Responsible Task Automation: Empowering Large Language Models as Responsible Task Automators

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Abstract

The recent success of Large Language Models (LLMs) signifies an impressive stride towards artificial general intelligence. They have shown a promising prospect in automatically completing tasks upon user instructions, functioning as brain-like coordinators. The associated risks will be revealed as we delegate an increasing number of tasks to machines for automated completion. A big question emerges: how can we make machines behave responsibly when helping humans automate tasks as personal copilots? In this paper, we explore this question in depth from the perspectives of feasibility, completeness and security. In specific, we present Responsible Task Automation (ResponsibleTA) as a fundamental framework to facilitate responsible collaboration between LLM-based coordinators and executors for task automation with three empowered capabilities: 1) predicting the feasibility of the commands for executors; 2) verifying the completeness of executors; 3) enhancing the security (e.g., the protection of users' privacy). We further propose and compare two paradigms for implementing the first two capabilities. One is to leverage the generic knowledge of LLMs themselves via prompt engineering while the other is to adopt domain-specific learnable models. Moreover, we introduce a local memory mechanism for achieving the third capability. We evaluate our proposed ResponsibleTA on UI task automation and hope it could bring more attentions to ensuring LLMs more responsible in diverse scenarios. The research project homepage is at `https://task-automation-research.github.io/responsible_task_automation/`.

1 Introduction

Recent advanced Large Language Models (LLMs) [3, 28, 27, 6, 7, 10, 32, 40] exhibit powerful language understanding, reasoning, generation, generalization and alignment capabilities in a vast suite of real-world scenarios. LLMs acquire generic knowledge on open-domain tasks by scaling up deep learning, which marks a significant milestone in the advancement towards artificial general intelligence. Beyond language tasks, LLMs are empowered with multi-modal perception and generation capabilities through collaboration with domain-specific models [39, 30, 36]. They have been revolutionizing the field of task automation by connecting LLMs to various domain-specific models or APIs, in which LLMs serve as brain-like coordinators while domain-specific models or APIs function as action executors [18, 33, 10].

Adopting LLMs to constructing a general-purpose copilot for automating diverse tasks is still in an incipient exploration stage. Taking the interaction with UIs as an example, browsing and interacting with various websites and APPs to achieve their diverse intentions (*e.g.*, searching in websites, online shopping, setting changing, *etc.*) are almost indispensable for many people's daily life. Some of them require a hierarchical action architecture [2, 1] where a high-level instruction from human known as

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task-level goal needs to be decomposed into a series of low-level step-wise instructions for actual execution. Such complex multi-step tasks requires each step to be reasonably planned and reliably executed in line with human intentions. This actually poses significant challenges in the compatibility between LLM-based coordinators and their executors without intervention in their training. Their reliable collaboration requires LLM-based coordinators to be very familiar with the capabilities of executors, and to replan the task execution when necessary upon the command completeness of executors. Existing works [36, 39, 30, 18] just tell LLMs the powers of executors with model/API descriptions via heavy prompt engineering. However, these descriptions are commonly manually written and summary-like, which are inadequate to describe the executors' capabilities and cannot reflect the execution completeness for LLMs. In addition, LLMs are also possible to have insufficient awareness of the task goals and environments, thus issuing unreasonable instructions to executors. As an increasing number of tasks are delegated to machines for automated completion, the exposure to risks will grow, which necessitates addressing the reliability issue with a sense of urgency.

In this work, we propose ResponsibleTA as a fundamental multi-modal framework to empower LLMs as responsible task automators in three aspects: 1) ***Feasibility***: ResponsibleTA predicts the feasibility of low-level commands generated by the LLM-based coordinator and return the results to LLMs for replanning before action execution. This capability aims to minimize the risks and time consumption of having the executors perform unachievable instructions, making task automation more controllable and efficient. 2) ***Completeness***: ResponsibleTA checks the execution results of low-level commands step-by-step and provides feedbacks timely for the LLM-based coordinator to allow it reschedule next steps more reasonably. This capability can improve the success rates of automated task completion. 3) ***Security***: ResponsibleTA augments LLMs with edge-deployed memories, which allows user-sensitive information are hidden during the interaction with cloud-deployed LLMs and are only stored and used locally on users' devices. This capability reduces or avoids the transmission of users' sensitive information between the cloud-deployed LLMs and edge-deployed executors, thus lowering the leakage risk of users' privacy. Empowering LLMs with these capabilities, ResponsibleTA achieves automatic verification before and after each execution step, which improves not only the success rate but also the completion efficiency with thoughtful security guarantees for users.

In addition to the framework design of ResponsibleTA, we investigate the implementations of three core functionalities of ResponsibleTA as an empirical study in a practical application scenario (*i.e.*, UI task automation). Its goal is to automatically ground target UI elements and interact with them via automatic clicking and typing operations based on task instructions from users, which is of high demands in both academia and industry. For feasibility and completeness, we propose and compare two technical paradigms for their implementations. One paradigm is to leverage generic knowledge of LLMs themselves via prompt engineering. The other paradigm is to train domain-specific models specifically responsible for these two functionalities as external assistants of the coordinators and executors. We observe that leveraging LLMs themselves is inferior to adopting domain-specific models, demonstrating that domain-specific knowledge is crucial for enhancing the reliability of LLMs in task automation. For security, we introduce a local memory and propose a mechanism design to use it for endowing ResponsibleTA with security guarantees.

The contributions of this work can be summarized as follows:

- We present a fundamental multi-modal framework, dubbed as ResponsibleTA, which empowers LLMs with the capabilities of feasibility prediction, completeness verification and security protection for automatically completing tasks in a responsible manner.
- We propose and compare two technical paradigms for implementing the feasibility prediction and completeness verification functionalities of ResponsibleTA in UI task automation scenarios. One is to leverage internal knowledge of LLMs themselves while the other is to train domain-specific models as external assistants.
- We introduce a local memory mechanism to endow ResponsibleTA with the capability of security protection for user privacy, and showcase its effectiveness in some representative practical cases.

2 Related Works

2.1 Development of Large Language Models

Starting from the language model Bert [9], the pretraining-finetuning scheme is a common practice in many natural language processing (NLP) and computer vision (CV) problems. By bringing data and

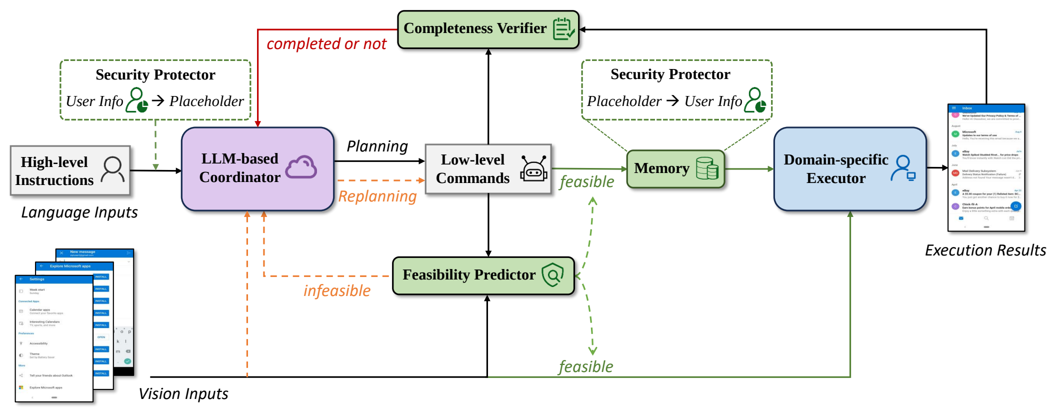


Figure 1: The framework of the proposed ResponsibleTA. It augments the cloud-deployed LLM-based coordinator with feasibility protector, completeness verifier and a local memory, achieving its responsible collaboration with the domain-specific executor. They are all detailed in the main text.

models to a larger scale, GPT-3 [3] demonstrates that LLMs obtain the ability of in-context learning, where LLMs can quickly adapt to a new task given only a few examples as prompts. Furthermore, InstructGPT [29] finetunes GPT-3 with a dataset of human demonstrations to make LLMs follow users' intents. Recently, ChatGPT [28] and GPT-4 [27] demontrate excellent ability in generating complete answers to users' natural language questions. Considering that these LLMs only deal with language tokens, Kosmos-1 [12] extends its training set to image-text data and shows capability in visual question answering and multimodal dialog. In the meanwhile, there are concurrent LLMs such as PaLM [6, 7] and PaLM-E [10], and open-source efforts such as LLaMA [32] and OPT [40]. Despite the strong performance, answers generated by LLMs are not always reliable. Our work aims to empower LLMs to be reliable in the area of task automation.

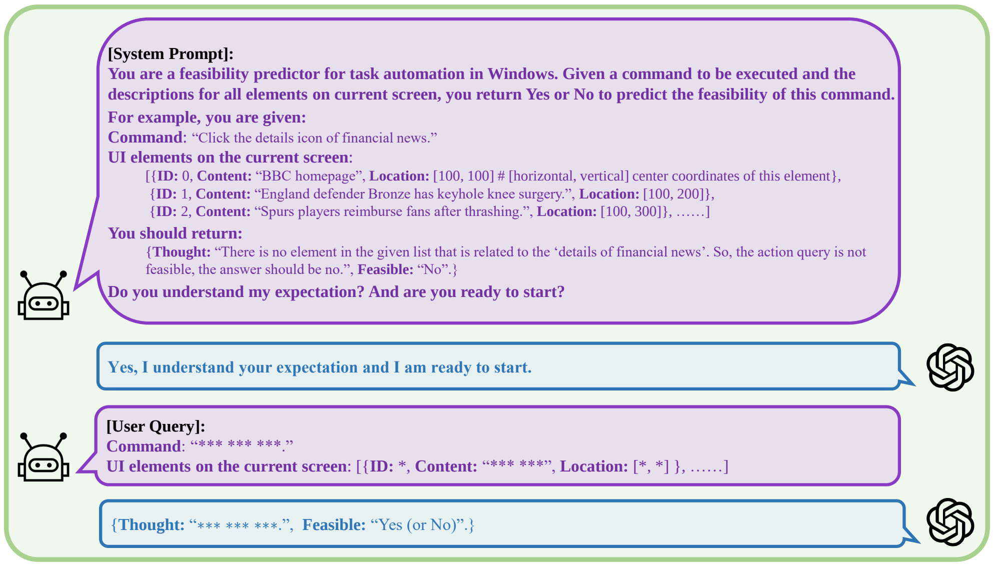
2.2 Large Language Models for Task Automation

LLMs are able to serve as actors or coordinators/planners for digital or physical AI task automation. When functioning as actors, the outputs of LLMs are executable actions [25, 1], which is limited to natural language processing tasks. Towards broader applications in physical [13, 1, 20, 10, 18], simulated physical [34, 35] and digital [30, 36, 39, 18] environments, LLMs usually act as a brain-like coordinator to process human high-level instructions into step-wise executable machine commands and hand them over to domain-specific models/APIs for actual execution. Along this route, LLMs have been opening up infinite possibilities for task automation and putting forward higher requirements for the reliability of automated systems meanwhile. The knowledge defects or biases of LLMs and the gap between LLMs and executors both possibly lead to potential risks in the failure of task completion or even causing harm to users [11]. Previous work [1] attempts to address the executability issue by training an external model to critic the outputs of LLM. It delivered success in simple robotic environments [1] but is demonstrated hard to be applied to complex environments with more objects and diverse actions [31, 37]. Besides, [35, 37] track the execution results for the follow-up planning of LLMs. To the best of our knowledge, we are the first to systematically study the reliability of LLM-based task automation from feasibility, completeness and security perspectives.

3 Method

3.1 ResponsibleTA Framework

ResponsibleTA is a fundamental multi-modal framework for empowering LLMs as responsible task automators. The goal is to comprehensively enhance the reliability of employing LLMs as coordinators, while adopting domain-specific models/APIs as executors, for automatically completing tasks in according with human instructions. It achieves reliability enhancement with three empowered capabilities: feasibility prediction, completeness verification and security protection.


[System Prompt]:

You are a feasibility predictor for task automation in Windows. Given a command to be executed and the descriptions for all elements on current screen, you return Yes or No to predict the feasibility of this command.

For example, you are given:

Command: “Click the details icon of financial news.”

UI elements on the current screen:

[{**ID:** 0, **Content:** “BBC homepage”, **Location:** [100, 100] # [horizontal, vertical] center coordinates of this element},
{**ID:** 1, **Content:** “England defender Bronze has keyhole knee surgery.”, **Location:** [100, 200]},
{**ID:** 2, **Content:** “Spurs players reimburse fans after thrashing.”, **Location:** [100, 300]}, ……]

You should return:

{**Thought:** “There is no element in the given list that is related to the ‘details of financial news’. So, the action query is not feasible, the answer should be no.”, **Feasible:** “No”.}

Do you understand my expectation? And are you ready to start?

Yes, I understand your expectation and I am ready to start.

[User Query]:

Command: “*** *** ***.”

UI elements on the current screen: [{**ID:** *, **Content:** “*** ***”, **Location:** [*, *] }, ……]

{**Thought:** “*** *** ***.”, **Feasible:** “Yes (or No)”.}

Figure 2: Illustration of our prompt engineering based paradigm for implementing the feasibility predictor in our proposed ResponsibleTA.

As shown in Figure 1, ResponsibleTA takes high-level instructions (*i.e.*, task goals) from human as inputs and parses them into low-level (*i.e.*, step-wise) commands with a pretrained LLM for action planning. To ensure the low-level command is reasonably generated and correctly executed at each step, we introduce a feasibility predictor and a completeness verifier in ResponsibleTA. Before each execution, the feasibility predictor assesses whether the generated low-level command is executable in practice upon the current screenshot and this command itself. It will ask the LLM-based coordinator for a replanning via prompt engineering when the command is judged as infeasible, otherwise feed the command to the executor when feasible. When reaching the pre-set maximum number of replanning attempts, the LLM will terminate the current task and offer feedbacks for users. After each execution, the completeness verifier checks whether the execution result aligns with the goal of given low-level command. Replanning will be launched by LLM once an invalid or unfulfilled execution is detected. Note that we input the UI element information on the screen to the LLM in linguistic form through a trained screen parsing model only when replanning is needed, so as to protect personal information on users' screens as much as possible. (See supplementary for more details.) Moreover, we integrate a security protector into ResponsibleTA to allow user-sensitive information to be stored locally. With this module, users are allowed to replace all sensitive information by their predefined placeholders, and translates them back when sending the commands to edge-deployed executors for local execution. As a result, ResponsibleTA enhances the internal alignment between the coordinator and executors, and provides security guarantees for users as a responsible task automation framework.

We employ UI task automation as a practical application scenario for in-depth investigation and experiments, so as to 1) showcase the effectiveness of ResponsibleTA intuitively and 2) state the implementations of three core modules in ResponsibleTA clearly. Its goal is to automate the interaction tasks between human and UIs (*e.g.*, searching in websites, playing media, online shopping, changing settings, *etc*.). We train a domain-specific executor to automatically ground the target UI element by predicting its spatial coordinates for clicking or typing, with a given low-level command and the corresponding screenshot as the inputs. Since this is not the emphasis in this work, we place the detailed model design and training of the executor in the experiment section and supplementary.

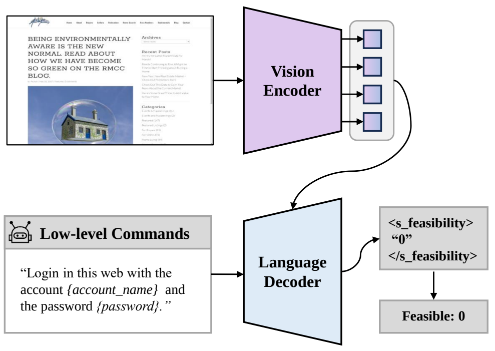
3.2 Feasibility Predictor

The feasibility predictor takes the low-level command and the current screenshot as inputs to predict the feasibility of this command. It contributes to avoiding the execution of a infeasible or dangerous command by asking for replanning once infeasible. Here, we introduce two technical paradigms for its implementation, and compare their effectiveness in the following experiment section.

Prompt engineering based paradigm. This paradigm is designed to leverage the internal generic knowledge of a LLM for achieving feasibility prediction. We first design a system prompt as the launching prompt to tell LLM our task goal and expected outputs together with some specific demonstrations. Considering that most of advanced LLMs (*e.g.*, ChatGPT, GPT-4) have not integrated or released their input interfaces for other modalities (*e.g.*, vision) except for language, we train a screen parsing model to translate the screenshots into a series of UI elements where each element is represented in linguistic description with its *index*, *text content*, *location* and *type*. More details of this model can be found in Sec. A.2 of the supplementary material. We organize the linguistic descriptions of all UI elements at the current screenshot as a structured form (*i.e.*, dictionary), and input it together with the low-level command at the current step as the user queries for each task instance. The system prompt and the demonstrations of user queries of our proposed feasibility predictor are illustrated in Figure 2 in detail.

Domain-specific model based paradigm. This paradigm aims to address the feasibility prediction by training a domain-specific model, *i.e.*, an external expert. Here, we devise an end-to-end multi-modal model with its architecture inspired by the Pix2Seq modelling idea [4]. As shown in Figure 3, our Domain-Specific Feasibility Predictor, referred to as DSFP, consists of a transformer-based vision encoder and a transformer-based language decoder. Given an image $\mathbf{X} \in \mathbb{R}^{H\times W\times C}$, the vision encoder captures the features of $\mathbf{X}$ and embeds it into n_v d-dimensional tokens denoted by $\{\mathbf{v}_i|\mathbf{v}_i \in \mathbb{R}^d, 1 \le i \le n_v\}$. The low-level command is tokenized to be n_t d-dimensional text tokens denoted by $\{\mathbf{t}_i|\mathbf{t}_i \in \mathbb{R}^d, 1 \le i \le n_t\}$. Then the sets $\{\mathbf{v}\}$ and $\{\mathbf{t}\}$ are fed into the language decoder to generate the prediction results in linguistic form.

To make the above architecture design unified to other tasks, such as completeness verification introduced subsequently, we model the outputs of its decoder in a structured linguistic form as "<*task_prompt*> *{results}* </*task_prompt*>" following [14, 38]. Here, "<*task_prompt*>" and "</*task_prompt*>" denotes the start and end in the linguistic sequence for the results, respectively. And "*{results}*" denotes the actual contents of the results. For the feasibility predictor of ResponsibleTA, "<*task_prompt*>" and "</*task_prompt*>" are instantiated to be "<*s_feasibility*>" and "</*s_feasibility*>", respectively. The "*{results}*" could be 0 or 1 where 0 represents "*infeasible*" while 1 denotes "*feasible*".


BEING ENVIRONMENTALLY AWARE IS THE NEW NORMAL. READ ABOUT HOW WE HAVE BECOME SO GREEN ON THE RMCC BLOG.
Vision Encoder
Low-level Commands
"Login in this web with the account *{account_name}* and the password *{password}*."
Language Decoder
<s_feasibility> "0" </s_feasibility>
Feasible: 0
Figure 3: Illustration of our domain-specific model based paradigm for implementing the feasibility predictor in ResponsibleTA.

3.3 Completeness Verifier

The completeness verifier in ResponsibleTA takes the executed command and the screenshot after execution as its inputs to assess the completeness of this command. It in fact plays the role of handling the internal alignment between the LLM-based coordinator and the executor to ensure the reliability of their collaboration. For each step, the verifier provides a feedback for the LLM-based coordinator to tell whether the execution result of the executor aligns with its expectation at this step so that it can remedy erroneous or biased execution timely via a replanning operation. It forms a loop to endow ResponsibleTA with the capability of self-correction. We showcase its effectiveness in the case study in the experiment section.

We also propose and compare two technical paradigms for implementing this module, which are similar with those of the feasibility predictor introduced as above. For conciseness, we only state the differences with the feasibility predictor here and place more details in our supplementary. For the prompt engineering based paradigm, we share the screen parsing model with that in the feasibility predictor, and update the system prompt and user queries in line with the goal of completeness verification. Their contents are detailed in the supplementary. For the domain-specific model based paradigm, we adopt the same model architecture and the output format with those of the feasibility predictor, but feed the executed command and the screenshot after execution as its inputs. Here, "<*task_prompt*>" and "</*task_prompt*>" are instantiated to be "<*s_completeness*>" and

"*</s_completeness*>", respectively. The "*{results}*" could be 0 or 1 where 0 represents "*incomplete*" while 1 denotes "*complete*".

3.4 Security Protector

Many tasks that users need to be automated involve their private information. For example, online shopping or computer configuration may require the credit card, account and password information of users. The security protector in ResponsibleTA is designed to enable the sensitive information from users to be stored and used locally, obviating the transmission of them to the cloud-deployed LLM and reducing information leaky risks. To this end, the security protector uses a NER model (*e.g.*, Bert-NER [19]) to automatically detect the sensitive information in users' instructions, and replace them with a information placeholder denoted by "*{info_name}*". Then, it stores "*{info_name}*" and its corresponding real contents using a dictionary structure into an edge-deployed memory. When received a command from LLM, the security protector translates the information placeholder back to its original contents, then sends the translated command to executors for local execution. For example, when users ask ResponsibleTA to change the shipping address in a shopping website, their old and new address are represented as "*{old_address}*" and "*{new_address}*", respectively, when interacting with the cloud-deployed LLMs, and are translated back for local executors.

4 Experiments

4.1 Datasets and Implementation Details

Feasibility prediction dataset. We collect data for feasibility prediction from Common Crawl[2], an open repository of web crawl data. We sample about 40K web pages from this open repository, yielding 1.1M image-text pairs. Among them, 1M pairs are used for training while the remaining 100K pairs are for testing. For each web page, we extract leaf elements and assign captions to them from HTML entries such as *inner-text*, *value*, *alt*, *aria-label*, *label-for*, and *placeholder*. Subsequently, we employ a randomized algorithm to generate low-level commands for elements by leveraging their captions. Example commands include "select the *{element_caption}* item", "click the item to the right of *{element_caption}*", "enter *{words}* into *{element_caption}*", "scroll until *{element_caption}*", *etc*. All of these commands are deemed as feasible. Infeasible commands are generated based on fake element captions that do not appear in the current web page.

Completeness verification dataset. This dataset is also based on publicly available web pages. This dataset leverages the transitions between two web pages, i.e., it jumps to page B by clicking an element in page A. Based on the transitions we are able to define a positive example of completeness as a 3-tuple [screenshot A, *{element_caption}*, screenshot B]. We generate negative examples by substituting the 3-tuple with fake items. Overall, this dataset includes 113K web pages with 1.2M image-text pairs for training and 6K web pages with 60K image-text pairs for testing.

The data for task automation executor is based on the feasibility prediction dataset. We place more details about the dataset configuration and model implementation in our supplementary.

4.2 Quantitative Results

We evaluate afore-introduced two technical paradigms for implementing the feasibility predictor and completeness verifier in ResponsibleTA. The experiment results are in Table 1. Due to the heavy cost and efficiency of the testing with LLMs, we randomly sample 5K image-text pairs from the test splits on feasibility prediction and completeness verification for evaluating the prompt engineering based paradigms. As for domain-specific models based paradigms, we evaluate them on the same 5K image-text pairs (abbreviated as DSM in Table 1) as well as on the entire test splits (abbreviated as DSM$^+$ in Table 1). As shown in Table 1, we can find that *DSM-based* and *DSM-based*$^+$ perform very closely under these two test settings. This indicates our sampled 5K image-text pairs are diverse and representative enough for providing convincing evaluation results.

[2]`https://commoncrawl.org/the-data/`

Table 1: The results of quantitative evaluation for the proposed feasibility prediction and completeness verification modules. "AP", "Acc" and "F1" are short for the average precision, accuracy and F1 score metrics, respectively. The superscript "+" denotes the result evaluated on a larger test dataset.

Models	**Feasibility Prediction**			**Completeness Verification**		
	Acc (%)	AP	F1	Acc (%)	AP	F1
LLM-based (ChatGPT)	65.7	0.631	0.546	61.1	0.564	0.704
LLM-based (GPT-4)	68.9	0.669	0.583	62.9	0.575	0.721
DSM-based	74.8	0.818	0.671	83.8	0.803	0.833
DSM-based^{+}	75.3	0.823	0.678	83.5	0.804	0.829

Accuracy of feasibility prediction. As shown in Table 1, GPT-4 is more powerful than ChatGPT for feasibility prediction. And the *DSM-based* feasibility predictor outperforms the *LLM-based (GPT-4)* one by 5.9%, 0.149, 0.088 in accuracy, average precision and F1 score, respectively, on feasibility prediction. These results demonstrate the superior performance of the domain-specific models based paradigm relative to prompt engineering based paradigm on feasibility prediction.

Accuracy of completeness verification. From the in Table 1, we observe that *DSM-based* feasibility predictor outperforms the *LLM-based (GPT-4)* one by 20.9%, 0.228, 0.112 in accuracy, average precision and F1 score, respectively, on completeness verification, showing a similar tendency with that on feasibility prediction. It also indicates the performance superority of adopting a domain-specific model as the completeness verifier in ResponsibleTA.

As above, we can find the domain-specific model based paradigms perform consistently better than prompt engineering based paradigms on implementing these two functionalities of ResponsibleTA. Despite this, the advantage of prompt engineering based paradigms is that they do not require the collection of specific data for training, offering better flexibility in practical deployment.

4.3 Case Study and Demonstration

We analyze the performance and behaviors of our proposed ResponsibleTA via real-world case study on 12 tasks, considering that there are no fledged benchmarks in this research field yet. Besides, we conduct ablation study on these tasks by comparing *Baseline*, *Baseline+Fea.* and *Baseline+Fea.+Com.* where *Baseline+Fea.+Com.* is the complete version of ResponsibleTA. Their configurations are detailed in the caption of Table 2. The security predictor is installed in all models.

Ablation study and analysis. We report the specific completion progress and the final success status over all 12 real-world tasks in Table 2. As for the success ratio, we can find that *Baseline* does not reach the final success on 9 out of 12 tasks. For these 9 tasks, 5 of them are successfully remedied by the feasibility predictor on its own. On top of it, the completeness verifier help turn 2 of them to the final success in addition. It can be seen that the feasibility predictor and the completeness verifier in ResponsibleTA can significantly improve the success ratio of task automation by providing feedbacks for LLM-based coordinator so that it can replan timely. *How our ResponsibleTA achieves this* will be elaborated in detail in the subsequent text.

Besides the benefits of improving the success rate, our proposed ResponsibleTA can effectively reduce the number of invalid instruction executions thanks to its feasibility predictor. This conclusion is drawn by comparing the valid steps and total execution steps for *Baseline* and *Baseline+Fea.* models. Thus, our ResponsibleTA can avoid the risks when executing those invalid steps.

Moreover, we further verify the role of ResponsibleTA on security protection by comparing using placeholders and real user information on the No.7 and No.10 tasks. We experimentally find that launching the security protector neither affects the task success rate nor increases the number of invalid executions on these two cases for all three models. It can effectively obviate the need of uploading user-sensitive information to the cloud.

How ResponsibleTA remedies failure cases? Here, we take a close look into a specific case for detailed analysis on how ResponsibleTA remedies a failure case to achieve success in the end. We illustrate specific execution processes of the first 4 steps for the No.9 task in Figure 4. The execution

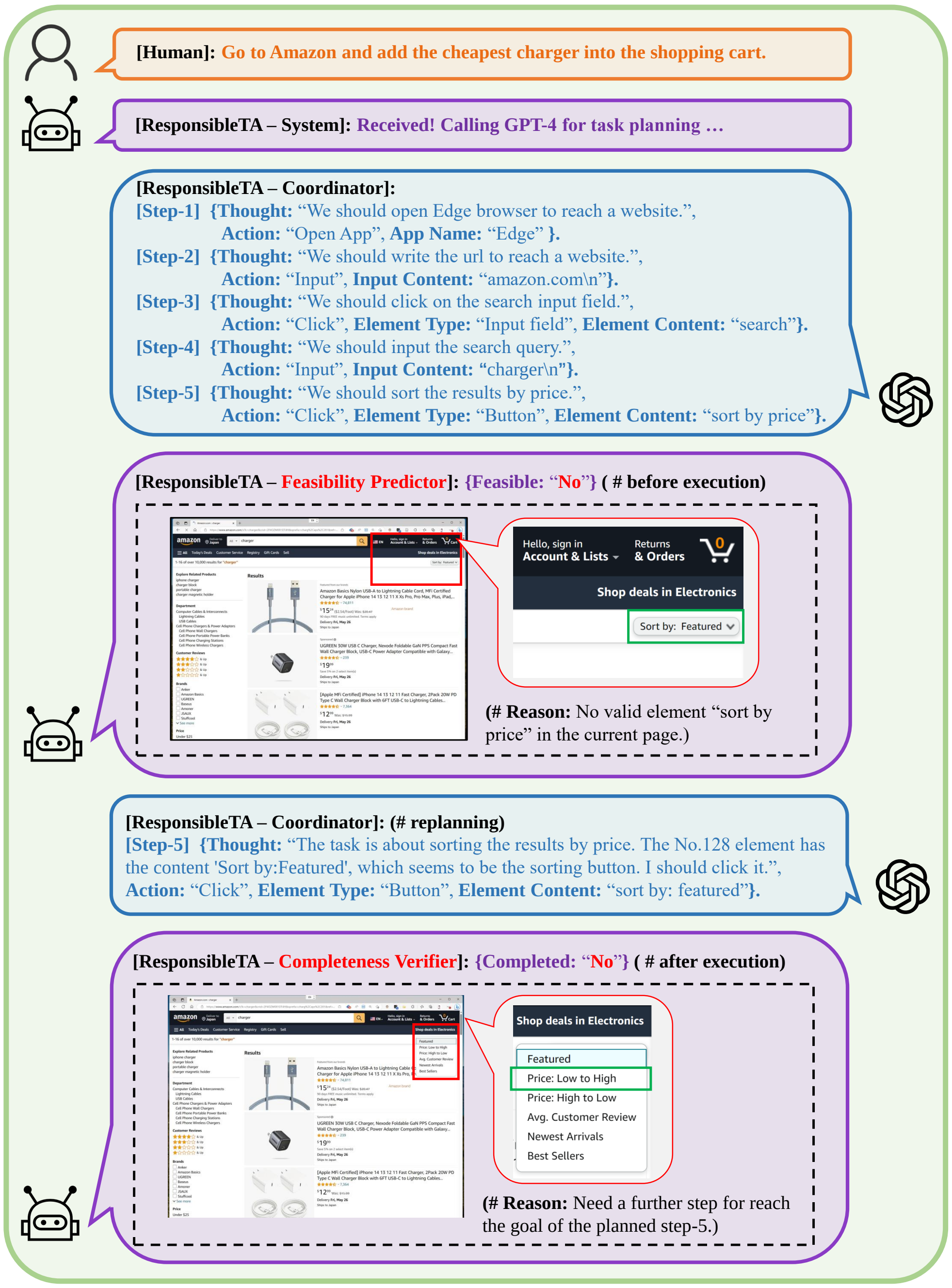
Table 2: The case study results of task automation in the real world. The "*Baseline*" denotes the model consisting of a LLM-based coordinator and a task automation executor, without our proposed feasibility prediction and completeness verification modules. The "*+Fea.*" and "*+Com.*" refers to adding the feasibility prediction module and adding the completeness module, respectively. We represent each execution result with its "*Progress*" and "*End Status*". Here, the "*Progress*" is shown in the form of the number of "*valid steps / total execution steps (human expert steps)*", in which "*human expert steps*" refers to the step number of completing given instruction by a human expert. For the "*End Status*", ✓ means the task goal has been achieved in the end while ✗ indicates it has not.

No.	**High-level Instruction**	**Baseline**		**Baseline+Fea.**		**Baseline+Fea.+Com.**	
		Progress	End Status	Progress	End Status	Progress	End Status
1	Open football news in bbc.com.	4/4 (4)	✓	4/4 (4)	✓	4/4 (4)	✓
2	Find the view setting page in Outlook.	4/4 (4)	✓	4/4 (4)	✓	4/4 (4)	✓
3	Navigate to the language setting in my Windows11.	3/3 (3)	✓	3/3 (3)	✓	3/3 (3)	✓
4	Find the system setting for text size in my Windows11.	1/3 (3)	✗	3/3 (3)	✓	3/3 (3)	✓
5	Help me open the latest received e-mail in my Outlook.	2/3 (3)	✗	3/3 (3)	✓	3/3 (3)	✓
6	Go to github.com and check issues that mentioned me, already logged in.	2/5 (4)	✗	4/4 (4)	✓	4/5 (4)	✓
7	Log in Instacart with username {username} and password {password}.	5/6 (6)	✗	6/6 (6)	✓	6/6 (6)	✓
8	Go to Amazon and add a pair of gloves into the shopping cart.	4/6 (6)	✗	6/6 (6)	✓	6/6 (6)	✓
9	Go to Amazon and add the cheapest charger into the shopping cart.	4/7 (9)	✗	5/5 (9)	✗	9/9 (9)	✓
10	Add my Costco's loyalty card number {card_num} in the website {web_url}.	2/6 (6)	✗	3/3 (6)	✗	6/7 (6)	✓
11	Create a meeting at 2023/04/15 14:00-14:30 in Outlook.	3/6 (8)	✗	3/3 (8)	✗	3/3 (8)	✗
12	Search the Cpython repo and download its zip file in github.com.	5/7 (8)	✗	6/6 (8)	✗	6/6 (8)	✗

for remaining steps and the corresponding prompts are omitted here for brevity. As shown in Figure 4, the LLM-based coordinator generates feasible low-level commands for the first 4 steps, and the corresponding execution is smooth for these steps. For the 5-th step, the coordinator originally thinks we should click the button with the content of "sort by price". It is seemingly a reasonable command but does not match the current web page in fact, because there is no matched button. At this point, the *Baseline* model executes this infeasible command in a seemingly random manner, leading to 4 valid steps in total. When ResponsibleTA has the feasibility predictor, this module will return "infeasible" signal to the coordinator so that it can replan upon additionally provided screen page information. After the replanning, the coordinator gives a feasible command, *i.e.*, click the "Sort by: Featured" button, and yields one more valid step. Despite this, *Baseline+Fea.* still fails for the next step since it does not realize that another click operation is further needed to achieve the goal of sorting by price. This can be effectively remedied by the complete version of ResponsibleTA thanks to its completeness verifier. With the assist of this module, ResponsibleTA add such click operation for the "Price: Low to High" button before executing subsequent steps via another replanning. In this way, it adjusts the planned actions timely and contributes to the eventual success.

5 Limitation

We have to admit that it is difficult, even impossible, to cover all aspects of a newly devised system in a single academic paper. This paper makes contributions and delivers insights from the perspectives of framework design and technical paradigm comparison. Its remaining limitations lie in two aspects: 1) benchmark construction; 2) specific model design/iteration aimed at pursuing high performance for this new domain. We here call on the community to address them with our work as a start point.



[Human]: Go to Amazon and add the cheapest charger into the shopping cart.

[ResponsibleTA – System]: Received! Calling GPT-4 for task planning …

[ResponsibleTA – Coordinator]:
[Step-1] **{Thought:** "We should open Edge browser to reach a website.",
Action: "Open App", **App Name:** "Edge" **}.**
[Step-2] **{Thought:** "We should write the url to reach a website.",
Action: "Input", **Input Content:** "amazon.com\n"**}.**
[Step-3] **{Thought:** "We should click on the search input field.",
Action: "Click", **Element Type:** "Input field", **Element Content:** "search"**}.**
[Step-4] **{Thought:** "We should input the search query.",
Action: "Input", **Input Content:** "charger\n"**}.**
[Step-5] **{Thought:** "We should sort the results by price.",
Action: "Click", **Element Type:** "Button", **Element Content:** "sort by price"**}.**

[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} (# before execution)

(**# Reason:** No valid element "sort by price" in the current page.)

[ResponsibleTA – Coordinator]: (# replanning)
[Step-5] **{Thought:** "The task is about sorting the results by price. The No.128 element has the content 'Sort by:Featured', which seems to be the sorting button. I should click it.",
Action: "Click", **Element Type:** "Button", **Element Content:** "sort by: featured"**}.**

[ResponsibleTA – Completeness Verifier]: {Completed: "No"} (# after execution)

(**# Reason:** Need a further step for reach the goal of the planned step-5.)

Figure 4: Detailed case study about how our proposed feasibility predictor and completeness verifier in ResponsibleTA remedy the failure case to achieve success on the No.9 task in Table 2. The 6-th to 9-th steps are omitted for brevity. GPT-4 [27] is used as the LLM-based coordinator.

6 Conclusion and Broader Impact

In this paper, we present a fundamental multi-modal framework, ResponsibleTA, for empowering LLMs as responsible task automators. In specific, we enhance LLMs with three core capabilities, *i.e.*, feasibility prediction, completeness verification and security protection. Moreover, we propose and compare different technical paradigms for implementing these core functionalities. We experimentally observe that domain-specific models deliver superior performance compared to prompt engineering based solutions on their implementations, while the later one does not require collecting domain-specific data for model training. Besides, we also demonstrate the effectiveness of our proposed ResponsibleTA and provide explanations on how our ResponsibleTA works intuitively through case study. As for the broader impacts, we hope our work can inspire more excellent works on the related benchmark construction, method design and functionality extension on top of this work in the future.

References

[1] Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Omar Cortes, Byron David, Chelsea Finn, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, et al. Do as i can, not as i say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691*, 2022.

[2] Pierre-Luc Bacon, Jean Harb, and Doina Precup. The option-critic architecture. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017.

[3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *NeurIPS*, volume 33, pages 1877–1901, 2020.

[4] Ting Chen, Saurabh Saxena, Lala Li, David J Fleet, and Geoffrey Hinton. Pix2seq: A language modeling framework for object detection. *ICLR*, 2022.

[5] Ting Chen, Saurabh Saxena, Lala Li, Tsung-Yi Lin, David J Fleet, and Geoffrey E Hinton. A unified sequence interface for vision tasks. *Advances in Neural Information Processing Systems*, 35:31333–31346, 2022.

[6] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.

[7] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*, 2022.

[8] MDN contributors. Dom, 2021. `https://developer.mozilla.org/en-US/docs/Web/API/Document_Object_Model/Introduction`.

[9] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*, pages 4171–4186, 2019.

[10] Danny Driess, Fei Xia, Mehdi SM Sajjadi, Corey Lynch, Aakanksha Chowdhery, Brian Ichter, Ayzaan Wahid, Jonathan Tompson, Quan Vuong, Tianhe Yu, et al. Palm-e: An embodied multimodal language model. *arXiv preprint arXiv:2303.03378*, 2023.

[11] Kai Greshake, Sahar Abdelnabi, Shailesh Mishra, Christoph Endres, Thorsten Holz, and Mario Fritz. More than you've asked for: A comprehensive analysis of novel prompt injection threats to application-integrated large language models. *arXiv preprint arXiv:2302.12173*, 2023.

[12] Shaohan Huang, Li Dong, Wenhui Wang, Yaru Hao, Saksham Singhal, Shuming Ma, Tengchao Lv, Lei Cui, Owais Khan Mohammed, Qiang Liu, et al. Language is not all you need: Aligning perception with language models. *arXiv preprint arXiv:2302.14045*, 2023.

[13] Wenlong Huang, Pieter Abbeel, Deepak Pathak, and Igor Mordatch. Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. In *International Conference on Machine Learning*, pages 9118–9147. PMLR, 2022.

[14] Geewook Kim, Teakgyu Hong, Moonbin Yim, JeongYeon Nam, Jinyoung Park, Jinyeong Yim, Wonseok Hwang, Sangdoo Yun, Dongyoon Han, and Seunghyun Park. Ocr-free document understanding transformer. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXVIII*, pages 498–517. Springer, 2022.

[15] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[16] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*, 2019.

[17] Chenxia Li, Weiwei Liu, Ruoyu Guo, Xiaoting Yin, Kaitao Jiang, Yongkun Du, Yuning Du, Lingfeng Zhu, Baohua Lai, Xiaoguang Hu, Dianhai Yu, and Yanjun Ma. Pp-ocrv3: More attempts for the improvement of ultra lightweight ocr system, 2022.

[18] Yaobo Liang, Chenfei Wu, Ting Song, Wenshan Wu, Yan Xia, Yu Liu, Yang Ou, Shuai Lu, Lei Ji, Shaoguang Mao, et al. Taskmatrix.ai: Completing tasks by connecting foundation models with millions of apis. *arXiv preprint arXiv:2303.16434*, 2023.

[19] David Lim. dslim/bert-base-ner, 2023. `https://huggingface.co/dslim/bert-base-NER`.

[20] Bill Yuchen Lin, Chengsong Huang, Qian Liu, Wenda Gu, Sam Sommerer, and Xiang Ren. On grounded planning for embodied tasks with language models. *AAAI*, 2023.

[21] Thomas F. Liu, Mark Craft, Jason Situ, Ersin Yumer, Radomir Mech, and Ranjitha Kumar. Learning design semantics for mobile apps. In *The 31st Annual ACM Symposium on User Interface Software and Technology*, UIST '18, pages 569–579, New York, NY, USA, 2018. ACM.

[22] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10012–10022, 2021.

[23] Chengqi Lyu, Wenwei Zhang, Haian Huang, Yue Zhou, Yudong Wang, Yanyi Liu, Shilong Zhang, and Kai Chen. Rtmdet: An empirical study of designing real-time object detectors, 2022.

[24] Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In *Proceedings of the European conference on computer vision (ECCV)*, pages 116–131, 2018.

[25] Vincent Micheli and François Fleuret. Language models are few-shot butlers. *arXiv preprint arXiv:2104.07972*, 2021.

[26] Microsoft. Microsoft ui automation, 2023. `https://learn.microsoft.com/en-us/dotnet/framework/ui-automation/ui-automation-overview`.

[27] OpenAI. Gpt-4, 2023. `https://openai.com/research/gpt-4`.

[28] OpenAI. Introducing chatgpt, 2023. `https://openai.com/blog/chatgpt`.

[29] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Gray, et al. Training language models to follow instructions with human feedback. In *NeurIPS*, 2022.

[30] Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. Hugginggpt: Solving ai tasks with chatgpt and its friends in huggingface. *arXiv preprint arXiv:2303.17580*, 2023.

[31] Mohit Shridhar, Xingdi Yuan, Marc-Alexandre Côté, Yonatan Bisk, Adam Trischler, and Matthew Hausknecht. Alfworld: Aligning text and embodied environments for interactive learning. *arXiv preprint arXiv:2010.03768*, 2020.

[32] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.

[33] Sai Vemprala, Rogerio Bonatti, Arthur Bucker, and Ashish Kapoor. Chatgpt for robotics: Design principles and model abilities. Technical Report MSR-TR-2023-8, Microsoft, February 2023.

[34] Ryan Volum, Sudha Rao, Michael Xu, Gabriel DesGarennes, Chris Brockett, Benjamin Van Durme, Olivia Deng, Akanksha Malhotra, and William B Dolan. Craft an iron sword: Dynamically generating interactive game characters by prompting large language models tuned on code. In *Proceedings of the 3rd Wordplay: When Language Meets Games Workshop (Wordplay 2022)*, pages 25–43, 2022.

[35] Zihao Wang, Shaofei Cai, Anji Liu, Xiaojian Ma, and Yitao Liang. Describe, explain, plan and select: Interactive planning with large language models enables open-world multi-task agents. *arXiv preprint arXiv:2302.01560*, 2023.

[36] Chenfei Wu, Shengming Yin, Weizhen Qi, Xiaodong Wang, Zecheng Tang, and Nan Duan. Visual chatgpt: Talking, drawing and editing with visual foundation models. *arXiv preprint arXiv:2303.04671*, 2023.

[37] Yue Wu, So Yeon Min, Yonatan Bisk, Ruslan Salakhutdinov, Amos Azaria, Yuanzhi Li, Tom Mitchell, and Shrimai Prabhumoye. Plan, eliminate, and track–language models are good teachers for embodied agents. *arXiv preprint arXiv:2305.02412*, 2023.

[38] Zhengyuan Yang, Zhe Gan, Jianfeng Wang, Xiaowei Hu, Faisal Ahmed, Zicheng Liu, Yumao Lu, and Lijuan Wang. Unitab: Unifying text and box outputs for grounded vision-language modeling. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXXVI*, pages 521–539. Springer, 2022.

[39] Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Ehsan Azarnasab, Faisal Ahmed, Zicheng Liu, Ce Liu, Michael Zeng, and Lijuan Wang. Mm-react: Prompting chatgpt for multimodal reasoning and action. *arXiv preprint arXiv:2303.11381*, 2023.

[40] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022.

[Supplementary Material]

A Further Model Introduction

We elaborate the three core modules in our proposed ResponsibleTA, *i.e.*, the feasibility predictor, completeness verifier and security protector, with their modeling in Sec.3 and their used datasets in Sec.4 in the main body of our paper. Besides these three core modules, in ResponsibleTA, we also train a domain-specific command executor and a screen parsing model. The domain-specific command executor aims to locate the target UI element by predicting its spatial coordinates for automating clicking or typing operations in accordance with given commands. And the screen parsing model converts a given screenshot into a series of element-wise descriptions in linguistic form, which plays the role of inputting the information of a screenshot in linguistic form to the LLM-based coordinator in two scenarios: 1) when replanning; 2) when employing the prompt engineering based paradigms for implementing the feasibility predictor or completeness verifier, as proposed. This model is needed in consideration to that most of LLMs have not developed or released their visual input APIs currently. These two modules are not the highlights of this work. We thus detail them in this supplementary material.

A.1 Domain-specific Executor

The domain-specific executor is a multimodal model that accepts both a screenshot and a command as its inputs. It is analogous to the domain-specific model-based paradigm introduced for implementing the feasibility predictor or completeness verifier in the main text. Inspired by Pix2Seq modeling [4, 5], we employ the same architecture design for this model with that of the feasibility predictor as illustrated in Figure 2 of the main text. It requires different instantiations for the structured output format, *i.e.*, "*<task_prompt> {results} </task_prompt>*". In this model, the "*<task_prompt>*" and "*</task_prompt>*" are instantiated by "*<locate_element>*" and "*</locate_element>*", respectively. And the "*{results}*" is organized as "*<x_min> {x_{min}} </x_min> <y_min> {y_{min}} </y_min> <x_max> {x_{max}} </x_max> <y_max> {y_{max}} </y_max>*" wherein $[x_{min}, y_{min}, x_{max}, y_{max}]$ denotes the coordinates of the top-left and bottom-right points of the bounding box corresponding to the target UI element. It achieves 0.51 mIoU for locating the target UI elements in given commands.

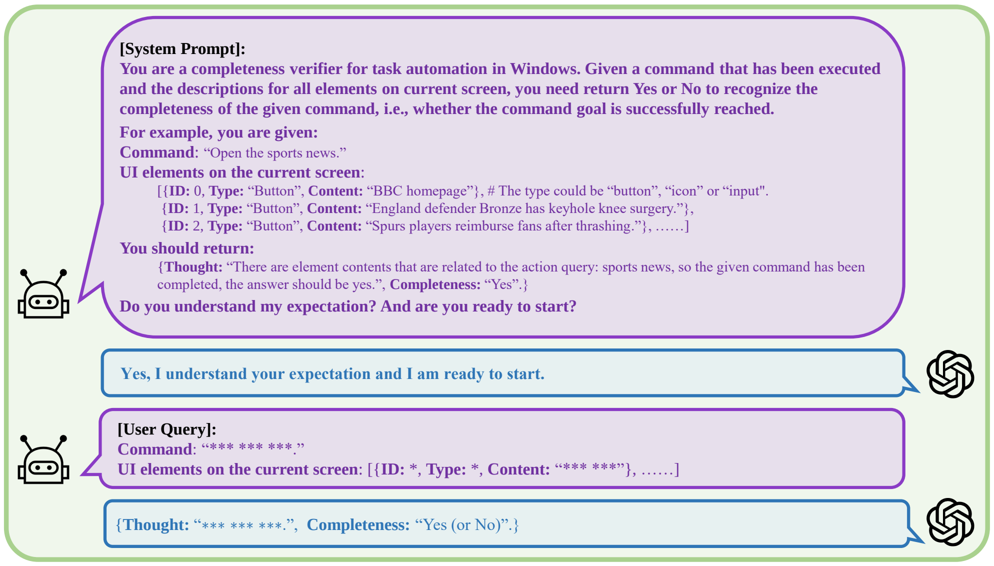
A.2 Screen Parsing Model

The screen parsing model aims to detect all UI elements in a given screenshot and recognize their attributes, *i.e.*, the location, text content, and type. Regarding the type attribute, we categorize each UI element into one of *button*, *input*, and *icon*. This model is a mixture of expert models including element detector, text detector, text recognizer, and icon recognizer. For a given UI screenshot, the element detector first locates all UI elements. Then, for button and input elements, the text detector locates their text regions when texts are available, and the text recognizer extracts their text contents. For icon elements, icon recognizer recognizes their categories as the text contents. Specifically, for element detector, we adopt RTMDet [23]-style architecture with ShuffleNetv2-1.0x [24] backbone. It achieves 0.710 mAP on the test set introduced as follows. For text detector and text recognizer, we employ the off-the-shelf models from PaddleOCRv3 [17]. For icon recognition, we use ShuffleNetv2-1.0x [24] as the backbone of the icon classifier and use a fully connected layer as the classification head. Our icon recognizer achieves 95.7% averaged accuracy on the test set.

B Further Dataset Introduction

We elaborate the datasets used for domain-specific feasibility predictor and completeness verifier in the main text. In this section, we further introduce the data for aforementioned domain-specific executor and screen parsing model.

The dataset for domain-specific executor consists of all feasible screenshot-instruction pairs from the feasibility prediction dataset introduced in Sec.4.1 of the main text. Its training split contains 0.5M samples from 38K desktop screenshots, and its testing split contains 27K samples from 2K desktop screenshots. For the element detector in the screen parsing model, we collect a dataset upon publicly available web pages and windows apps, comprising around 1.5M screenshots with 1.2M of them as


[System Prompt]:
You are a completeness verifier for task automation in Windows. Given a command that has been executed and the descriptions for all elements on current screen, you need return Yes or No to recognize the completeness of the given command, i.e., whether the command goal is successfully reached.
For example, you are given:
Command: "Open the sports news."
UI elements on the current screen:
[{**ID:** 0, **Type:** "Button", **Content:** "BBC homepage"}, # The type could be "button", "icon" or "input".
{**ID:** 1, **Type:** "Button", **Content:** "England defender Bronze has keyhole knee surgery."},
{**ID:** 2, **Type:** "Button", **Content:** "Spurs players reimburse fans after thrashing."}, ……]
You should return:
{**Thought:** "There are element contents that are related to the action query: sports news, so the given command has been completed, the answer should be yes.", **Completeness:** "Yes".}
Do you understand my expectation? And are you ready to start?

Yes, I understand your expectation and I am ready to start.

[User Query]:
Command: "*** *** ***."
UI elements on the current screen: [{**ID:** *, **Type:** *, **Content:** "*** ***"}, ……]

{**Thought:** "*** *** ***.", **Completeness:** "Yes (or No)".}

Figure 5: Illustration of our prompt engineering based paradigm for implementing the completeness verifier in our proposed ResponsibleTA.

the training split and 0.3M of them as the testing split. For these data, we obtain the annotations of UI elements, *i.e.*, their types and bounding boxes, from their tree-structure metadata, *i.e.*, DOM [8] and UIA [26]. Only leaf nodes are used. For the icon classifier in the screen parsing model, we build a dataset based on a public one (Rico [21]), which contains 14,043 icon images with 14 frequently used icon categories. Its training split contains 12,637 samples while its test split contains 1,405 samples.

C More Implementation Details

C.1 Training Details

As introduced, in ResponsibleTA, the feasibility predictor, completeness verifier and domain-specific executor share the same model architecture design as shown in Figure 3 of the main text. For this architecture, we employ Swin Transformer [22] and BART model [16] as its vision encoder and language decoder, respectively. For all of them, we first pretrain the entire model on document understanding tasks introduced in [14] and then finetune it on those datasets for feasibility prediction, completeness verification and command execution. Unless specifically stated, we perform the finetuning on each task for 20 epochs using 8 NVIDIA V100 GPUs, with a batch size of 2 on each GPU card. The height and width of screenshots are resized to 960 and 1280, respectively. We use the Adam optimizer [15] and set the initial learning rate to be 1×10^{-4}. Besides, we apply a cosine learning rate annealing schedule and a gradient clipping technique with the maximum gradient norm of 1.0.

C.2 Prompt Design Details

Similar to the proposed paradigms for implementing the feasibility predictor, we also introduce two analogical paradigms for implementing the completeness verifier in our proposed ResponsibleTA. Regarding the prompt engineering based paradigm, we detail its related prompt design as illustrated in Figure 5 for clearer introduction and better reproducibility.

D More Experiment Results

In Figure 4 of the main text, we have depicted the automation process of the first five steps on a specific task (*i.e.*, Task 9 in Table 2 of our main text) to show how our proposed feasibility predictor and completeness verifier pla their roles in turning an originally failed case into a successful one.

Here, in Sec.D.1, we provide its complete version with its part-1 (from the beginning to the 6-th step) illustrated in Figure 6 and its part-2 (from the 7-th step to the end) illustrated in Figure 7. Furthermore, we provide a failure case (illustrated in Figure 8) and its analysis in Sec.D.2.

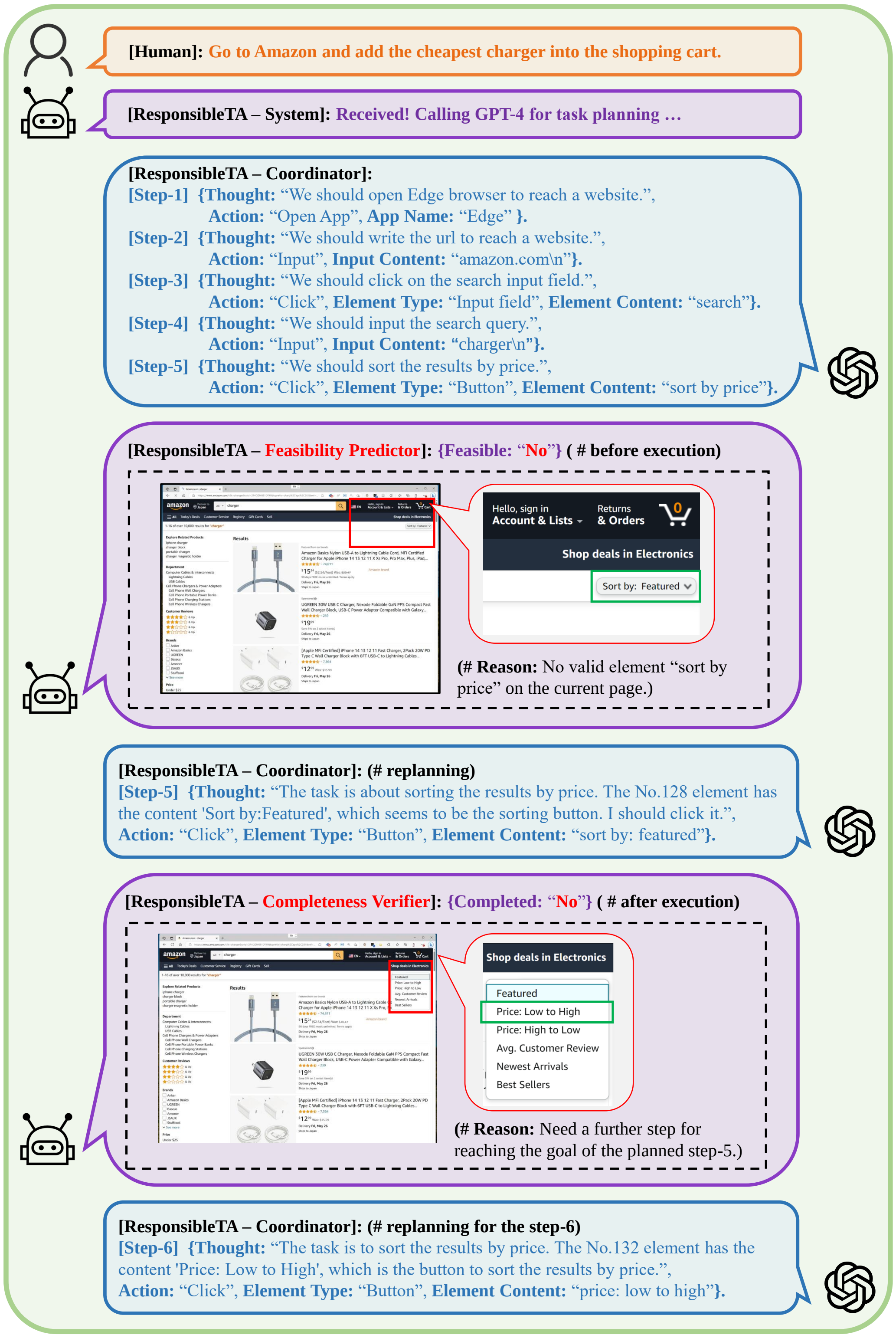
D.1 A Successful Case and Its Analysis

Note that the in-depth analysis for the part-1 of this case is in Sec.4.3 of the main text. We provide the detailed analysis regarding its part-2 here. As shown in Figure 7, the GPT-4 based coordinator in ResponsibleTA originally plans to click the button with the content of "cheapest charger". However, in the real web page, there is no matched element on the current page. At this time, the feasibility predictor considers this planned command as an infeasible one before execution, and asks the coordinator for a replanned command upon the information of the current page. Then, the coordinator thinks we should click the element containing charge information with the smallest y-coordinate so that this step is correctly processed. The coordinator plans for the next step, *i.e.*, adding the selected item to the shopping cart. It gives an infeasible command again since there is no "add to chart" item on the current page. This planned goal requires two execution operations to be completed in actual. With the help of the feasibility predictor and completeness verifier, our ResponsibleTA utimately achieves the purpose of adding the item to the shopping cart by clicking the "See All Buying Options" button followed by the "Add to Cart" button. As such, the human instruction "*Go to Amazon and add the cheapest charger into the shopping cart.*" is successfully automated.

From the detailed analysis of this case, we can intuitively understand the functions of the feasibility predictor and completeness verifier in ResponsibleTA. In specific, the feasibility predictor can intercept unreasonably planned commands. And the completeness verifier checks whether the actual executed operations have achieved the intended goals step-by-step. They serve as a double guarantee for ResponsibleTA to responsibly achieve task automation before and after command execution, by providing feedbacks for the coordinator so that it can perform replanning timely.

D.2 A Failure Case and Its Analysis

We describe a failure case (*i.e.*, the No.12 task in Table 2 of our main text) that the feasibility predictor and completeness verifier cannot remedy, as illustrated in Figure 8. This failure happens in automating the human instruction "*Search the Cpython repo and download its zip file in github.com.*". In most GitHub repositories, we can achieve the download purpose by directly clicking the "Download ZIP" button. However, in some GitHub repositories, such as the one in our illustrated failure case, the "Download ZIP" button is hidden in a secondary menu. In this case, we are required to complete the download of the ZIP file through two operations: first clicking the "Local" button, and then clicking the "Download ZIP" button. As shown in Figure 8, although our proposed module accurately detects that the commands given by the coordinator are infeasible, the coordinator has not been able to provide correct and feasible commands via its replanning. This task is ultimately terminated when the preset maximum number of replanning attempts is reached. This failure case implies that the knowledge of current LLMs is generic but may not be perfect, and there is room for our proposed ResponsibleTA to become more powerful as the capabilities of LLMs improve.



[Human]: Go to Amazon and add the cheapest charger into the shopping cart.

[ResponsibleTA – System]: Received! Calling GPT-4 for task planning …

[ResponsibleTA – Coordinator]:
[Step-1] **{Thought:** "We should open Edge browser to reach a website.",
Action: "Open App", **App Name:** "Edge" **}.**
[Step-2] **{Thought:** "We should write the url to reach a website.",
Action: "Input", **Input Content:** "amazon.com\n"**}.**
[Step-3] **{Thought:** "We should click on the search input field.",
Action: "Click", **Element Type:** "Input field", **Element Content:** "search"**}.**
[Step-4] **{Thought:** "We should input the search query.",
Action: "Input", **Input Content:** "charger\n"**}.**
[Step-5] **{Thought:** "We should sort the results by price.",
Action: "Click", **Element Type:** "Button", **Element Content:** "sort by price"**}.**

[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} (# before execution)

(# Reason: No valid element "sort by price" on the current page.)

[ResponsibleTA – Coordinator]: (# replanning)
[Step-5] **{Thought:** "The task is about sorting the results by price. The No.128 element has the content 'Sort by:Featured', which seems to be the sorting button. I should click it.",
Action: "Click", **Element Type:** "Button", **Element Content:** "sort by: featured"**}.**

[ResponsibleTA – Completeness Verifier]: {Completed: "No"} (# after execution)

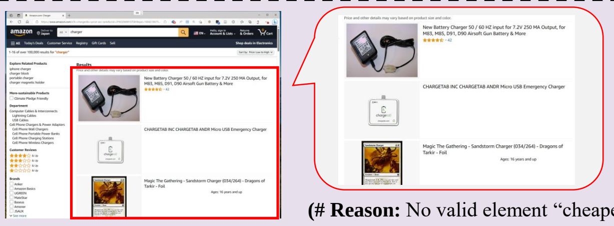
(# Reason: Need a further step for reaching the goal of the planned step-5.)

[ResponsibleTA – Coordinator]: (# replanning for the step-6)
[Step-6] **{Thought:** "The task is to sort the results by price. The No.132 element has the content 'Price: Low to High', which is the button to sort the results by price.",
Action: "Click", **Element Type:** "Button", **Element Content:** "price: low to high"**}.**

Figure 6: Illustration of a successful case (*i.e.*, the No.9 task in Table 2 of our main text) about how our proposed feasibility predictor and completeness verifier in ResponsibleTA remedy the failure case to achieve success. This figure depicts the part-1 of its complete version, *i.e.*, from the 1-th step to the 6-th step. GPT-4 [27] is used as the LLM-based coordinator.

[ResponsibleTA – Coordinator]:
[Step-7] {Thought: "I should select the cheapest charger.",
Action: "Click", **Element Type:** "Button", **Element Content:** "cheapest charger"**}.**

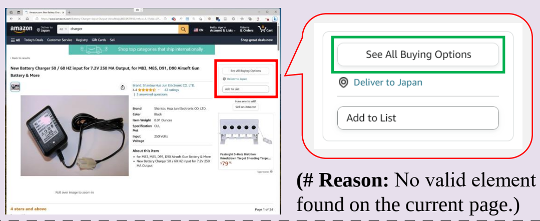
[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} (# before execution)


New Battery Charger 50 / 60 HZ input for 7.2V 250 MA Output, for M83, M85, D91, D90 Airsoft Gun Battery & More
CHARGETAB INC CHARGETAB ANDR Micro USB Emergency Charger
Magic The Gathering - Sandstorm Charger (034/264) - Dragons of Tarkir - Foil

(# Reason: No valid element "cheapest charger" found on the current page.)

[ResponsibleTA – Coordinator]: (# replanning for the step-7)
[Step-7] {Thought: "The task is about selecting the cheapest charger. The ID 138, ID 152, and ID 164 elements are the three elements containing charger information. The cheapest charger should be the one with the smallest y-coordinate among the charger elements. The ID 138 element is the one with the smallest y-coordinate among them.",
Action: "Click", **Element Type:** "Button", **Element Content:** "new battery charger"**}.**
[ResponsibleTA – Coordinator]:
[Step-8] {Thought: ""I should add the charger to the shopping cart.",
Action: "Click", **Element Type:** "Button", **Element Content:** "add to chart"**}.**

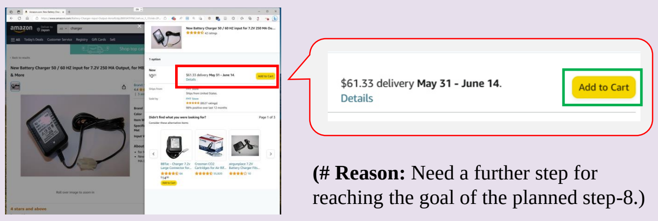
[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} (# before execution)



(# Reason: No valid element "add to chart" found on the current page.)

[ResponsibleTA – Coordinator]: (# replanning for the step-8)
[Step-8] {Thought: "The task is about adding the cheapest charger to the shopping cart. The ID 147 element is the charger, and the ID 148 element is the 'See All Buying Options' button which should be clicked to add the charger to the cart.",
Action: "Click", **Element Type:** "Button", **Element Content:** "see all buying options"**}.**

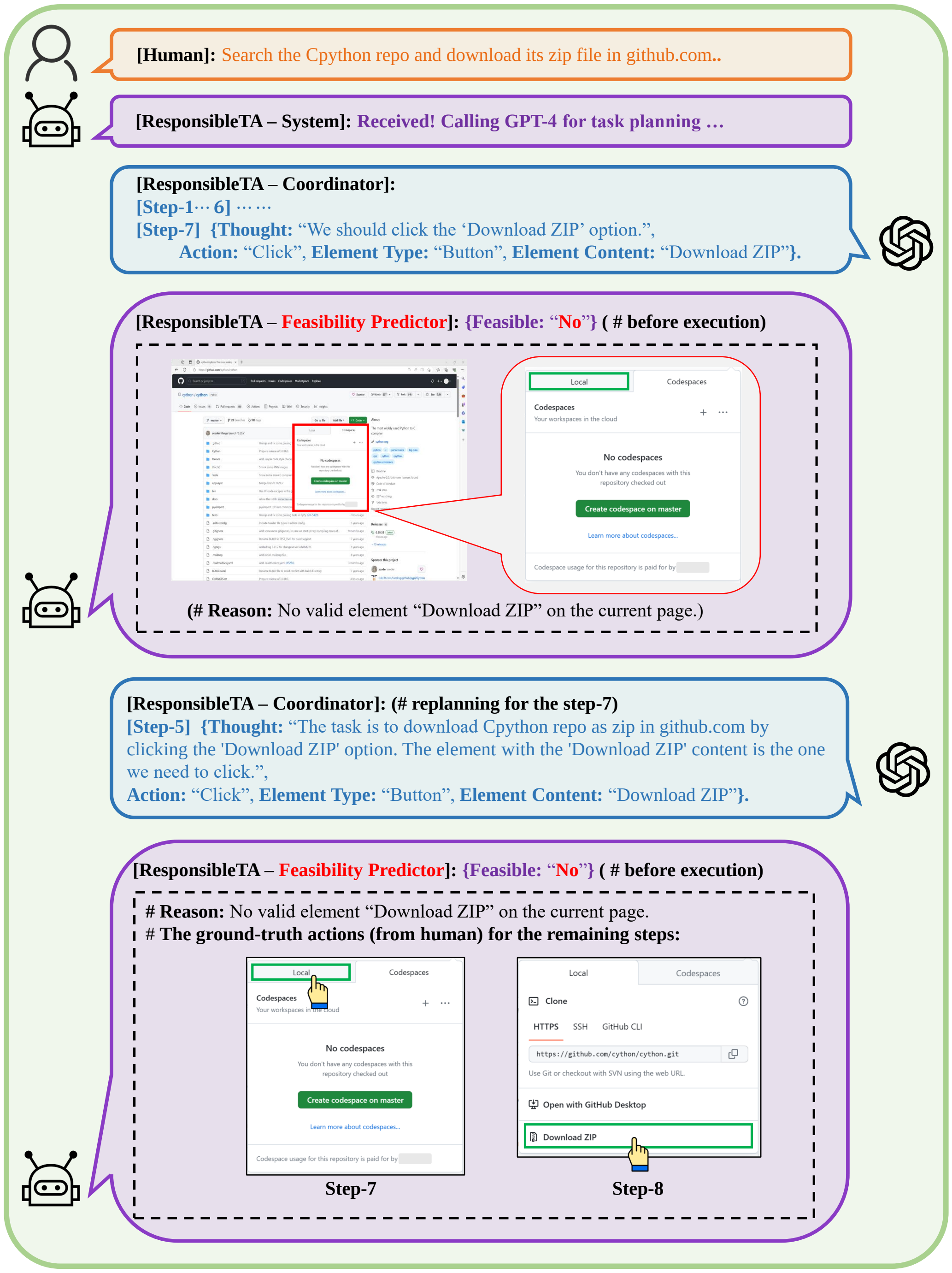
[ResponsibleTA – Completeness Verifier]: {Completeness: "No"} (# after execution)



(# Reason: Need a further step for reaching the goal of the planned step-8.)

[ResponsibleTA – Coordinator]: (# replanning for the step-9)
[Step-9] {Thought: "The task is to add the cheapest charger to the shopping cart. And the ID 138 element is the 'add to chart' button.",
Action: "Click", **Element Type:** "Button", **Element Content:** "add to chart"**}.**

Figure 7: Continuing from the Figure 6 in this supplementary material, this figure depicts the part-2 of the complete automation process of No.9 task, *i.e.*, from the 7-th step to the end.



[Human]: Search the Cpython repo and download its zip file in github.com..

[ResponsibleTA – System]: Received! Calling GPT-4 for task planning …

[ResponsibleTA – Coordinator]:
[Step-1⋯ 6] ⋯ ⋯
[Step-7] **{Thought:** "We should click the 'Download ZIP' option.",
Action: "Click", **Element Type:** "Button", **Element Content:** "Download ZIP"**}.**

[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} **(# before execution)**

(# Reason: No valid element "Download ZIP" on the current page.)

[ResponsibleTA – Coordinator]: (# replanning for the step-7)
[Step-5] **{Thought:** "The task is to download Cpython repo as zip in github.com by clicking the 'Download ZIP' option. The element with the 'Download ZIP' content is the one we need to click.",
Action: "Click", **Element Type:** "Button", **Element Content:** "Download ZIP"**}.**

[ResponsibleTA – Feasibility Predictor]: {Feasible: "No"} **(# before execution)**

# Reason: No valid element "Download ZIP" on the current page.
# The ground-truth actions (from human) for the remaining steps:

Local
Codespaces
Codespaces
Your workspaces in the cloud
No codespaces
You don't have any codespaces with this repository checked out
Create codespace on master
Learn more about codespaces...
Codespace usage for this repository is paid for by
Clone
HTTPS
SSH
GitHub CLI
https://github.com/cython/cython.git
Use Git or checkout with SVN using the web URL.
Open with GitHub Desktop
Download ZIP
Step-7
Step-8

Figure 8: Illustration of a failure case (*i.e.*, the No.12 task in Table 2 of our main text). The first six steps are omitted in this figure for the brevity. GPT-4 [27] is used as the LLM-based coordinator.