPT establishes a new edge as it iterates through the Derive phase to execute previously unknown sub-tasks. Note that, these sub-task edges are not unique to individual screens but are shared across all screens within the same node.

**Task.** After MobileGPT successfully completes the user instruction, it stores the task as a collection of node and sub-task pairs. This representation effectively indicates which sub-task needs to be executed on which page. Consequently, MobileGPT can bypass all three phases of learning—Explore, Select, and Derive when executing previously learned tasks. Additionally, it facilitates state-agnostic task execution; Regardless of which app page the app is currently on, MobileGPT can find which sub-task to execute.

### 4.2 Sub-task based Screen classification

Since an app page (i.e., a node) is a group of app screens that share the same list of sub-tasks, our memory architecture requires an accurate classification of app screens based on

their functionalities. However, traditional screen classification methods [28, 68] are not suitable for this, as they focus primarily on the screen’s appearance, rather than its specific functionality.

A brute-force approach to classify screens by their sub-tasks would be to run the Explore phase (i.e., extract a list of available sub-tasks) each time we encounter a new screen and fuzzy match with those in the memory. However, this would incur significant overhead and cost both during the offline Explore phase and the actual task execution. Therefore, MobileGPT introduces a lighter approach to a sub-task-based screen classification: instead of checking if a screen *has* the same list of sub-tasks, it verifies if the screen can *perform* those sub-tasks.

To achieve this, MobileGPT documents the key UI elements needed to carry out each of the sub-tasks identified during the Explore phase (see Section 3.2). These UI elements serve as requirements for performing a specific sub-task. For example, the key element for the following sub-task ‘Search’:

---

```
{ name: "Search", desc: "Search for a contact", params: [...], UI_index: 3 }
```

---

would be the search button:

---

```
<button UI_index=3 id="search_button" description="Search"/>
```

---

Then, each time MobileGPT arrives at a new screen, it verifies if the current screen includes key UI elements required by each sub-task. Specifically, we check if the screen representation has a UI that matches the attributes (e.g., ui\_id, description, and class\_name) of the key UI elements. If the screen representation has matching UIs for all of the node’s sub-tasks, we categorize the screen under that node.

If no matching node is found, MobileGPT undergoes the Explore phase with the current screen representation. However, before creating a new node, MobileGPT calculates the cosine similarity between the screen’s newly generated sub-tasks and those of existing nodes to ensure that no existing node has the same list of sub-tasks. If a match is found, we map the screen to the node and update its sub-task information without creating a new node. This double-check process minimizes the creation of redundant nodes, preventing already established sub-task edges from becoming obsolete.

In our evaluation, where MobileGPT encountered and classified 269 app screens, this method showed only 3 false positives (misclassifying different app pages as the same node) and no false negatives (failing to find the correct page node). The result is significantly better compared to existing SotA text-based [28] and vision-based [68] screen classification methods, which had 38, and 57 false positives, and 14, and 28 false negatives, respectively.

## 5 Flexible Task Recall

When recalling tasks or sub-tasks, the specific details of each action should be adjusted to the current context of its execution. To address this, MobileGPT employs the attribute-based pattern matching and LLM’s few-shot learning capability [5] to adjust and reproduce actions flexibly and accurately.

### 5.1 Attribute-based Action Adaptation.

There are two cases where we need to adjust the action. The first case is when a task parameter changes. For instance, if the user instruction changes from “Send a message to Bob” to “Send a message to Alice”, we need to search and click for “Alice” instead of “Bob”. The second case is when there is an alteration in the screen’s content. For example, in a contact page, the hierarchical position of a specific contact (i.e., index of the UI) may change if contacts are added or removed. To effectively handle both scenarios, MobileGPT generalizes and adapts actions to both the parameters and the screen contents.

**Generalizing Actions.** When learning a new sub-task, MobileGPT stores actions in a generalized format to ensure that they are reusable across different contexts. This involves two steps: Screen Generalization and Parameter Generalization. For a given action (e.g., `click (ui_index=5)`), MobileGPT first generalizes it against the current screen representation by locating the target UI and recording its key attributes (e.g., id, text, description). Then, each key attributes are generalized further against the task parameters by comparing their values with the current sub-task’s parameter values. If a match is found, the attribute’s value is replaced with the corresponding parameter’s name. For example, given a sub-task `select(contact_name: "Bob")` and a screen representation:

---

```
<!-- Contact list-->
<button index=5 id="contact" text="Bob"/>
<button index=6 id="contact" text="Alice"/>
```

---

the action ‘`click (ui_index=5)`’ gets generalized as follows:

---

```
click(ui_index=5) → 1. click(id:"contact", text: "Bob")
                           → 2. click(id:"contact", text:[contact_name])
```

---

Consequently, the next time we perform the sub-task ‘`select`’, MobileGPT can adjust the action to click any other contact.

**Adapting Actions.** When recalling the whole task, MobileGPT simply replays the given sequence of sub-tasks, bypassing all Explore, Select, and Derive phases. Yet, we still need to fill in the parameters for each sub-task. To do so, before executing each sub-task, MobileGPT queries LLM to slot-fill parameters based on the user instruction and the current screen representation. Similar to the Select phase, if parameter values are unknown (e.g., missing from the instruction), MobileGPT asks the user for the information.

To adapt an action to a new context, we simply reverse the aforementioned two generalization steps based on the

given sub-task parameters and the screen representation. Specifically, MobileGPT substitutes parameter names in the target UI’s attributes fields with the actual values and identifies the UI element that matches these updated attributes. For example, in the sub-task ‘`select(contact_name: "Alice")`’, the action for clicking a contact gets modified as follows:

---

```
click(id:"contact", text:"[contact_name]")
→ 1. click(id:"contact", text: "Alice") → 2. click(ui_index=5)
```

---

This two-step generalization and adaptation technique allows us to correctly locate the target UI in response to the change in the task parameters and screen.

**Benefits.** One advantage of using *sub-task parameters* for the action adaptation lies in its ability to handle ambiguities and incompleteness often found in real-world user instructions. A prior work [26], which generalizes actions based on the words in the instruction, finds it difficult to handle incomplete instructions like “*Send a message to Bob*,” where the message content is missing, and implicit instructions like “*Call the first contact from the recent call*,” where the contact name isn’t explicitly stated. These types of instructions lack key information needed for direct action generalization.

On the other hand, MobileGPT effectively addresses this challenge by proactively asking for and deriving information required to perform the task incrementally, at the sub-task level. For aforementioned examples, before performing the sub-task `send(message_content)`, it asks the user for the missing message content, and before performing the sub-task `call(contact_name)`, it fills in the contact name autonomously by looking at the recent call list. This allows MobileGPT to generalize and adapt tasks even if the user instruction is not entirely clear.

## 5.2 In-context Action Adaptation

The attribute-based adaptation method is not a one-size-fits-all solution, as several factors can lead to failure. First, the target UI may not include any key attributes for generalization. Second, multiple UIs could share the same attributes. Third, UIs may change unexpectedly with app updates.

Therefore, when the attribute-based adaptation fails, we resort to LLM to re-derive the action once again. However, LLMs are inherently non-deterministic. This means there is no guarantee they will replicate a previously correct action. Worse yet, if the LLM had made a mistake in the past, it has a high probability of repeating the same error.

To address this issue, we leverage the few-shot learning capability of the LLM [5, 65] to produce more accurate and reliable responses. When querying the LLM, we present it with an example of how the action (i.e., one that rule-based adaptation failed) has been derived in the past. Specifically, the example includes a prior user instruction, an abbreviated version of the past screen representation, and its correct

output. Notably, the output in the example could either be an action originally generated by the LLM during the Derive phase or one that has been modified by the user through the HITL task repair. In any case, the provided example always demonstrates a successful result. By providing such examples, we effectively guide the LLM to produce consistent responses based on its memory. Moreover, if the example action is one that has been corrected by the user, it helps LLM to not repeat the same mistakes it has committed previously.

## 6 Implementation

**LLM Agents.** MobileGPT employs multiple LLM agents to cycle through the Explore, Select, Derive, and Recall phases. Each agent is equipped with a model tailored to its specific operational requirements. For Explore, Select, and Derive agents, which involve mobile screen understanding and multi-step reasoning, we used the most capable GPT-4 language model. For translating user instructions to the high-level task representation and slot-filling parameters, we opted for the faster and more economical GPT-3.5 Turbo model.

**App Launch.** Before executing the task, MobileGPT recommends the most appropriate apps for the given task. It does so by crawling Google Play app descriptions for each app installed on the user’s device and storing them in the vector database [47] using the text-embedding model [42]. Then, when a user gives an instruction, MobileGPT retrieves and presents the top three most relevant apps based on their descriptions. After the user makes a selection, MobileGPT launches the app and loads its corresponding app memory to proceed with the task.

**Reproducing only the effective actions.** In task recall, not every action needs to be repeated in the exact same order as originally performed. When reproducing actions without definite target UI elements (i.e., scroll, sliding), it checks whether its subsequent action can be executed on the current screen by looking for the subsequent action’s target UIs instead. If it is, the system skips all the scrolls in between and directly performs the subsequent action. Only if it isn’t, the system reproduces the stored scroll actions. When more scrolls are needed than what is stored, MobileGPT transitions to the few-shot learning adaptation, where the Derive agent can perform additional scrolls. This adaptive approach ensures efficient task execution while maintaining accuracy.

## 7 Evaluation

### 7.1 Dataset

The main contribution of MobileGPT lies in improving performance for repeated tasks and sub-tasks. However, traditional datasets (e.g., AITW [51], MoTiF [6], META-GUI [59], PixelHelp [30]) do not capture this aspect, as they focus on

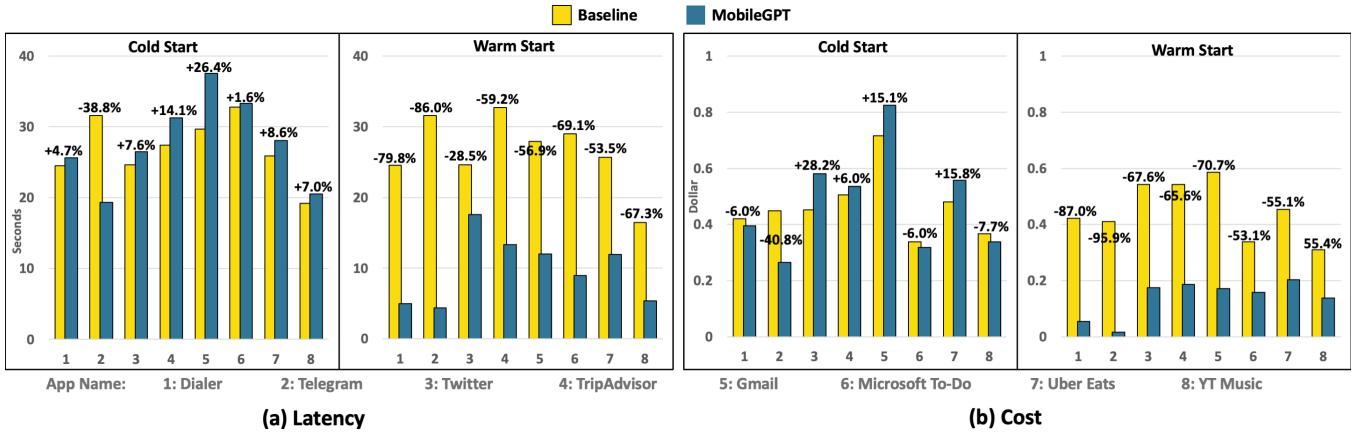


Figure 5: Average task latency and cost of MobileGPT and GPT4-Baseline

task diversity with a highly independent set of user instructions. Furthermore, their instructions are detailed step-by-step guidelines (e.g., “open the device’s settings app and then tap ‘Network & Internet’”), which is not at a desirable level of abstraction for regular users.

Therefore, we created a dataset<sup>3</sup> designed to assess how effectively a system can learn from one instruction and adapt to another with high-level tasks. The dataset includes 80 tasks spread across eight widely used off-the-shelf mobile apps: Google Dialer, Telegram, Twitter, TripAdvisor, Gmail, Microsoft To-Do, Uber Eats, and YouTube Music. Each task is accompanied by two user instructions with different task parameters—totaling 160 user instructions. For example, the task of “Post Reply” for Twitter comes with two instructions: “Post reply to Elon Musk’s new tweet” and “Post reply to Bill Gate’s new tweet saying ‘Reply from MobileGPT.’” These instruction pairs are designed to evaluate a system’s ability to grasp a high-level task from one instruction and apply it to another. The average episode length of the dataset is 5.3, on par with the AITW dataset.

## 7.2 Experimental Setup

Across the evaluation, we used a Google Pixel 6 smartphone. **Baselines.** We evaluate MobileGPT’s performance in comparison with three baselines: AppAgent [69], AutoDroid [66], and a custom GPT-4 powered task automator, referred to as GPT4-baseline. AppAgent is a vision-language model (GPT-4-turbo) based task automator that uses apps’ screenshots to execute tasks. AutoDroid is an LLM (GPT-4) based task automator. The custom GPT4-baseline is designed to share the same prompting techniques as MobileGPT while following the traditional Derive-only structure employed in prior approaches [61, 66, 67]. This allows us to measure only the performance gains attributable solely to MobileGPT’s unique

structural design. Without this isolation, it would be difficult to determine if the performance originates from the design itself or simply from the better prompts.

**Dataset.** In evaluating AppAgent and AutoDroid, some user instructions had to be omitted from the benchmark due to limitations in their open-source prototypes. Specifically, the limitations pertained to unsupported input events (e.g., long-click, question answering) and other technical issues such as the inability to parse screen layouts. As a result, 152 user instructions (76 tasks) were used to evaluate AppAgent, and 95 instructions (48 tasks) were used for AutoDroid.

**Procedure.** The evaluation is divided into two stages. The first stage (*cold-start*) executes the first set of instructions for each task, and the second stage (*warm-start*), executes the second set of instructions. This procedure is designed to evaluate how well MobileGPT learns the task from the first set of instructions and reuses them for the subsequent instruction set.

To identify errors during task execution, we monitored each step manually. When an error occurs, deviating from the expected path, we allowed systems three extra attempts for self-correction. For MobileGPT and GPT4-baseline, if the systems failed to return to the correct path, we manually repaired the error using the human-in-the-loop task repair, and let the system continue the task. However, for AppAgent and AutoDroid, which lack such repair mechanisms, we had to stop the task and exclude it from further analysis.

**Offline Preparation.** Before beginning the tasks, we used a random explorer, randomly interacting with the UIs, to *explore* each target app. For each app, we had it discover 50 unique app pages, which typically took between 10 to 15 minutes. These app pages accounted for 89.65% (104 out of 116) of the app pages required by our task dataset. The remaining app pages, along with those unsuitable for random exploration (such as those involving payments or sensitive

<sup>3</sup>The dataset is available at: <https://github.com/mobile-gpt/MobileGPT>

App Name	Average Memory Hit Rate	
	Cold-Start	Warm-Start
Google Dialer	35.9%	95.8%
Telegram	50.1%	98.6%
Twitter	31.7%	80.1%
TripAdvisor	29.1%	89.3%
Gmail	6.7%	70.6%
Microsoft To-Do	27.8%	92.6%
Uber Eats	26.1%	78.0%
YouTube Music	18.0%	87.2%

Table 1: MobileGPT Average Memory Hit Rate per App.

information), can be explored offline by monitoring user interactions with the app. The total cost for this random exploration was \$32.35, which is deemed reasonable considering that this preparation is a one-time process.

### 7.3 Efficiency

**Cold Start.** Figure 5 compares the latency and cost<sup>4</sup> of MobileGPT and GPT4 baseline. For the initial *cold start*, despite the additional Select phase that MobileGPT employs to decompose the tasks into sub-tasks, latency and cost only increases by an average of 3.9% and 0.6%, respectively, compared to the baseline.

Moreover, MobileGPT even outperforms the baseline for Telegram. This is because MobileGPT enables learned sub-tasks to be reusable across different tasks. Table 1 shows the average memory hit rate for each app. The memory hit rate represents the percentage of actions retrieved directly from the memory without involving the LLM. Since LLM is the primary contributor to the latency, a higher cold-start hit rate translates to less time spent learning the new task. Telegram well exemplifies this; since many of its tasks involve a common sub-task of searching a specific contact, MobileGPT outperforms the baseline by a large amount, even for the cold-starts. Conversely, Gmail exhibits a low memory hit rate (6.7%), as its tasks have few overlapping sub-tasks. While our current results suggest that Gmail is not taking advantage of our design when learning new tasks, we expect the latency and cost to decrease exponentially as it accumulates more sub-tasks.

**Warm Start.** During the *warm start*, where we repeat the same task but with different user instructions, MobileGPT significantly reduces the latency and cost, achieving 62.5% and 68.8% improvements over the GPT4 baseline, respectively. This high level of efficiency is largely due to MobileGPT having already learned the necessary sub-tasks and actions during the initial cold-start stage. The effectiveness of MobileGPT can vary depending on the memory hit rate. The memory hit

<sup>4</sup>At the time of evaluation, the LLM costs (per 1K tokens) were: GPT-4 \$0.03, GPT-3.5 Turbo \$0.003, GPT-4-Turbo \$0.01

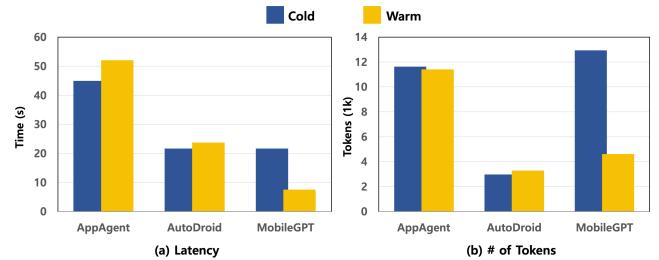


Figure 6: Average task latency and number of tokens of AppAgent, AutoDroid, and MobileGPT

rate for *warm start* does not always reach 100% because some actions require LLM for its adaptation (i.e. when attribute-based adaptation fails). Nevertheless, even in the worst-case scenario where no actions are adaptable (e.g., Twitter Task 8), our evaluation results suggest that MobileGPT performs better than the baseline.

**Comparison to other systems.** Figure 6 illustrates the average task latency and cost for AppAgent, AutoDroid, and MobileGPT. Note that the comparisons were made only for tasks that were successfully completed by all three systems (16 tasks). AppAgent exhibits significantly higher latency because it uses the GPT4-turbo model, which operates at half the speed of the GPT-4 model employed by AutoDroid and MobileGPT. We compare the number of tokens instead of the actual cost because the pricing for GPT4-turbo and GPT-4 differs. AutoDroid uses significantly fewer tokens due to its unique screen parsing technique—a method that can be equally applied to MobileGPT to further optimize its cost. Excluding such external factors, The comparison demonstrates a trend similar to that between GPT4-baseline and MobileGPT (i.e., Figure 5). Specifically, MobileGPT demonstrates slightly higher latency and cost during cold starts but becomes significantly faster and cheaper during warm starts.

Given the recurrent nature of mobile tasks [15, 20, 34, 57], it is reasonable to assume that the cold-start is less common compared to the warm-starts. Therefore our approach, which substantially reduces the cost of these more common warm starts, at the expense of a relatively small increase in the cold-start cost, is highly practical in real-world scenarios.

### 7.4 Accuracy

**Task Completion Accuracy.** Table 2 shows the task completion rate. We omit warm-start accuracy for baselines, as it is nearly identical to their cold-start accuracy. A task is considered complete if the system successfully navigates to the target screen without any human intervention. Interestingly, despite using the most advanced model, AppAgent exhibits the lowest task accuracy. This discrepancy arises because AppAgent relies solely on screenshot images for processing,

Success Rate(%)	AppAgent	AutoDroid	GPT4-baseline	MobileGPT	
				Cold	Warm
Task	60.5	68.75	71.25	82.5	98.75

**Table 2: Task completion rate.**

which proves inadequate for text-heavy applications such as Gmail, Twitter, and Telegram.

Most notably, MobileGPT successfully completed nearly all tasks during the warm-start, with only one exception. This demonstrates its capability to adapt and reproduce learned tasks precisely and consistently, even when task parameters and screen contents change.

Furthermore, MobileGPT demonstrates a higher task completion rate, even during the initial cold-start stages. This improvement can be traced back to MobileGPT’s ability to reuse sub-tasks learned from one task to another, which prevents it from repeating the same mistakes across tasks. For instance, finding a contact in Telegram requires using a search button rather than scrolling through the contact list. In its first task, MobileGPT tries to scroll to find the contact. However, after correcting itself through self-feedback generation and learning to search for a contact, it directly proceeds to click the search button for subsequent tasks, without scrolling through the list.

On the other hand, the baseline systems almost always try to scroll through the contacts, repeating the same mistakes across tasks. Furthermore, we have observed that baselines occasionally fail or operate inefficiently during the warm start stage, even if it has successfully completed the task in the cold start. This inconsistency underscores the non-deterministic nature of the LLMs, which can produce varying outputs depending on factors including task parameters, screen representation, and even the timing of the query.

**Step Accuracy.** We further analyze the accuracy by examining LLM queries at each step of the tasks. In MobileGPT, each step is divided into multiple phases. Table 3 shows the accuracy of each phase and the overall step accuracy. Specifically, MobileGPT undergoes Explore, Select, and Derive phases when learning a new task (cold-start), and undergoes sub-task slot-filling and in-context action adaptation when recalling learned tasks (warm-start). If any one of these phases fails, the entire step is considered a failure.

Nevertheless, MobileGPT demonstrates higher step accuracy compared to the GPT4-baseline (92.4%), even for cold-starts. This improved performance is attributed to MobileGPT’s ability to distribute the reasoning loads for each step across several phases, similar to how the Chain-of-thought prompting [65] improves LLM accuracy by breaking down a problem into a sequence of intermediate steps before arriving at the final answer. For instance, the action ‘ask’—requesting

Accuracy (%)	Task Learning			Task Recall	
	Explore	Select	Derive	Slot Filling	In-context Adaptation
Phase	96.4%	96.2%	99.1%	99.5%	100%
Step		95.5%			99.8%

**Table 3: MobileGPT’s step and phase accuracy.**

additional information from the user—involves complex reasoning steps of identifying the necessary information and recognizing that the information is missing. In the GPT4-baseline, such reasoning steps are confined to a single query, resulting in a low accuracy of 33% for the action ‘ask’. Conversely, MobileGPT splits these reasoning steps between the Explore and Select phases: identifying the parameters in *Explore* and filling them in during *Select*. This distribution of reasoning loads enables MobileGPT to perform ‘ask’ action with 100% accuracy.

When recalling previously learned tasks (warm-start), MobileGPT exhibits near-perfect accuracy, with only one slot-filling query failing. Notably, MobileGPT achieves 100% accuracy for in-context adaptation. During our evaluation, out of 327 primitive actions, 53 actions (16.2%) were not generalizable using attribute-based generalization methods and therefore required in-context adaptation using LLM. As a result, LLM was able to adapt all 53 actions to new instructions and screens. Among all apps, Uber Eats had the highest percentage of actions requiring in-context adaptation (34%), and Telegram had the lowest (0%). This is likely because Telegram has static screen layouts and clear, well-formatted instructions (e.g., “send message to Bob”, “Delete chat with Bob”), whereas Uber Eats features dynamic screen layouts and often includes implicit or incomplete instructions (e.g., “Order me a pizza” lacking restaurant, pizza type, delivery option, and payment information).

Furthermore, the results showcase the effectiveness of our Human-in-the-Loop task repair mechanism, which ensures reliable memory construction despite the non-deterministic and sometimes unreliable nature of LLMs. Our few-shot learning approach to action adaptation successfully guides LLM in generating correct answers, even when it failed to do so in the cold start. For example, when instructed to recover a deleted email from the Gmail app, MobileGPT initially failed to open the delete option because there were two seemingly identical ‘More Options’ buttons on the screen. However, in the warm start, the LLM successfully derived an action to click the correct button when given an example that conveys which button was clicked among the two.

Scenario	Overall Usability (7-point-scale)		
	PbD	Baseline	MobileGPT
New Task	3.2	4.4	4.7
Repeat Task	3.0	4.3	6.1
Similar Task	3.0	4.3	5.7

Table 4: Usability score for different task scenarios.

## 7.5 User Study

**Participants and Study Procedure.** We recruited 23 participants (16 male, 7 female, mean age 23.2,  $\text{stdev}=3.5$ ,  $\text{max}=32$ ,  $\text{min}=19$ ) through an online community posting. Participants received a compensation of 12 USD. The first session evaluated the overall usability of MobileGPT compared to the Samsung Bixby Macro (Programming by Demonstration) and the GPT4-baseline. The second session assessed the usability of MobileGPT’s human-in-the-loop task repair mechanisms. Each session lasted 30 minutes. The recruitment and the experiments were in accordance with our institution’s IRB policies and the consent forms.

In the first session, participants were asked to perform the following three instructions using the three aforementioned task automation tools: 1) *"Find me available hotels in Las Vegas from November 10 to November 15"*, 2) *"Find me hotels in New York"*, and 3) *"Find me restaurants in Las Vegas."* These instructions were designed to evaluate the usability of automation tools in the three scenarios: *i*) executing a new task, *ii*) repeating the same task but with different parameters, and *iii*) executing a new albeit similar task. After each instruction, participants rated each tool’s usability on a 7-point Likert scale. After completing all instructions, participants ranked the tools based on their preferences and indicated whether they were willing to use the tool in the real world.

In the second session, participants learned how to use MobileGPT’s repair mechanisms to correct the LLM’s mistakes. After the tutorial, they executed the instruction *"Modify Tom’s phone number to 123-456-789"* using MobileGPT. During the study, MobileGPT was set to make pre-defined mistakes. These mistakes covered all three areas of repair—Explore, Select, and Derive. Participants had no prior information about the specific mistake the system would make. Following the task, they assessed the usability of the repair mechanism using the System Usability Scale (SUS) [4]. Additionally, they evaluated the necessity and effectiveness of the repair mechanism, along with their accuracy tolerance for a task automator with and without the repair mechanism.

**Session 1: Overall usability.** Table 4 shows the usability scores for each task automation tool across scenarios. Throughout the scenarios, participants generally found PbD inefficient because they needed to re-create the macro script even at the slightest change in the screen or instructions,

and the baseline as convenient but too slow. In contrast, MobileGPT initially had a usability score similar to the baseline in the first scenario, but showed significant improvement in the subsequent tasks, with Mann-Whitney U Test results of ( $U=216.5$ ,  $p=0.26$ ), ( $U=24.0$ ,  $p=4.8e^{-8}$ ), and ( $U=67.5$ ,  $p=6.5e^{-6}$ ), respectively—“(MobileGPT) performs the task accurately at a fairly high speed. Possibly faster than doing it by hand. Seems to have good generalizability” (P4), “It was a little sluggish for things that I hadn’t done before, but it was still faster than the baseline and I figured it would get faster with more training” (P7). This trend suggests that MobileGPT’s ability to quickly reproduce tasks and adapt learned sub-tasks to related tasks greatly enhances its usability. This is corroborated by the post-survey results, where all but one participant favored MobileGPT the most, and all participants expressed willingness to use MobileGPT in real-world applications, compared to 35% and 30% for the baseline and PbD tools, respectively.

**Session 2: Human-in-the-loop Memory Repair.** MobileGPT’s memory repair mechanism achieved an average score of 64.6 ( $\text{std}=16.9$ ) on the System Usability Scale, indicating it as “ok” user-friendliness [3]. While there is room for improvement, the score is regarded as acceptable considering the high complexity of the given repair mission (repairing all three phases within a single task) and the fact that many participants were unfamiliar with the concept of autonomous agents making mistakes.

In the post-survey, participants highly rated both the necessity and effectiveness of the repair mechanism, with scores of 4.7 and 4.8 out of 5, respectively. Moreover, their acceptable accuracy threshold for an automator *without* a repair mechanism is 96% (average), whereas, with a repair mechanism, it drops to 84%. This suggests that participants are more lenient with accuracy expectations when a repair mechanism is present, recognizing its value in task automation.

## 8 Related Work

**Using LLM in UI Task automation.** Recently, there have been multiple attempts to use LLMs for task automation [40, 61, 66, 67, 69], capitalizing on their ability to understand and execute tasks without prior training or user demonstrations. Most notably, AutoDroid [66] and AppAgent [69] augment LLMs with app-specific domain knowledge using offline explorer to better understand mobile apps and perform their tasks with greater accuracy. However, the practicality of LLMs in real-world task automation remains uncertain due to their inherent unreliability and high costs. MobileGPT addresses these limitations by augmenting LLMs with app memory that store and recall tasks with low costs.

**Caching LLM responses.** Fundamentally, MobileGPT is built upon the principles of caching LLMs’ responses. Similar works involve caching commonly occurring token states

for faster inference [10], caching LLM responses to address similar queries [71], and training smaller models to reproduce cached responses [50, 58]. Yet, existing studies have concentrated on the use of LLMs in chatbot applications. To our knowledge, MobileGPT is the first to explore caching in the context of an LLM-based Task automator.

**Macro Mining.** Another line of work closely related to MobileGPT is macro mining [16, 18, 30, 31, 60], which aims to generate macro scripts without human intervention. Among others, Li et al. [16] employ LLM to discover sub-tasks within app traces and combine them to form task-oriented macros. However, a common challenge in using macros is the generalization of actions. Existing approaches tackle this challenge through embedding-based screen matching and attribute-based UI matching. However, these methods often fail when screen similarity is ambiguous or UIs lack important attributes. MobileGPT, on the other hand, successfully overcomes these challenges by employing sub-task-based screen classification and in-context action adaptation.

**LLM-based Autonomous Agent in other fields.** LLMs demonstrate significant potential in automating human tasks. Consequently, researchers across various fields have attempted to expand the capabilities of LLMs by integrating UI interactions [40, 51, 66, 67], programming tools [52, 54], APIs [24, 32, 46, 49, 53, 56], and games [45, 62, 72]. MobileGPT is unique in its ability to generate a higher-level action space (i.e., sub-tasks) on its own and utilize them for different goals (i.e., user instruction). This approach can be extended to other fields, as many digital tasks share common and recurring sub-tasks.

## 9 Discussion

**Security & Privacy.** The screen representation could include personal information such as name and phone number. This could pose a privacy risk when sent to the LLM. To address this, we could use the Personal Identifier Information (PII) Scanner [38, 48] to identify personal information from the prompt and mask it with non-private placeholders.

In addition, certain actions—e.g., agreeing to terms of service or confirming a payment—should be performed under supervision. To address this concern, we give the LLM an option to choose ‘*get user confirm*’ action during the Derive phase. This ensures that we identify any risky action and request the user’s confirmation.

**Sharing App Memory.** MobileGPT currently stores memory on a local basis, meaning each device has its own version of app memory. To enhance this, the memory can be shared or crowd-sourced to create a large-scale app memory. This approach can effectively eliminate the need for each user to learn tasks individually, making the cold-start learning stage even less common. To accommodate the varying devices, app memory can be categorized based on the device form

factor, as the app interface varies depending on the form factor (e.g., smartphone or tablet device). The diversity of the device resolution is not a concern, as MobileGPT identifies UI elements using their hierarchical structure (i.e., index), not their pixel coordinates.

**Unsupported Apps.** Our current implementation does not support mobile apps that fail to provide text representation of their screen layouts. These include apps that use third-party UI engines (e.g., Flutter, Web App, etc) and screens that are mostly images (e.g., map, camera). To overcome this, we can use screen-to-text translation models [21, 23, 68, 70] or vision language models (VLM) [33, 43, 64] to process both the screenshot and the text-based screen representation.

**Using Vision Language Model.** We have performed a feasibility study on using a VLM (GPT-4-turbo) within MobileGPT. We have found that MobileGPT achieves higher accuracy when given both the screenshot and the screen representation. One limitation, however, is the increased latency of the VLM compared to text-only LLMs. Nonetheless, because MobileGPT can minimize the number of queries through memory caching, the higher per-query latency leads to a more pronounced benefit of MobileGPT’s design.

## 10 Conclusion

We have presented MobileGPT, a novel LLM-based mobile task automator that enhances the efficiency and reliability of task automation by emulating human cognitive processes of decomposing and learning new tasks. We expect MobileGPT to further solidify the role of intelligent automation in everyday technology use.

## References

- [1] anthropic. 2023. *Talk to Claude*. anthropic. Retrieved Nov 11, 2023 from <https://claude.ai/>
- [2] Apple. 2023. *Use Siri on all your Apple devices*. Meta. Retrieved Nov 11, 2023 from <https://support.apple.com/en-us/HT204389>
- [3] Aaron Bangor, Philip Kortum, and James Miller. 2009. Determining what individual SUS scores mean: Adding an adjective rating scale. *Journal of usability studies* 4, 3 (2009), 114–123.
- [4] John Brooke. 1996. Sus: a “quick and dirty”usability. *Usability evaluation in industry* 189, 3 (1996), 189–194.
- [5] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.
- [6] Andrea Burns, Deniz Arsan, Sanjna Agrawal, Ranjitha Kumar, Kate Saenko, and Bryan A Plummer. 2022. A dataset for interactive vision-language navigation with unknown command feasibility. In *European Conference on Computer Vision*. Springer, 312–328.
- [7] Carlos G Correa, Mark K Ho, Frederick Callaway, Nathaniel D Daw, and Thomas L Griffiths. 2023. Humans decompose tasks by trading off utility and computational cost. *PLOS Computational Biology* 19, 6 (2023), e1011087.
- [8] Carlos G Correa, Mark K Ho, Fred Callaway, and Thomas L Griffiths. 2020. Resource-rational task decomposition to minimize planning

- costs. *arXiv preprint arXiv:2007.13862* (2020).
- [9] Pinar Erten and Oguzhan Ozdemir. 2020. The Digital Burnout Scale Development Study. *İnönü Üniversitesi Eğitim Fakültesi Dergisi* 21 (10 2020). <https://doi.org/10.17679/inuefd.597890>
- [10] In Gim, Guojun Chen, Seung-seob Lee, Nikhil Sarda, Anurag Khandelwal, and Lin Zhong. 2023. Prompt cache: Modular attention reuse for low-latency inference. *arXiv preprint arXiv:2311.04934* (2023).
- [11] Google. 2023. *Create your own accessibility service*. Google. Retrieved Nov 11, 2023 from <https://developer.android.com/guide/topics/ui/accessibility/service>
- [12] Google. 2023. *Hey Google*. Google. Retrieved Nov 11, 2023 from <https://assistant.google.com/>
- [13] Zhibin Gou, Zhihong Shao, Yeyun Gong, Yelong Shen, Yujiu Yang, Nan Duan, and Weizhu Chen. 2023. Critic: Large language models can self-correct with tool-interactive critiquing. *arXiv preprint arXiv:2305.11738* (2023).
- [14] Emilie Munch et al Gregersen. 2023. Digital dependence: Online fatigue and coping strategies during the COVID-19 lockdown. *Media, Culture, and Society* (2023).
- [15] Emitza Guzman and Walid Maalej. 2014. How do users like this feature? a fine grained sentiment analysis of app reviews. In *2014 IEEE 22nd international requirements engineering conference (RE)*. Ieee, 153–162.
- [16] Forrest Huang, Gang Li, Tao Li, and Yang Li. 2023. Automatic Macro Mining from Interaction Traces at Scale. *arXiv preprint arXiv:2310.07023* (2023).
- [17] Peter C Humphreys, David Raposo, Tobias Pohlen, Gregory Thornton, Rachita Chhaparia, Alistair Muldal, Josh Abramson, Petko Georgiev, Adam Santoro, and Timothy Lillicrap. 2022. A data-driven approach for learning to control computers. In *International Conference on Machine Learning*. PMLR, 9466–9482.
- [18] Peter C Humphreys, David Raposo, Tobias Pohlen, Gregory Thornton, Rachita Chhaparia, Alistair Muldal, Josh Abramson, Petko Georgiev, Adam Santoro, and Timothy Lillicrap. 2022. A data-driven approach for learning to control computers. In *International Conference on Machine Learning*. PMLR, 9466–9482.
- [19] Akshay Kumar Jagadish, Marcel Binz, Tankred Saanum, Jane X Wang, and Eric Schulz. 2023. Zero-shot compositional reinforcement learning in humans. (2023).
- [20] Chakajkla Jesdabodi and Walid Maalej. 2015. Understanding usage states on mobile devices. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. 1221–1225.
- [21] Kenton Lee, Mandar Joshi, Iulia Turc, Hexiang Hu, Fangyu Liu, Julian Eisenschlos, Urvashi Khandelwal, Peter Shaw, Ming-Wei Chang, and Kristina Toutanova. 2023. Pix2Struct: Screenshot Parsing as Pretraining for Visual Language Understanding. *arXiv:2210.03347 [cs.CL]*
- [22] Sunjae Lee, Hoyoung Kim, Sijung Kim, Sangwook Lee, Hyosu Kim, Jean Young Song, Steven Y Ko, Sangeun Oh, and Insik Shin. 2022. A-mash: providing single-app illusion for multi-app use through user-centric UI mashup. In *Proceedings of the 28th Annual International Conference on Mobile Computing And Networking*. 690–702.
- [23] Gang Li and Yang Li. 2023. Spotlight: Mobile UI understanding using vision-language models with a focus. (2023).
- [24] Minghao Li, Feifan Song, Bowen Yu, Haiyang Yu, Zhoujun Li, Fei Huang, and Yongbin Li. 2023. Api-bank: A benchmark for tool-augmented llms. *arXiv preprint arXiv:2304.08244* (2023).
- [25] Tao Li, Gang Li, Jingjie Zheng, Purple Wang, and Yang Li. 2022. MUG: Interactive Multimodal Grounding on User Interfaces. *arXiv preprint arXiv:2209.15099* (2022).
- [26] Toby Jia-Jun Li, Amos Azaria, and Brad A. Myers. 2017. SUGILITE: Creating Multimodal Smartphone Automation by Demonstration. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) (CHI '17). Association for Computing Machinery, New York, NY, USA, 6038–6049. <https://doi.org/10.1145/3025453.3025483>
- [27] Toby Jia-Jun Li, Yuanchun Li, Fanglin Chen, and Brad A Myers. 2017. Programming IoT devices by demonstration using mobile apps. In *End-User Development: 6th International Symposium, IS-EUD 2017, Eindhoven, The Netherlands, June 13–15, 2017, Proceedings* 6. Springer, 3–17.
- [28] Toby Jia-Jun Li, Lindsay Popowski, Tom Mitchell, and Brad A Myers. 2021. Screen2vec: Semantic embedding of gui screens and gui components. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [29] Toby Jia-Jun Li and Oriana Riva. 2018. KITE: Building conversational bots from mobile apps. In *Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services*. 96–109.
- [30] Yang Li, Jiacong He, Xin Zhou, Yuan Zhang, and Jason Baldridge. 2020. Mapping natural language instructions to mobile UI action sequences. *arXiv preprint arXiv:2005.03776* (2020).
- [31] Yuanchun Li and Oriana Riva. 2021. Glider: A reinforcement learning approach to extract UI scripts from websites. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1420–1430.
- [32] Yaobo Liang, Chenfei Wu, Ting Song, Wenshan Wu, Yan Xia, Yu Liu, Yang Ou, Shuai Lu, Lei Ji, Shaoguang Mao, et al. 2023. Taskmatrix.ai: Completing tasks by connecting foundation models with millions of apis. *arXiv preprint arXiv:2303.16434* (2023).
- [33] Haotian Liu, Chunyuan Li, Qingsheng Wu, and Yong Jae Lee. 2023. Visual instruction tuning. *arXiv preprint arXiv:2304.08485* (2023).
- [34] Huaxiao Liu, Xinglong Yin, Shanshan Song, Shanquan Gao, and Mengxi Zhang. 2022. Mining detailed information from the description for App functions comparison. *IET Software* 16, 1 (2022), 94–110.
- [35] Martin Lövdén, Benjamín Garzón, and Ulman Lindenberger. 2020. Human skill learning: expansion, exploration, selection, and refinement. *Current Opinion in Behavioral Sciences* 36 (2020), 163–168.
- [36] Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegrefe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, et al. 2023. Self-refine: Iterative refinement with self-feedback. *arXiv preprint arXiv:2303.17651* (2023).
- [37] meta. 2023. *Introducing Llama 2*. meta. Retrieved Nov 11, 2023 from <https://ai.meta.com/llama/>
- [38] Microsoft. 2023. *How to detect and redact Personally Identifying Information (PII)*. Microsoft. Retrieved Nov 11, 2023 from <https://learn.microsoft.com/en-us/azure/ai-services/language-service/personally-identifiable-information/how-to-call>
- [39] MultiOn. 2023. *The world's first Personal AI Agent*. MultiOn. Retrieved Nov 11, 2023 from <https://www.multion.ai>
- [40] Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, et al. 2021. Webgpt: Browser-assisted question-answering with human feedback. *arXiv preprint arXiv:2112.09332* (2021).
- [41] openai. 2023. *Creating safe AGI that benefits all of humanity*. openai. Retrieved Nov 11, 2023 from <https://openai.com/>
- [42] OpenAI. 2023. *New and improved embedding model*. OpenAI. Retrieved Nov 11, 2023 from <https://openai.com/blog/new-and-improved-embedding-model>
- [43] OpenAI. 2023. *Vision*. OpenAI. Retrieved Nov 11, 2023 from <https://platform.openai.com/docs/guides/vision>
- [44] OthersideAI. 2023. *Your AI assistant for everyday tasks*. OthersideAI. Retrieved Nov 11, 2023 from <https://www.hyperwriteai.com/personal-assistant>
- [45] Joon Sung Park, Joseph C O'Brien, Carrie J Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. *arXiv preprint arXiv:2304.03442*

- (2023).
- [46] Shishir G Patil, Tianjun Zhang, Xin Wang, and Joseph E Gonzalez. 2023. Gorilla: Large language model connected with massive apis. *arXiv preprint arXiv:2305.15334* (2023).
- [47] Pinecone. 2023. *Long-Term Memory for AI*. Pinecone Systems. Retrieved Nov 11, 2023 from <https://www.pinecone.io/>
- [48] Endpoint Protector. 2023. *Cutting-Edge PII Scanner*. Endpoint Protector. Retrieved Nov 11, 2023 from <https://www.endpointprotector.com/solutions/ediscovery/pii-scanner>
- [49] Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, et al. 2023. Toolllm: Facilitating large language models to master 16000+ real-world apis. *arXiv preprint arXiv:2307.16789* (2023).
- [50] Guillem Ramírez, Matthias Lindemann, Alexandra Birch, and Ivan Titov. 2023. Cache & distil: Optimising API calls to large language models. *arXiv preprint arXiv:2310.13561* (2023).
- [51] Christopher Rawles, Alice Li, Daniel Rodriguez, Oriana Riva, and Timothy Lillicrap. 2023. Android in the wild: A large-scale dataset for android device control. *arXiv preprint arXiv:2307.10088* (2023).
- [52] Jingqing Ruan, Yihong Chen, Bin Zhang, Zhiwei Xu, Tianpeng Bao, Guoqing Du, Shiwei Shi, Hangyu Mao, Xingyu Zeng, and Rui Zhao. 2023. Tptu: Task planning and tool usage of large language model-based ai agents. *arXiv preprint arXiv:2308.03427* (2023).
- [53] Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. Toolformer: Language models can teach themselves to use tools. *arXiv preprint arXiv:2302.04761* (2023).
- [54] Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueling Zhuang. 2023. Hugginggpt: Solving ai tasks with chatgpt and its friends in huggingface. *arXiv preprint arXiv:2303.17580* (2023).
- [55] Significant-Gravitas. 2023. *AutoGPT: the heart of the open-source agent ecosystem*. github. Retrieved Nov 11, 2023 from <https://github.com/Significant-Gravitas/AutoGPT>
- [56] Yifan Song, Weimin Xiong, Dawei Zhu, Cheng Li, Ke Wang, Ye Tian, and Sujian Li. [n. d.]. Restgpt: Connecting large language models with real-world applications via restful apis. CoRR, abs/2306.06624, 2023. doi: 10.48550. *arXiv preprint arXiv:2306.06624* ([n. d.]).
- [57] Christoph Stanik, Marlo Haering, Chakajkla Jesdabodi, and Walid Maalej. 2020. Which app features are being used? Learning app feature usages from interaction data. In *2020 IEEE 28th International Requirements Engineering Conference (RE)*. IEEE, 66–77.
- [58] Ilias Stogiannidis, Stavros Vassos, Prodromos Malakasiotis, and Ion Androutsopoulos. 2023. Cache me if you Can: an Online Cost-aware Teacher-Student framework to Reduce the Calls to Large Language Models. *arXiv preprint arXiv:2310.13395* (2023).
- [59] Liangtai Sun, Xingyu Chen, Lu Chen, Tianle Dai, Zichen Zhu, and Kai Yu. 2022. META-GUI: Towards Multi-modal Conversational Agents on Mobile GUI. *arXiv preprint arXiv:2205.11029* (2022).
- [60] Daniel Toyama, Philippe Hamel, Anita Gergely, Gheorghe Comanici, Amelia Glaese, Zafarali Ahmed, Tyler Jackson, Shibli Mourad, and Doina Precup. 2021. Androidenv: A reinforcement learning platform for android. *arXiv preprint arXiv:2105.13231* (2021).
- [61] Bryan Wang, Gang Li, and Yang Li. 2023. Enabling conversational interaction with mobile ui using large language models. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [62] Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. 2023. Voyager: An open-ended embodied agent with large language models. *arXiv preprint arXiv:2305.16291* (2023).
- [63] Lei Wang, Wanyu Xu, Yihuai Lan, Zhiqiang Hu, Yunshi Lan, Roy Ka-Wei Lee, and Ee-Peng Lim. 2023. Plan-and-solve prompting: Improving zero-shot chain-of-thought reasoning by large language models. *arXiv preprint arXiv:2305.04091* (2023).
- [64] Wenhui Wang, Zhe Chen, Xiaokang Chen, Jiannan Wu, Xizhou Zhu, Gang Zeng, Ping Luo, Tong Lu, Jie Zhou, Yu Qiao, et al. 2023. Visionllm: Large language model is also an open-ended decoder for vision-centric tasks. *arXiv preprint arXiv:2305.11175* (2023).
- [65] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems* 35 (2022), 24824–24837.
- [66] Hao Wen, Yuanchun Li, Guohong Liu, Shanhai Zhao, Tao Yu, Toby Jia-Jun Li, Shiqi Jiang, Yunhao Liu, Yaquin Zhang, and Yunxin Liu. 2023. Empowering llm to use smartphone for intelligent task automation. *arXiv preprint arXiv:2308.15272* (2023).
- [67] Hao Wen, Hongming Wang, Jiaxuan Liu, and Yuanchun Li. 2023. DroidBot-GPT: GPT-powered UI Automation for Android. *arXiv preprint arXiv:2304.07061* (2023).
- [68] Jason Wu, Siyan Wang, Siman Shen, Yi-Hao Peng, Jeffrey Nichols, and Jeffrey P Bigham. 2023. WebUI: A Dataset for Enhancing Visual UI Understanding with Web Semantics. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [69] Zhao Yang, Jiaxuan Liu, Yucheng Han, Xin Chen, Zebiao Huang, Bin Fu, and Gang Yu. 2023. Appagent: Multimodal agents as smartphone users. *arXiv preprint arXiv:2312.13771* (2023).
- [70] Xiaoyi Zhang, Lilian de Greef, Amanda Sweeny, Samuel White, Kyle Murray, Lisa Yu, Qi Shan, Jeffrey Nichols, Jason Wu, Chris Fleizach, et al. 2021. Screen recognition: Creating accessibility metadata for mobile applications from pixels. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [71] Hanlin Zhu, Banghua Zhu, and Jiantao Jiao. 2024. Efficient Prompt Caching via Embedding Similarity. *arXiv preprint arXiv:2402.01173* (2024).
- [72] Xizhou Zhu, Yuntao Chen, Hao Tian, Chenxin Tao, Weijie Su, Chenyu Yang, Gao Huang, Bin Li, Lewei Lu, Xiaogang Wang, et al. 2023. Ghost in the Minecraft: Generally Capable Agents for Open-World Environments via Large Language Models with Text-based Knowledge and Memory. *arXiv preprint arXiv:2305.17144* (2023).