VIMO: A GENERATIVE VISUAL GUI WORLD MODEL FOR APP AGENTS

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ABSTRACT

App agents, which autonomously operate mobile Apps through GUIs, have gained significant interest in real-world applications. Yet, they often struggle with longhorizon planning, failing to find the optimal actions for complex tasks with longer steps. To address this, world models are used to predict the next GUI observation based on user actions, enabling more effective agent planning. However, existing world models primarily focus on generating only textual descriptions, lacking essential visual details. To fill this gap, we propose ViMo, the first Visual world **Model** designed to generate future App observations as images. For the challenge of generating text in image patches, where even minor pixel errors can distort readability, we decompose GUI generation into graphic and text content generation. We propose a novel data representation, the Symbolic Text Representation (STR), to overlay text content with symbolic placeholders while preserving graphics. With this design, ViMo employs a STR Predictor to predict future GUIs' graphics and a GUI-text Predictor for generating the corresponding text. Moreover, we deploy ViMo to enhance agent-focused tasks by predicting the outcome of actions. Experiments show that ViMo establishes visual world models as a compelling alternative to language-based approaches, producing visually plausible and functionally effective GUIs that empower App agents with more informed decisions.

1 Introduction

Recent advancements in Large Language Models (LLMs) ¹ have unlocked new possibilities for deploying AI agents across diverse fields (Li et al., 2023; Gou et al., 2023; Rawles et al., 2024b). A notable application is the smartphone application (App) agents (Rawles et al., 2024a; Wang et al., 2024a), designed to directly interact with Graphical User Interfaces (GUIs) to perform tasks autonomously and efficiently in a mobile operating system.

However, existing agents struggle with making decisions for tasks requiring longer steps (Chae et al., 2024). To address this "long-horizon" limitation, an increasing number of studies have introduced world models, which predict how GUIs evolve in response to user actions (Gu et al., 2024). Yet, these models typically rely on language to describe future observations. These language-based descriptions often fail to capture the intricate visual details, such as the location and colour of GUI elements, necessary for a precise representation (Chae et al., 2024). A seemingly straightforward solution is to execute action candidates on App emulators. However, real-world execution is impractical for scalable planning since actions like payments or repeated purchases are difficult to backtrack. Similar concerns have motivated the broader world-model community to explore ML-based simulators (Li et al., 2025; Hafner et al., 2019; Hu et al., 2022). We tackle the problem in the GUI domain by designing a GUI world model capable of predicting hypothetical observations in the visual modality.

To build a visual GUI world model capable of generating plausible future GUI observations that are visually consistent with user actions, a straightforward approach involves generating each pixel of a GUI using image generations (Brooks et al., 2023; Rombach et al., 2022). Although these methods demonstrate promising results, such as the GUI graphic generation on the location, style, and colour of GUI elements (Wei et al., 2024), or scene-text generation in a style that aligns the visual

¹By LLMs, we refer to the concept of foundation models that accept various modalities (e.g., visual language models (VLMs), multimodal LLMs (MLLMs)) while producing textual sequences (W. contributors, 2024).

Figure 1: GUIs generated by image-based methods (UI-Diffuser (Wei et al., 2024), TextDiffuser-2 (Chen et al., 2024c), and IP2P (Brooks et al., 2023) fine-tuned on GUI dataset, denoted as IP2P*).

context (Chen et al., 2024c; Zhang et al., 2024c), they still display distortions in the text rendering, particularly for small-sized text where each pixel is critical for accurately identifying and representing the text (see Fig. 1 for an illustration).

To address the challenges of accurately generating high-fidelity text content within a GUI, we propose ViMo, the first visual GUI world model. ViMo decouples the generation of graphic and text content into distinct processes, using a novel data representation named Symbolic Text Representation (STR). In STR, each text content is replaced (overlayed) with a text symbol, a rectangle-shaped placeholder with a defined border and fill colours, functioning as a special GUI element. Thus, we simplify the task of text content generation to text symbol generation, which reframes the problem to the localisation of the text within a GUI. Based on STR, ViMo employs a STR Predictor and a GUI-text Predictor to generate the graphic and the text content respectively. Specifically, the STR predictor is implemented as a diffusion model, taking the current STR, extracted from the given GUI, and a user action as inputs to generate the STR of the next GUI. Meanwhile, the GUI-text predictor, implemented based on an LLM, leverages the STR generated by the STR predictor to produce the corresponding text for each text symbol. Finally, the predicted STR and the generated text are combined to produce the next GUI.

We evaluated ViMo in three distinct scenarios to comprehensively demonstrate its effectiveness. First, we assessed its world model capability, where the quality of the generated GUIs was measured using visual similarity, instructional accuracy, and action readiness scores. Each score was examined through both automatic metrics and user studies. These assessments provided a robust and holistic evaluation of how visually precise and contextually plausible the generated GUIs were. Second, we tested ViMo in an agent-focused task to evaluate its benefits for existing App agents and its superiority over other language-based and image-based world models. In this setup, given a goal and the current App observation, the agent selected optimal actions to achieve the goal (Wang et al., 2024a). By accurately predicting the next GUI based on the current observation and an action, ViMo enabled the agent to better anticipate action outcomes and make more informed decisions. This experiment demonstrated the model's effectiveness in enhancing decision-making for App agents. Finally, we evaluated ViMo's real-world applicability under online navigation and zero-shot generalisation settings. These scenarios assessed the model's ability to perform in real-time interactions and to generalise to previously unseen Apps, further demonstrating its generalisation capabilities and practical value in dynamic environments.

Our main contributions are summarised as follows:

- We propose ViMo, the first generative visual GUI world model that predicts App observations in a visual modality, capable of more realistic and concrete visual GUI predictions compared to contemporary language-based methods.
- To address the challenge of strict pixel-level accuracy required to avoid distorted or blurred text generation in a GUI, we propose a Symbolic Text Representation (STR), overlaying text with uniform text symbols (placeholders) to simplify text content generation to text location generation. Then ViMo leverages an LLM to generate the corresponding text content for each text symbol.
- Extensive experiments demonstrated the effectiveness of ViMo in both world model evaluation and agent-focused tasks. Specifically, ViMo achieved an average 29.14% and 182.74% relative improvement over existing world models in terms of automatic metrics and user studies, respectively. Moreover, ViMo boosted the step-wise action prediction accuracy of App agents, achieving a 14.07% relative performance gain. In the online navigation setup, ViMo increased the task completion rate from 33.19% to 40.95%, yielding a substantial improvement of 7.76%.

2 RELATED WORKS

2.1 APP AGENT

App agents, powered by LLMs, have advanced task automation on mobile Apps (Wen et al., 2024b; Chen et al., 2024a; Zhang et al., 2024a;b; Lee et al., 2023). These agents interact with GUIs by emulating human actions. Approaches in this domain are broadly divided into *language-based* and *multi-modality-based* methods. Language-based methods rely on textual description of the App observation and the user goal to generate appropriate actions (Wen et al., 2024a; Li et al., 2024), while multi-modality-based methods enhance this capability by incorporating GUIs for a more comprehensive understanding of the interface (Christianos et al., 2024; Wang et al., 2024b). However, these approaches struggle with long-horizon tasks that require multiple interdependent actions and a deep understanding of dynamic environments (Chae et al., 2024). For this challenge, a straightforward solution is to use real-world emulators to simulate GUI changes from user actions, enabling App agents to navigate complex scenarios and improve decision-making accuracy. However, emulators face significant drawbacks, including the safety risks from real-world interactions, such as repeatedly sending messages or making purchases. To overcome these, world models have gained attention as a more efficient alternative, not only in agents (Chae et al., 2024; Gu et al., 2024), but also in broader domains such as robotics (Li et al., 2025; Zhou et al., 2024) and self-driving (Hu et al., 2022).

2.2 WORLD MODEL

By observing the real world, world models can predict how the environment evolves in response to an action (LeCun, 2022; Ding et al., 2024). For instance, GameNGen (Valevski et al., 2024) predicts how a game system will respond to user actions. Notably, the ability to anticipate potential outcomes of actions has proven to be highly beneficial in informing decision-making processes (Pascanu et al., 2017; Yang et al., 2024; Schrittwieser et al., 2020; Hafner et al., 2019). Inspired by their success, world models have emerged to predict the next observation on websites. These models (Chae et al., 2024; Gu et al., 2024; Liu et al., 2023) typically take a website observation and an action as inputs to generate a textual description of the next observation. While websites provide multiple sources of information, including the actual site and their CSS or HTML source files, mobiles present a more limited context, as only the GUIs are typically accessible. Moreover, such text-only descriptions often lack the precise visual details required for accurately predicting future observations, highlighting the need for a visual world model capable of generating high-fidelity future GUI images.

2.3 GUI GENERATION

With the rapid advancements in image generation techniques (Rombach et al., 2022; Kumari et al., 2023; Cao & Gong, 2024), previous methods have explored generating GUI directly in pixel space. For instance, layout generation methods generate the location of GUI elements (Lu et al., 2023; Zheng et al., 2023; Sobolevsky et al., 2023; Zhao et al., 2019), scene-text generation methods generate text that aligns with the visual context (Chen et al., 2024c; Zhang et al., 2024c; Chen et al., 2024b; Zeng et al., 2024), UI-diffuser (Wei et al., 2024) fine-tune a stable diffusion model to generate mobile GUIs conditioned on text prompts. For the next GUI generation conditioned on current GUI observation and a user action, it seems straightforward to resort to an image-and-text-conditioned approach (Brooks et al., 2023). However, we find that pixel-based image generation struggles with rendering text accurately, as even minor pixel prediction errors can lead to distortions, particularly for small-sized text (see Fig. 1 for examples).

In this work, we advance beyond existing approaches that generate GUI entirely (graphic and text) at the pixel level. Instead, we render graphics as image pixels and generate text as language tokens, enabling a more accurate method for GUI generation.

3 METHOD

In this section, we first define our setup in Subsection 3.1. Then, we introduce ViMo in Subsection 3.2. Finally, we demonstrate how ViMo can be applied to enhance existing App agents in real-world scenarios (Subsection 3.3). All the prompts in this section are listed in the Appendix.

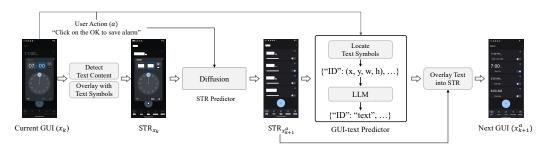


Figure 2: Framework of our ViMo. We first detect text content (actual words) in the current GUI (x_k) and overlay it with text symbols (rectangle-shaped placeholders with a black border and white fill), to create STR_{x_k} . Then STR_{x_k} and the user action (a) are input to the STR predictor to generate the STR of the next GUI $(STR_{x_{k+1}^a})$. Next, text symbols within $STR_{x_{k+1}^a}$ are located and assigned unique ID token. Then the LLM predicts the text content corresponding to each token. Finally, the next GUI image is constructed by overlaying the predicted text into the STR.

3.1 PROBLEM SETUP

In general, a GUI world model processes a given GUI Image x_k at step k, and user action a, to predict the effect of a on x_k and simulate the next GUI. Formally, this can be expressed as:

$$x_{k+1}^{a} = f(x_k, a), (1)$$

where $f(\cdot)$ represents the world model, and x_{k+1}^a denotes the predicted next (k+1) GUI image after applying a to x_k . In the following, we explain in detail of our world model.

3.2 VIMO: GENERATIVE VISUAL GUI WORLD MODEL

To tackle the limitation of existing methods (Wei et al., 2024; Chen et al., 2024c; Brooks et al., 2023) in generating visually plausible text for a GUI, as shown in Fig. 1, we propose ViMo, a novel generative visual GUI world model that decouples the graphic and text content generation. As shown in Fig. 2, we first detect and remove all the text in the GUI by overlaying it with a text symbol to create the Symbolic Text Representation (STR). Then a STR predictor is leveraged for determining the STR representation of the next GUI with a pixel-based diffusion process. Finally, a GUI-text predictor is proposed to generate the text content for each symbol using an LLM, followed by a handcrafted design to overplay the text into the STR image to create the next GUI. Their details are specified in the following.

3.2.1 STR: Symbolic Text Representation

To develop a GUI prediction model that eliminates the need to generate specific text content, we propose the Symbolic Text Representation (STR), where all the text content (actual words) within the GUI image is symbolised (overlayed) with uniform text symbols (placeholders). To be specific, we create an STR representation from a given GUI image with three steps: 1) using an OCR model (Shi et al., 2016; Qiao et al., 2020) to detect text within the GUI; 2) masking the detected text by overlaying it with a box filled with white and bordered in black; 3) we leverage an LLM to filter out static text displayed on static GUI elements and preserve it in the image, as it does not involve any semantic evolution or dynamic changes and remains unchanged as part of specific elements such as a keyboard or a clock face. Additionally, we empirically find that predicting this static text with complex spatial patterns poses significant challenges for the LLM.

Through the above process, GUI images are transformed into the STR representation, where the text content is abstracted into a text symbol, relaxing the task of generating semantic text content into predicting text symbols that indicate the location and size.

3.2.2 STR PREDICTOR

Building on the powerful generative capability of diffusion-based models (Rombach et al., 2022), we introduce a STR predictor specifically trained to understand a given STR and a user action,

Algorithm 1 Enhancing App Agent with Generative Visual GUI World Model

Input: Current GUI Observation x_k , A goal g, A visual world model ViMo, A selection model $S(\cdot)$.

Output: Action to be applied on x_k to achieve g.

Generate action options \mathcal{A} with n actions $\{a^i\}$ (Eq. (4)).

for i = 1 to n do

Leverage ViMo to synthesise the next GUI observation conditioned on a^i and x_k , denoted as $x_{k+1}^{a^i}$ (Eq. (5)).

end for

Use $S(\cdot)$ to identify the optimal action with predicted observation (Eq. (6)).

enabling it to generate the corresponding next STR effectively. In particular, we fine-tune a pretrained stable diffusion model (Rombach et al., 2022) to predict the next STR, conditioned on the STR of the current GUI and the user action. Given a STR representation (STR $_{x_k}$) extracted from GUI (x_k), the process starts with the encoding of STR $_{x_k}$ into a latent representation (Kingma & Welling, 2013): $z = \mathcal{E}(\text{STR}_{x_k})$. Gaussian noise is then added to this representation to create z_t at timestep t. A denoising autoencoder is subsequently trained to predict the Gaussian noise in the latent representation, aiming to reverse the noise addition. The objective is defined as:

$$L = \mathbb{E}_{\mathcal{E}(\mathrm{STR}_x), \epsilon \sim \mathcal{N}(0, I), t} \Big[\|\epsilon - \epsilon_{\theta}(z_t, \mathcal{E}(\mathrm{STR}_{x_k}), t, a)\|_2^2 \Big], \tag{2}$$
 where ϵ_{θ} is a U-Net (Ronneberger et al., 2015) architecture conditioned on a timestep t , a text prompt

where ϵ_{θ} is a U-Net (Ronneberger et al., 2015) architecture conditioned on a timestep t, a text prompt a (action), the visual input z_t and the image condition STR_{x_k} . To support the condition on images, we follow IP2P (Brooks et al., 2023) to add additional input channels to the first convolutional layer, concatenating the image condition $\mathcal{E}(STR_{x_k})$ with the noised latent z_t . After training, our STR predictor is capable of synthesising the next STR ($STR_{x_{k+1}}$) for STR_{x_k} with action instruction a.

3.2.3 GUI-TEXT PREDICTOR

Given a STR representation generated by our STR predictor, we design a GUI-text predictor to generate plausible text for the text symbols in the STR based on its graphics. Specifically, we first locate the text symbols in the STR by colour matching and boundary detection. This outputs the location of text symbols, along with their unique ID tokens assigned via enumeration, denoted as \mathcal{T} . Then we leverage the image processing and task understanding ability of LLM to predict the text content based on its context in STR. This process can be formulated as:

$$text_{x_{k+1}^a} = LLM(STR_{x_{k+1}^a}, x_k, a, \mathcal{T}), \tag{3}$$

where $\mathrm{STR}_{x_{k+1}^a}$ denotes the STR representation of x_{k+1}^a . $\mathrm{text}_{x_{k+1}^a}$ contains the predicted text content for each text symbol, associated with its ID token. This design ensures flexible and accurate text generation tailored to the predicted GUI STRs as the context. Finally, we overlay each text content $(\mathrm{text}_{x_{k+1}^a})$ to $\mathrm{STR}_{x_{k+1}^a}$ to reconstruct the predicted GUI image (x_{k+1}^a) . To be specific, text symbols are replaced with the corresponding text based on coordinates, with dynamic styling determined by the symbol's size and surrounding colours. More details are provided in the Appendix.

3.3 VIMO ENHANCED APP AGENT

Motivated by that App agents usually face limitations in long-horizon planning to make optimal decisions on action selection (Chae et al., 2024), we leverage the proposed ViMo to enhance the decision-making of App agents.

To be specific, we break down the process into three steps: action option generation, action outcome synthesis, and action selection. In the first step, the App agent generates n action options, as follows:

$$\mathcal{A} = \operatorname{Agent}(x_k, g), \tag{4}$$

where $A = \{a^1, a^2, \dots, a^n\}$ denotes the action option set, x_k is the current GUI image at step k, and g is the given user goal. With these action options, our world model ViMo is leveraged to synthesise the outcome (next GUI) of these actions as follows:

$$x_{k+1}^{a^i} = \mathbf{ViMo}(x_k, a^i), \tag{5}$$

Table 1: GUI quality evaluation. s_{gc} indicates the GUI consistency, s_{ia} instructional accuracy, s_{ar} action readiness score and s_h the harmonic average between the 3 metrics. Δs_h is the relative performance gains of our ViMo over other methods. IP2P* denotes finetuing of IP2P on our dataset.

Method		Aut	omatic I	Metric				User Sti	udy	
Michiod	s_{gc}	s_{ia}	s_{ar}	s_h	Δs_h	s_{gc}	s_{ia}	s_{ar}	s_h	Δs_h
HTML-vision	0.70	85.77	62.79	0.72	5.39%	0.31	11.32	9.01	0.23	282.61%
IP2P*	0.74	63.57	70.15	0.69	10.20%	0.82	58.92	52.81	0.63	39.68%
UI-diffuser	0.60	39.61	38.75	0.44	71.82%	0.36	14.32	8.56	0.27	225.93%
ViMo (Ours)	0.74	75.39	78.68	0.76	-	0.89	91.12	84.71	0.88	-

where $x_{k+1}^{a^i}$ denotes the synthesised next GUI of applying action a^i on x_k . Finally, each action a^i and its corresponding predicted outcome $x_{k+1}^{a^i}$ are fed into an LLM-based selection model, which identifies the optimal action based on the generated GUIs. This process can be formulated as:

$$a_{se} = S\left(\{(a^i, x_{k+1}^{a^i})\}_{i=1}^n\right),\tag{6}$$

where a_{se} denotes the selected action, and $S(\cdot)$ is the selection model. This procedure is outlined in Algorithm 1. By predicting the next GUI, ViMo provides the agent with the potential outcome of an action, enabling it to make more informed decisions. We build the selection model to identify the best action in two steps. First, we query an LLM to evaluate all the action candidates, providing a judgment—either *valid* or *invalid*—and a confidence score for each action. Second, we query the LLM again to select the best action from the two highest-scoring actions. This process is motivated by our observation that, in over 70% of tasks, the difference between the top two scores is equal to or less than 0.1, indicating that both are likely optimal. By explicitly prompting the LLM to compare the top candidates, we go beyond coarse scoring and enable more detailed decision-making.

4 EXPERIMENTS

In this section, we begin by summarising our proposed STR dataset discussed in Subsection 3.2.1. Next, we tested the core capability of our ViMo, focusing on its GUI generation ability. Building on this, we demonstrated how the powerful GUI generation capability of ViMo can enhance the decision-making of App agents. Then, we studied our effectiveness in real-world App navigation tasks. Finally, we carried out the ablation study to validate the effectiveness of our model design. Specific setups and experiment details are elaborated in subsequent sections. Unless explicitly stated otherwise, GPT-40 (Hurst et al., 2024) was employed as the default LLM in the following sections.

4.1 Dataset Summarisation

Our STR dataset was constructed using data from two widely recognised and large-scale sources: Android Control (Li et al., 2024) and Android in the Wild (AITW) (Rawles et al., 2024b). From these sources, we respectively sampled 12 and 7 Apps, selecting those with rich data samples while filtering out noise. Android Control provides two types of user actions: 1) *action commands*: predefined actions (e.g., click, scroll) accompanied by specific parameters such as coordinates (x, y); 2) *action instructions*: actions described in natural languages, such as "click the plus icon". We used action instructions as conditions for our world model as this approach was more concrete and better utilised the pre-trained model in understanding natural language. For AITW, action commands were converted into action instructions using GPT-40 (Hurst et al., 2024). In total, we collected 19 Apps with 3,550 episodes, 23,620 images and 18,450 actions. To ensure both time-efficient and cost-efficient experiments, we followed prior App agent (Rawles et al., 2024b) on partial split evaluation. Specifically, we randomly sampled 57 episodes across 19 distinct Apps. Details including dataset collection, split summarisation and full-split experiments are provided in the Appendix.

4.2 WORLD MODEL ABILITY

We evaluated the GUI generation capability of ViMo by GUI quality evaluation. We included IP2P (Brooks et al., 2023) and UI-diffuser (Wei et al., 2024), both originally designed for image

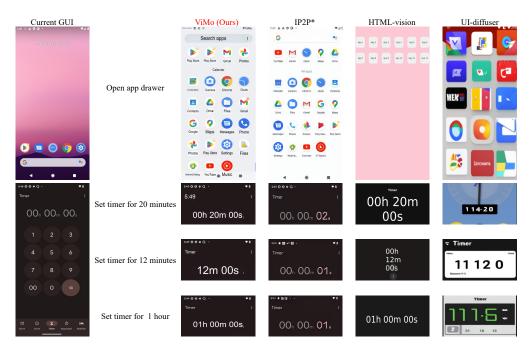


Figure 3: GUI generation comparison in graphic generation (Top) and text generation (Bottom).

editing and GUI generation. We fine-tuned IP2P on our dataset to generate everything of the GUI, including the text content and the graphic, denoted as IP2P*. We also leveraged an LLM to predict App observations in an HTML format, which were rendered into images, denoted as HTML-vision.

We leveraged 3 evaluation metrics: The GUI consistency score (s_{gc}) assessed the visual similarity between the ground truth and the generated next GUI; Instructional accuracy score (s_{ia}) determined whether the generated GUI adheres to the user action; Action readiness score (s_{ar}) evaluated whether the generated GUI retains valid elements essential for subsequent actions required to achieve the user goal. Both automatic evaluation and user studies were conducted. For the automatic evaluation, we used DINO (Caron et al., 2021) as the visual encoder to compute s_{gc} , and an LLM to evaluate s_{ia} and s_{ar} . For the user study, we invited 70 voluntary participants to complete questionnaires based on 80 GUI samples, generated by all 4 compared methods. For each sample, participants were asked three questions, one each for evaluating s_{gc} , s_{ia} , and s_{ar} . The prompts used for the LLM-based evaluations and full instructions for user study are provided in the Appendix.

As shown in Table 1, ViMo achieved the highest score on the harmonic average of the three automatic metrics, surpassing other methods with an average relative performance improvement of 29.14%. The results of the user study were consistent with the automatic evaluations, where ViMo demonstrated the best performance. Notably, HTML-vision and UI-diffuser performed significantly worse in human evaluation compared to their scores in the LLM-based assessment. This discrepancy likely arose because human evaluators perceived the outputs of these methods as visually unrealistic or functionally incoherent, leading to lower subjective scores in s_{gc} , s_{ia} and s_h .

Qualitative comparisons are presented in Fig. 3, under two scenarios: GUI graphic changes (Top) and text generation (Bottom, cropped for space efficiency). Experiments revealed that while the HTML-vision method exhibited greater flexibility in responding to user actions (as shown in the bottom examples), it failed to produce concrete details necessary for future actions (top). Conversely, IP2P* generated plausible GUI graphics but lacked flexibility in text content generation (also reflected by s_{gc} and s_{ia} in Table 1). This trade-off highlighted the superior balance of ViMo.

4.3 WORLD MODEL ENHANCED APP AGENT

This section demonstrates that: 1) ViMo enhanced the performance of App agents in decision-making; 2) ViMo outperformed other world models in enabling App agents to make more accurate decisions.

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Table 2: Decision optimisation comparison with App agents.

Modality

w/o WM

Language

Vision

World Model

w/o WM Change-text

HTML-text

HTML-vision UI-diffuser

IP2P* ViMo (Ours)

393 394 395

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Agent Type Leisure Work System Overall App Agent ER (Li et al., 2024) 31.76 46.15 34.13 34.50 AutoDroid (Wen et al., 2024a) 35.81 46.15 31.75 35.46 Language-Based 41 22 51.28 T3A (Rawles et al., 2024a) 42 86 43.13 T3A + ViMo (Ours) 50.00 58.97 45.24 49.20 APP-Agent (Zhang et al., 2023) 43.24 51.28 39.68 42.81 39.68 Mobile-Agent-v2 (Wang et al., 2024a) 43.92 53.85 43.45 Multi-Modality-Based M3A (Rawles et al., 2024a) 46.62 51.28 43.65 46.01 M3A + ViMo (Ours) 53.38 53.85 45.24 50.16

Table 3: Comapre World Models. Table 4: Zero-shot Evaluation.

Table 5: Online Evaluation.

Step Acc.	
46.01	
47.28	
46.65	
48.89	
47.60	
48.56	
50.16	

App Agent	LLM	Step Acc.
SeeAct	GPT-4-Turbo	33.9
M3A	GPT-4-Turbo	42.1
ER	Gemini 1.5 Pro	24.4
T3A	Gemini-2.0-Flash	41.4
T3A+ViMo	Gemini-2.0-Flash	46.8
M3A	Gemini-2.0-Flash	44.2
M3A+ViMo	Gemini-2.0-Flash	47.6

	App Agent	LLM	Task Acc.
	SeeAct	GPT-4-Turbo	15.50
	M3A	GPT-4-Turbo	25.40
	M3A	Gemini-1.5-Pro	22.80
-	T3A	GPT-4-Turbo	30.60
	T3A	Gemini-1.5-Pro	19.40
-	T3A	Gemini-2.0-Flash	33.19
	T3A + ViMo	Gemini-2.0-Flash	40.95

Comparison with App Agents. In this experiment, we collected 6 LLM-based App agents, which included three language-based methods: ER, AutoDroid, and T3A, as well as three multi-modality-based methods: APP-Agent, Mobile-Agent-v2, and M3A. We applied our ViMo into M3A and T3A following the process in Subsection 3.3. Moreover, we followed the previous works (Rawles et al., 2024b; Li et al., 2024) to use the step accuracy (the number of correct actions divided by the number of overall actions) to quantify the model performance. To provide more detailed results, we categorised the Apps into three groups: "Leisure", "Work" and "System". Table 2 demonstrates that ViMo was beneficial to the App agent, achieving a relative performance gain of 9.01% for M3A and 14.07% for T3A. These findings highlighted the effectiveness of our proposed world model in providing App agents with enhanced decision-making capability. Additional information about the categorisation and experiments with more App agents are provided in the Appendix.

Comparison with World Models. We evaluated the ability of ViMo to enhance App agent decision-making by comparing it against existing world models. In addition to vision-based world models discussed in Subsection 4.2, we also incorporated two language-based world models (Gu et al., 2024; Chae et al., 2024), utilising Change-text to generate textual descriptions capturing differences between consecutive observations and HTML-text to predict App observations in an HTML format. Then, we applied each world model to M3A App agents. Table 3, together with Appendix Table 9, illustrates that vision-based methods consistently outperform language-based world models, thereby reinforcing our motivation for developing visual GUI world models. Moreover, our approach achieves superior performance over existing world models, underscoring its effectiveness and advantage.

4.4 REAL-WORLD APPLICATIONS

Practical Deployment. ViMo was designed to be lightweight and easily deployable. The minimum requirement for deployment is a GPU with 16 GB of memory. Moreover, ViMo was implemented as a plug-and-play API that required only a single function call, making integration straightforward. Inference time on V100 GPU is 8 seconds on a STR image generation and 30 seconds on GUI-text prediction. We collected and compared the inference time with existing methods in the Appendix.

Generalisation to New Apps. Generalisation is a crucial capability for real-world applications. To assess the generalisation performance of our method on new Apps that were unseen during training, we conducted a zero-shot evaluation using data from the Android Control dataset (Li et al., 2024), explicitly excluding Apps encountered during training. As shown in Table 4, ViMo substantially outperformed the baseline and achieved 47.6%, underscoring its robustness and adaptability to novel App environments. Additional visualisations of unseen scenarios are provided in the Appendix.

Online Evaluation. To further demonstrate the effectiveness of ViMo in realistic App navigation scenarios, we conducted an online evaluation using the AndroidWorld dataset (Rawles et al., 2024a),

which comprises 116 distinct navigation tasks. Performance was measured using the task success rate (Task Acc.). As illustrated in Table 5, ViMo achieved a notable improvement of 7.76% over the baseline method, highlighting its effectiveness and reliability in real-world settings.

4.5 ABLATION STUDY

In this section, we ablated on three key components of ViMo: 1) preserving static text within the image to simplify the text generation task; 2) using action instructions instead of action commands as the conditioning input for ViMo; and 3) varying the number of iterations, where each iteration corresponds to one roll-out step into the future during GUI prediction.

Firstly, for the challenge of predicting static text from specific GUI elements, such as keyboard, number pad or clock face, which typically did not involve text changes and exhibited complex spatial patterns, we retained static text within the image (Subsection 3.2.1). This approach eliminated the need for the LLM to generate such static text while generating in pixels instead. Secondly, we proposed conditioning STR prediction on action instruction rather than action commands (Subsection 4.1). Ablation results are presented in Table 6, where "Static Text" indicates whether static text was retained in the images, and

Table 6: Ablations on preserving static text and using action instructions.

Static Text	Action Instr.	App A	Agent
		T3A	МЗА
N/A	N/A	43.13	
√	_	42.81	45.05
_	✓	47.28	48.88
✓	✓	42.81 47.28 49.20	50.16

Table 7: Ablation on the number of iterations.

Method	Iterations	Step Acc. (%)
T3A	N/A	39.94
	1	46.06
T3A+ViMo	2	46.65
	3	45.05

"Action Instr." denotes whether natural language instructions (" $\sqrt{}$ ") or abstract action commands ("-") were used as conditioning input to ViMo. The first row indicates the baseline where ViMo was not applied. The table shows that both components contributed significantly to performance improvements across the two App agents, highlighting their critical roles in enabling ViMo to generate high-quality GUIs. Visual comparison examples are provided in the Appendix for further illustration.

Our ViMo predicted future GUI observations, which could be recursively fed back as input to simulate further into the future. In this ablation study, we varied the iteration number to evaluate how extended roll-outs impact prediction accuracy. We took Gemini-2.0-Flash (Hassabis & Kavukcuoglu, 2024) as the LLM in this study. As shown in Table7, performing two iterations yielded the highest accuracy. However, this also led to increased computational cost. Therefore, we selected one step as a practical trade-off between performance and efficiency. We also observed a slight decline in performance at iteration 3 relative to iterations 1 and 2, indicating that extending the prediction horizon did not necessarily improve agent behaviour. This was likely due to that longer horizons introduced not only additional foresight but also a greater accumulation of prediction errors, whose detrimental effect could outweigh the potential benefits. Further analysis of error accumulation, user examples of ViMo with App agent, and comparisons with various world models are provided in the Appendix.

5 CONCLUSION

In this work, we introduced ViMo, a novel generative visual GUI world model designed to predict App observations in a visual modality, providing a more realistic and concrete approach compared to contemporary language-based models. To address the unique challenges of GUI generation, ViMo was equipped with the STR representation to simplify text content generation to text location prediction by overlaying text content with placeholders and delegating content generation to LLM. This innovation ensured high visual fidelity and avoided artefacts like distorted or blurred text. Through extensive experiments, we demonstrated that ViMo generated both visually plausible and functionally effective GUIs. Notably, ViMo boosted step-wise action prediction accuracy by a relative performance gain of 14.07%, underscoring its potential to enhance decision-making of App agents. Furthermore, real-world experiments demonstrated the strong generalisation ability of ViMo to unseen Apps, along with its robust performance in online navigation tasks under real-time environment interaction. Together with its superiority over language-based world models, these results highlighted the value of ViMo in advancing GUI world modelling in visual modality.

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In this Appendix, we first provide detailed explanations, including prompts related to our methods, descriptions of our STR dataset, and evaluation details. Then, we present additional experimental results. Finally, we present additional visualisations of our proposed ViMo for GUI generation.

A EXPERIMENTAL DETAILS

A.1 GUI-TEXT PREDICTOR

This subsection elaborates on the design and functionality of the GUI-text predictor, summarising its key components and providing a detailed explanation of its underlying processes.

Given a STR prediction, the GUI-text predictor starts by locating the text symbols. To be specific, we first detect black borders by identifying black pixels in the BGR colour space, generating a binary mask that indicates whether a pixel is black or not. A pixel is classified as black if its BGR values fall within the range [0,0,0] to [50,50,50]. Next, we identify rectangular regions within this mask by computing the ratio of the actual contour area to its corresponding bounding rectangle area. If this ratio exceeds 0.8, the region is considered a valid rectangle, allowing us to extract rectangles with black borders. For these detected regions, we further analyse their internal colour distribution to determine whether they contain the desired white colour. Specifically, we define white pixels as those with BGR values within the range [200,200,200] to [255,255,255]. If more than 50% of the pixels within a region fall within this range, the region is classified as a text symbol. Thus, the locations of text symbols are extracted, and we assign a unique identifier (ID) to each symbol through enumeration.

Building on this, we take as inputs the current GUI image x_k , an action a to be applied to this image, the predicted STR (STR $_{x_{k+1}^a}$), the location and unique ID token of the text symbols in the STR \mathcal{T} . Then we leverage an LLM to predict the text content for each text symbol. The process begins with preprocessing the STR by overlaying the ID token for each text symbol to the corresponding position in the STR image, resulting in a modified representation denoted as STR $_{k+1}^{ID}$. Next, we prompt an LLM to identify which text symbols will remain unchanged after the action a (see the prompt in Subsection G.1). These symbols are determined to not be affected by the action and have content identical to the previous GUI x_k . Based on the resulting ID list, we retrieve the corresponding pixels from the previous GUI x_k based on their location and update the STR representation. The updated image is still referred to as STR $_{k+1}^{ID}$ for simplicity.

Subsequently, the LLM is prompted to determine the semantic role of each text symbol by analysing its context (see the prompt in Subsection G.2). This semantic information, combined with STR_{k+1}^{ID} , is then used to predict the exact text content of each symbol (see the prompt in Subsection G.3).

Finally, to overlay a symbol with its actual text content, we perform the following steps: 1) For a given text symbol's location and corresponding text, the average background colour is computed by the average colour of the area on the edge of text symbol's coordinates; 2) The text colour is set to either white or black to ensure optimal contrast with the background colour, for better visibility; 3) The font size is calculated as the maximum size that allows the text to fit entirely within the boundaries of the text symbol, ensuring optimal use of space and readability.

A.2 ACTION SELECTION

In practice, our selection model, described in Section 3.3, identifies the best action in two steps. First, we query an LLM to evaluate all the action options, providing a judgment—either *valid* or *invalid*—and a confidence score for each action (see the prompt in Subsection G.4). These judgments are transformed into scores: if an action is judged *valid*, its score equals the confidence; if judged *invalid*, its score is the confidence multiplied by -1. This scoring reflects that higher confidence in a *valid* action yields a higher score, while higher confidence in an *invalid* action results in a lower (negative) score. Second, we query the LLM again to select the best action from the two highest-scoring actions (see the prompt in Subsection G.5). This step is motivated by our observation that, in over 70% of tasks, the difference between the top two scores is equal to or less than 0.1, indicating that both are likely optimal. By allowing the LLM to choose between them, we refine the selection beyond simply picking the action with the highest score.

Table 8: Summarisation of our STR dataset.

Split	App	Episode	Image	Instrucion
Train	19	2853	19010	14852
Val	19	349	2290	1774
Test	19	348	2320	1824
All	19	3550	23620	18450

Table 9: Decision optimisation comparisons on APP agent performance. Apps are categorised into "Leisure", "Work", and "System".

App Agent	World Model Modality	World Model	Leisure	Work	System	Overall
	w/o world model	w/o world model	41.22	51.28	42.86	43.13
	Languaga	Change-text	49.32	51.28	42.06	46.65
	Langugae	HTML-text	47.30	48.72	43.65	46.01
T3A		HTML-vision	50.68	53.85	43.65	48.24
	Vision	UI-diffuser	48.65	53.85	43.65	47.28
	VISIOII	IP2P	48.65	53.85	45.24	47.92
		ViMo (Ours)	50.00	58.97	45.24	49.20
	w/o world model	w/o world model	43.24	51.28	39.68	42.81
	Language	Change-text	45.96	56.41	45.24	46.96
	Langugae	HTML-text	44.59	56.41	45.24	46.33
APP-Agnet		HTML-vision	47.97	56.41	46.03	48.24
	Vision	UI-diffuser	47.30	56.41	44.44	47.28
	VISIOII	IP2P	47.30	58.97	45.24	47.92
		ViMo (Ours)	50.68	58.97	43.65	48.89
	w/o world model	w/o world model	43.92	53.85	39.68	43.45
	Languaga	Change-text	47.30	66.67	41.27	47.28
	Langugae	HTML-text	47.30	66.67	38.89	46.33
Mobile-Agent-v2		HTML-vision	50.00	66.67	41.27	48.56
	Vision	UI-diffuser	49.32	61.54	41.27	47.60
	VISIOII	IP2P	46.62	66.67	45.24	48.56
		ViMo (Ours)	50.00	66.67	44.44	49.84
	w/o world model	w/o world model	46.62	51.28	43.65	46.01
	Languaga	Change-text	51.35	51.28	41.27	47.28
	Langugae	HTML-text	50.68	51.28	40.48	46.65
M3A		HTML-vision	52.03	48.72	45.24	48.89
	Vision	UI-diffuser	50.00	48.72	44.44	47.60
	VISIOII	IP2P	52.03	48.72	44.44	48.56
		ViMo (Ours)	53.38	53.85	45.24	50.16

A.3 DATA COLLECTION

To ensure the quality and diversity of data samples for each App, while minimising noise, we collected App information from both Android Control (Li et al., 2024) and Android in the Wild dataset (AITW) (Rawles et al., 2024b) datasets. To be specific, out of 15,274 episodes in the Android Control, only 5,697 episodes include the "open_app" action. From these episodes, we extracted their "app name", identifying 758 unique applications. However, only 13 of these Apps had more than 50 samples. To enrich the dataset, we manually collected additional samples for these 13 Apps from the rest of the dataset. For AITW, we extracted App names by using the package name listed under the "current activity" field. After filtering out the noisy, 11 valid Apps remained. By combining the overlapping applications from both datasets, we obtained a total of 19 unique Apps. We split our dataset into "Train", "Validation" and "Test" splits, and we summarise our dataset under each split in Table 8.

Furthermore, we converted action commands into action instructions for AITW with specific prompts in Subsection G.6. We use Paddleocr (Shi et al., 2016) for STR generation.

A.4 EVALUATION

World Model Ability. For the results under automatic metrics presented in Table 1, we prompt LLM for the instructional accuracy score s_{ia} and action readiness score s_{ar} , as shown in Subsection G.7 and Subsection G.8 respectively. A generation is considered successful if "success" appears under "Status" for s_{ia} and "yes" under "ready for action" for s_{ar} . For the user study, we collected 80

Table 10: Trajectory synthesis evaluation. "T+L" denotes the accuracy of the whole trajectory with length L.

T+1	T+2	T+3	T+4
22.81	14.04	7.02	0
52.63	26.32	10.53	5.26
38.60	14.04	12.28	7.02
43.86	19.30	10.53	10.53
52.63	29.82	12.28	5.26
56.14	21.05	10.53	7.02
57.89	36.84	14.03	12.28
	22.81 52.63 38.60 43.86 52.63 56.14	22.81 14.04 52.63 26.32 38.60 14.04 43.86 19.30 52.63 29.82 56.14 21.05	22.81 14.04 7.02 52.63 26.32 10.53 38.60 14.04 12.28 43.86 19.30 10.53 52.63 29.82 12.28 56.14 21.05 10.53

Table 11: Evaluation on randomness by running the experiment 3 times (r1-r3) on our sampled test split. "All" denotes the evaluation of the full test split. s_{gc} , s_{ia} and s_{ar} are the metrics same with Table 1. s_h denotes their harmonic score. STD denote the standard deviation from r1 to r3.

World Model	s_{gc}	s_{ia}	s_{ar}	s_h
r1	0.7421	75.08	78.29	0.7582
r2	0.7323	75.63	77.64	0.7546
r3	0.7423	75.39	78.68	0.7605
STD	0.0057	0.23	0.42	0.0025
ALL	0.7389	75.37	78.20	0.7578

generated samples—20 from each of the four world models. We then asked 70 participants to answer three questions on each sample designed to reflect the s_{ia} , s_{gc} and s_{ar} scores, as detailed in Subsection G.9. For the s_{gc} , participants are asked to rate on a scale from 1 to 5. These scores were then normalised to the [0,1] range in Table 1.

World Model Enhanced App Agent. In Table 2, we categorised APPs based on their primary functions into three groups: **Leisures**, **Work**, and **System**. The **Leisure** category includes APPs commonly used for relaxation and entertainment, such as *Decathlon*, *eBay*, *Flipkart*, *Amazon*, *Adidas*, *Kitchen Stories*, *Booking.com*, *YouTube*, and *Vimeo*. The **Work** category comprises APPs typically associated with professional or productivity-related activities, including *Gmail*, *Drive*, and *Chrome*. Lastly, the *System* category encompasses APPs pre-installed in the Android operating system, such as *com.android.contacts*, *com.google.android.dialer*, *com.google.android.googlequicksearchbox*, *com.android.settings*, *com.google.android.APPs.maps*, and *com.android.vending*.

Ablation on Iteration Numbers. ViMo predicts future GUI observations, which can be recursively fed back as input to simulate further into the future. Taking the generative GUI as the current GUI, an agent was prompted to generate the action instructions based on the user goal (see the prompt in Subsection G.10). Then the action instruction and the GUI were fed into ViMo to generate the next GUI. In this study, we defined the iteration number as the number of times ViMo was called. We only use the final output as the signals during the candidate action selection phase, guiding the final selection among potential actions.

B ADDITIONAL EXPERIMENTAL RESULTS

Comparison with World Models. Table 3 compares our ViMo with existing world models under M3A App agent. To further highlight our superiority, Table 9 presents additional results of ViMo applied to T3A, APP-Agent, and Mobile-Agent-V2. The experimental results indicate that vision-based methods consistently outperform their language-based counterparts, thereby substantiating our motivation for developing visual GUI world models. Moreover, our approach achieves superior performance over existing world models, underscoring its effectiveness and advantage.

Generation Error Analysis. As discussed in Subsec. 4.5, our method ViMo can iteratively generate future GUIs. However, as the number of iterations increases, the accumulated error also grows. In

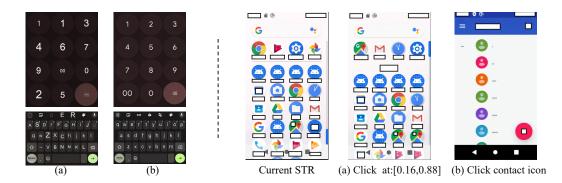


Figure 4: Qualitative ablation studies. Left: Static text generation. (a) Generating static text via an LLM; (b) Preserving the original text in the image by rendering it as image pixels. Right: STR generation under two input formats—(a) action command and (b) action instruction.

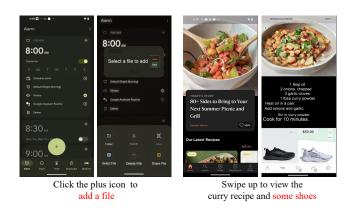


Figure 5: GUI generation conditioned on a novel combination of current GUI observation and user action.

addition to the evidence presented in Table 7, we conduct further experiments to analyse this iteration error and compare our approach with existing world models.

To this end, we design a trajectory synthesis evaluation to assess how well the GUIs generated by ViMo align with those observations in real-world environments over longer iterations. In this setup, the generated GUI is leveraged as the input to an App agent to generate the subsequent action, with higher-quality trajectories indicating a GUI more aligned with the real-world environment. Specifically, the GUIs generated by ViMo serve as the observation input for the App agent, which generates actions aimed at achieving the user's goal. These output actions are then evaluated to reflect whether the GUI representations offer concrete and reliable information for action prediction. This process is repeated for L steps, and we calculate the success rate of the entire L-step trajectory.

We employ an LLM as a judge to assess the alignment between the agent's simulated actions and the ground truth actions within a given trajectory. Specifically, an agent was prompted to generate the action instructions based on the given GUI and the user goal (see the prompt in Subsection G.10) and the LLM evaluated whether the simulated action lead to the same outcome as the ground truth action (see the prompt in Subsection G.11), a "yes" of the "Status" is calculated as a match.

As shown in Table 10, we compared ViMo against both visual- and language-based world models and demonstrated that while performance decreases across all world models with more iterations, our model significantly outperformed the other methods by providing more accurate and reliable information. This was reflected in higher trajectory prediction accuracy, underscoring the ability of our model to generate GUIs that aligned with the real-world environment.

Table 12: Inference time and step accuracy comparison across models.

Model	Inference Time	Step Accuracy (%)
Baseline (T3A)	\sim 4 minutes	43.13
Change-text	\sim 5 seconds	46.64
IP2P*	\sim 1.5 minutes	47.92
ViMo (Ours)	\sim 2 minutes	49.20









Figure 6: False examples where the text symbols are incorrectly represented, making them unrecognizable to indicate the location of text.

Randomness Study and Evaluation on Full Test Split. ViMo involves random factors, particularly from the use of LLMs. The LLM is prompted to generate plausible textual content, and in some cases, multiple reasonable options can be produced. For example, in Fig. 3, it shows "5:49 "on the top left corner for "set timer for 20 minutes" command and shows "Timer" for "set timer for 12 minutes", both are plausible and valid in the given context. However, the key functional element, the timer itself, is consistent with the user instructions in both cases. To evaluate their influence, we conducted the experiment three times, as summarised in Table 11 (r1-r3). The results demonstrate that the randomness does not significantly impact the performance or consistency of our method. Additionally, we focused on a randomly selected subset of examples for evaluation, with results from the full test set also included to illustrate that the observed differences are minor, as shown in Table 11 (compare ALL to r1-r3). We consider the subset results to provide an accurate and reliable approximation for our analysis.

Qualitative Ablation Analysis. In addition to the quantitative ablation results presented in Table 6, we also provide qualitative comparisons. Fig. 4 (left) illustrates the challenges faced by the LLM in predicting static text under complex spatial layouts. Fig. 4 (right) displays the STR generation of the same user intent but with different action types. It demonstrated that models learned with action commands failed to predict STR that aligns with the user's intent, whereas action instructions offered a more concrete description, enabling the model to better capture the intent.

Qualitative Generalisation Study. We studied the generalisation of ViMo in Fig. 5 by providing user actions that were not typically encountered within the App's standard context. For example, in the Clock App, a user action to "add a file" generated a Drive-style file selection window while retaining the Clock interface. Similarly, in the Kitchen Store App, ViMo can generate content corresponding to the action. These results emphasised ViMo's generalisation ability facing novel combinations of App observations and user actions.

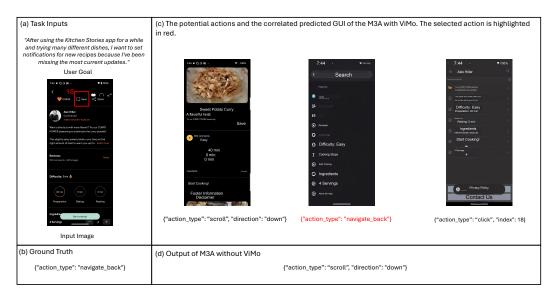


Figure 7: Example of how ViMo helps the App agent to select the correct action.

C PRACTICAL DEPLOYMENT

In this section, we report the computational efficiency of our method to demonstrate its practicality in real-world applications. The minimum hardware requirement is a GPU with 16 GB of memory. On a V100 GPU, STR image generation takes approximately 8 seconds, and GUI-text prediction takes around 30 seconds. In our setup, the total inference time per request is about 2 minutes, including model loading and communication overhead. Each request involves predicting future GUIs for three different user actions. Table 12 compares the inference time and step accuracy of ViMo with other world models. With an additional 2 minutes of inference time, ViMo achieves a notable accuracy improvement of 6.07%.

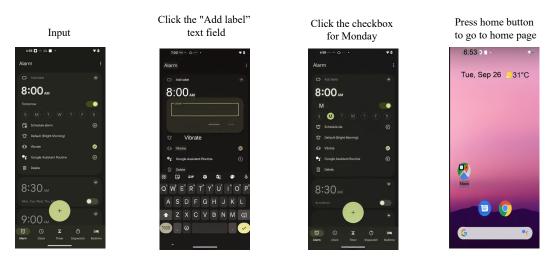


Figure 8: Visualisation of ViMo in generating GUIs given a single current GUI paired with different actions.

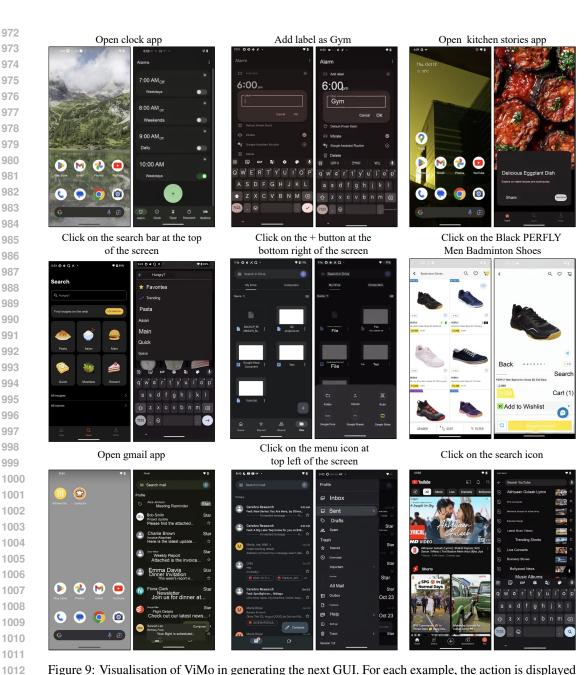


Figure 9: Visualisation of ViMo in generating the next GUI. For each example, the action is displayed at the top, with the current GUI shown on the left and the generated GUI on the right.

D LIMITATION

Fig. 6 illustrates failure cases where text symbols are not represented as our rectangle-shaped placeholders with a black border and white fill, making them unrecognisable as text symbols. Improving the representation of text symbols remains a potential direction for future work.

Ε ADDITIONAL VISUALISATION

Fig. 7 demonstrates how ViMo helps the M3A App agent make better action decisions. Fig. 8 showcases results generated from a single current GUI paired with different actions, further highlighting the versatility of our approach. Diverse visualisations are presented in Fig. 9 and Fig. 10. These

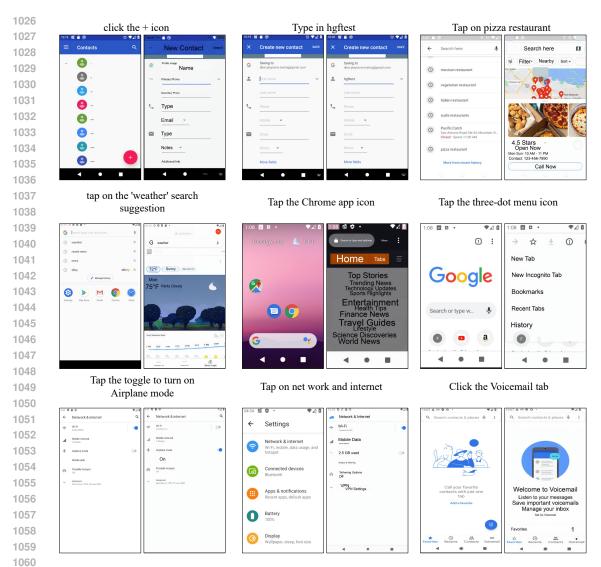


Figure 10: Visualisation of ViMo in generating the next GUI. For each example, the action is displayed at the top, with the current GUI shown on the left and the generated GUI on the right.

examples illustrate how our method effectively generates the next GUI based on the given action and current GUI observation, showcasing its ability to produce visually coherent and contextually accurate GUI simulations.

F STATEMENT ON LLM USAGE

We disclose that large language model (LLM) tools were used solely for language refinement of the manuscript, including improving grammar and polishing phrasing. LLMs were not used to generate scientific content, research ideas, experiment designs, data, analyses, or code. All suggestions and modifications from these tools were made under the direct supervision and final approval of the authors, and all authors are fully aware of and consent to this usage.

G PROMPTS

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G.1 PROMPT TO DECIDE THE TEXT SYMBOLS TO REMAIN UNCHANGED AFTER THE ACTION

```
1084
           You are a professional UI/UX analyst and your goal is to compare the two UI screenshots
1085
            and return their overlapping layout.
1086
            ### Inputs:

    **Current Screenshot**: The current mobile UI as an image.
    **Next UI Layout Screenshot**:

1087
1088
           - An image of the next mobile UI layout with all text replaced by white boxes.
           - Each box has a unique red ID label.
1089
            3. Use action: a user action described by language
1090
            Next UI Layout Screenshot is a result of a user action on the current screenshot, but
            the text elements are masked.
1091
            Please help me identify those layouts that are located in the same position, so I can
1092
            predict their text directly from the current screenshot.
            Usually, the system bar information should be included. Exclude elements from the
1093
            result if:
1094
            The content (text) changes as a result of the user action, even if the element exists
            in both screenshots.
1095
            Please be very very cautious about putting an ID on the list, which means you are very
1096
            very confident with this task. if you are unsure about some elements, please ignore
            them and do not put them on the list.
1097
            \#\#\# Output the list of existing elements : Return the results in the following JSON
1098
            format: ['id1','id2',...]
            ### Notes:
1099
           - Ensure the detected elements appear in both UI screenshots, which means their
1100
           surrounding context is the same.
            - Ensure identify those elements that their text will change by the user action and
1101
           exclude them from your response.
1102
           - Ensure identify those elements that share a similar context layout, but their absolute
           are not the same, and them from your response.
1103
           - Ensure only reply in pure JSON format, with no placeholders or comments.
1104
```

G.2 PROMPT TO DETERMINE THE SEMANTIC ROLE OF EACH TEXT SYMBOL

```
1108
1109
           You are a professional UI/UX analyst assigned to structure and analyse the semantics of
1110
           mobile UI screenshots.
           Your goal is to segment the UI and annotate box elements in a way that enhances
1111
           understanding of their roles and relationships within the interface.
           - Current Screenshot: A visual representation of the mobile UI.
           - Next UI layout screenshot: A visual representation of the next UI layout with all the
1113
           text masked with a white box. Each box has an ID number on it in red colour. - User
           Action: An action put on the current UI will result in the next UI.
1114
           - Box locations: a list of box locations to better help you to locate the boxes in the
1115
            format of 'id': id, 'Location':[x1,y1, width, height].
                                                                    ID indicates their ID number
           in the UI screenshot.
1116
           - UI_size: the width/height of the input images. They are the same size. The image
1117
           you received might be resized. Please scale it back for the locations.
1118
            Task:
           Structure the boxes in the Next UI layout screenshot with semantics based on the visual
1119
           input by following these steps:
           1, Divide the UI into Semantic Windows Group the UI into functional sections with a
1120
           specific name (e.g., "Header Windows," "Time Selector Panel").
1121
           2. Structure Text Elements in Each Semantic Window.
1122
           - Assign box elements to windows based on logical, visual relationships or semantic
           roles.
1123
           - For every element, structure output as :
           \star\starid: corresponding box retrieved from the box list and the Next UI layout screenshot.
1124
           **Role: A brief explanation of the role of this box. You should consider their [x1,y1]
1125
           to indicate their location, [w,h] to indicate their size to decide the role. It is
            important to consider the context for the role prediction. The role should be in
1126
           detail to distinguish it from other items in the same category.
1127
                                             "Category Name": [ "id":id, "Role": "Role" ,
           Output Format: { "Window Name":
           "id":id, "Role": "Role", ... ], "Category Name": [ "id":id, "Role": "Role", ...
1128
1129
           Key Guidelines:
           - Ensure to retrieve id from the given screenshot and box list.
1130
           - Avoid duplicating or omitting IDs.
1131
           - Every box element in the box location list must be included in the structured output.
           - Ensure there is no additional formatting, code blocks or placeholders in your
1132
           response; return only a clean JSON without any comments.
1133
```

1135 1136

11631164

G.3 PROMPT TO PREDICT THE EXACT TEXT CONTENT FOR EACH SYMBOL

```
1137
            Task: Plan the content for the next UI screen based on the provided inputs and
1138
            instructions.
1139
            Inputs:
            Current Screenshot: A visual representation of the mobile UI.
1140
            Next UI layout screenshot: A visual representation of the next UI layout with all
1141
            light yellow boxes indicating a text place. Each box has an ID number on it.
            User Instruction: A specific action or command that transitions the current UI to the
1142
            next UI state.
1143
            Semantics for the masks in Next UI screenshot: A structured map.
            Goal:
1144
            Predict the content (text) for each masked area in the next UI layout screenshot based
1145
            on the following steps:
            Map Affected Elements to the Next UI.
1146
            Align the affected elements with the yellow box coordinates on the next UI.
1147
            Predict the text for each yellow box based on the user instruction and the context of
            the current UI.
1148
            If you can not find any information about the text, predict a plausible text based on
1149
            its context.
            Ensure to use the semantics to help you understand the layout and predict the text. If
1150
            you think the semantics is wrong, please modify it in your
1151
            Output:
            Return the predictions in JSON format with the structure: {"Window Name ": "Category Name ": [ "id ": id, "text ": "text", "role ": "role", "id ": "id", "text": "text", "role": "role" ], , ... }
1152
1153
            Ensure to predict text based on the context.
1154
            Do not include any special characters.
1155
            Ensure there is no additional formatting, code blocks or placeholders in your response;
            return only a clean JSON without any comments.
1156
1157
```

G.4 Prompt to evaluate actions with a confidence score

```
1165
             You are an agent who can operate an Android phone on behalf of a user. When given
1166
             a user request, you will try to complete it step by step. At each step, a list of
1167
             descriptions for most UI elements on the current screen will be given to you (each
1168
             element can be specified by an index), together with a history of what you have done
             in previous steps. Based on these pieces of information and the goal, you must choose
1169
             to perform one of the actions in the following list (action description followed by the
1170
             JSON format) by outputting the action in the correct JSON format: action options from
             the dataset
1171
             The overall user goal/request is: {goal}
1172
             Here is a history of what you have done so far: {history} This is the action you picked
             in the latest step: {action}, whose semantic description is: {sum}
1173
             Your goal is to judge **whether the action you picked in the latest step is on the right track to the successful execution of the overall user goal/request**.
1174
            You will be given the screenshots before and after you perform the action
1175
            - The first screenshot corresponds to the UI state before you performed the action.
             - The second screenshot corresponds to the UI state after you performed the action.
1176
            Also here is the list of detailed information for some UI elements in the before
1177
             screenshot: {before elements}
1178
             Note that, the "after" screenshot is generated by the agent's world model. As such,
             it may not faithfully represent the real UI. For instance: Some UI elements in the simulated "after" screenshot may not exist in a real UI. Your evaluation should
1179
             consider the reliability of the UI predictions. If the "after" screenshot contains
1180
             unreasonable elements, this likely indicates a failure.
1181
             Now provide your judgment on the selected action in JSON format. Your response must
1182
             include:
             Reason: A detailed explanation of why the action is valid or invalid. Judgment: Your judgment must be either "valid" or "invalid".
1183
             Confidence: A confidence score between 0.0 and 1.0, reflects how likely your judgment
1184
             is correct.
1185
            You must follow this structure exactly: {Reason: ..., Judgement: "valid" or "invalid", Confidence:
1186
             Your Answer:
1187
```

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G.5 PROMPT TO SELECT THE OPTIMAL ACTIONS AMONG TWO HIGHEST-SCORING ACTIONS

```
1190
           You are an agent who can operate an Android phone on behalf of a user. When given
1191
            a user request, you will try to complete it step by step. At each step, a list of
            descriptions for most UI elements on the current screen will be given to you (each
1192
            element can be specified by an index), together with a history of what you have done
1193
            in previous steps. Based on these pieces of information and the goal, you must choose
            to perform one of the actions in the following list (action description followed by the
1194
            JSON format) by outputting the action in the correct JSON format action options from
1195
            the dataset
            The overall user goal/request is: {goal}
1196
            Here is a history of what you have done so far:{history}
1197
            Here is a list of descriptions for some UI elements on the current
            screen: {before elements}
1198
            Here are two candidate actions:
1199
           Action 1: {action_0}, described semantically as {sum_0}. The rationale for this
           action is: {act_re_0}
1200
           Action 2: {action_1}, described semantically as {sum_1}. The rationale for this action is: {act_re_1}
1201
           Hints for making your decision: {GUIDANCE}
1202
           - Both "more options" buttons and scrolling actions may reveal new content. Evaluate
1203
           which is more suitable for the goal.
           - Consider the history of previous actions. If prior steps involved repeated "scroll
1204
           down" actions, it is more likely that "scroll down" is the correct next step.
1205
           - If the user goal involves viewing reviews or similar tasks and the current screen
            already displays such content, "scroll down" may reveal more information.
1206
            Your task is to choose the best action from the two provided.
1207
            Now, provide your judgment in JSON format with the following structure:
            Reason: A detailed explanation of your choice, considering the hints above.
1208
            Choice: Action 1 or Action 2.
1209
            Your output must exactly match this format:
           {Reason: ..., Choice: Action 1 or Action 2}
1210
```

G.6 Prompt to convert action commands into action instructions

```
You are a professional UI/UX analyst specializing in identifying the semantics of dual
point actions between mobile UI screenshots.
Inputs:
Current Screenshot: A visual representation of the mobile UI.
Next Screenshot: A visual representation of the NEXT mobile UI.
Goal: A user intent on this Mobile interface.
touch_xy: the x,y coordinates for the touch point, as a percentage of the image
dimensions.
lift xy: the x,y coordinates for the lift point, as a percentage of the image
dimensions.
Your task is to analyse these elements describe the precise user action in plain
language and return your answer in plain string (e.g., "click the + icon", "scroll
If the two screenshots are identical, please return an empty string as "".
If the Next Screenshot does not seem to be one step away from the Current Screenshot,
return an empty string as "". One step means only one interaction with the cell phone.
Ensure there is no additional formatting, code blocks or placeholders in your response;
return only a clean string without any comments
```

G.7 PROMPT FOR INSTRUCTIONAL ACCURACY SCORE (s_{ia})

```
1231
            You are an expert in evaluating the performance of a mobile emulator. The mobile
1232
            emulator is designed to navigate the UI change based on human instruction.
1233
            Inputs:
            Current UI Screenshot: The present state of the cellphone's user interface.
1234
            Next UI Screenshot: The mobile emulator generated UI indicating the next state of the
1235
            cellphone's user interface based on human instruction.
            Human instruction: The action applied on the current UI screenshot.
1236
            Your goal is to determine whether the mobile emulator successfully predicts the next UI
1237
            image with current information and layout based on the current UI and the user action.
            *IMPORTANT*
1238
            Format your response into a JSON map as shown below:
1239
            "Thoughts": <your thoughts and reasoning process>, "Status": "success" or "failure",
1240
1241
            }
```

G.8 PROMPT FOR ACTION READINESS ACCURACY SCORE (s_{ar})

```
You are an expert in evaluating the performance of a mobile emulator. The mobile emulator is designed to navigate the UI change based on human instruction. Inputs:

UI Screenshot: The mobile emulator generated UI indicating the state of the cellphone's user interface.

User intent: The user goal to achieve.

Next action: the action will be applied to this UI.

Your goal is to determine whether the next action is validated on the UI Screenshot.

Please also indicate if it is still in the right App according to the goal.

*IMPORTANT* Format your response into a JSON map as shown below:

{
"Thoughts": <your thoughts and reasoning process>,
"In the right App": "yes" or "no"
"ready for action": "yes" or "yes",
}
```



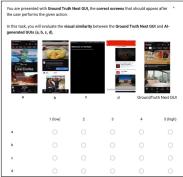




Figure 11: Screenshot of user study example.

G.9 Instructions for User Study

The following prompt provides the instructions for the user study. An example screenshot is shown in Fig. 11.

```
Question 1: You are presented with a mobile screen (Current GUI).
Your task is to evaluate whether the generated GUI correctly reflects the result of the user action applied on the current GUI. Answer "Yes" or "No" to each sample.
Question 2:
You are presented with Ground Truth Next GUI, the correct screens that should appear after the user performs the given action.
In this task, you will evaluate the visual similarity between the Ground Truth Next GUI and AI-generated GUI, scoring from 1-5.
Question 3:
In this task, you will validate whether a specific user action is valid on the generated GUI.
An action is considered valid if the required GUI element is visually presented on the screen. Answer "Yes" or "No" to each sample.
```

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G.10 Prompt to generate the action instruction based on the given GUI and the user goal

1299 You are an autonomous intelligent agent tasked with navigating a cell phone to accomplish specific tasks. You will be provided with the following information:

1. Initial UI screenshot: A visual representation of the initial state of the cell 1300 1301 phone's interface. 2. User Objective: This is the task you are trying to complete. 1302 3. Previous Action: An action sequence performed on the initial UI. 1303 4, Current UI states: A visual representation of the current state of the cell phone's 1304 interface, generated by a simulated environment. The initial image is the screenshot before actually performing all the previous 1305 actions. 1306 The current cell phone UI is generated by applying previous actions on the initial screenshot. 1307 Your Task: Please predict a single next step action to complete the given task based 1308 on current vision states. To be successful, it is very important to follow the following rules: 1309 You should only issue one action that is valid based on the current UI states.
 You should only issue one action at a time. Avoid issuing multiple actions like 1310 "do A and do B". 1311 3. Generate the action in plain text. For example, Scroll down to set the minute as 1312 15. 4. Issue "Stop." if you think the action is already completed. Ensure you only return 1313 the action, not other formats, comments or placeholders 1314

G.11 PROMPT TO EVALUATES WHETHER THE SIMULATED ACTION LEADS TO THE SAME OUTCOME AS THE GROUND TRUTH ACTION

```
You are an expert in evaluating the performance of a cell phone navigation agent. The
agent is designed to help a human user navigate a cellphone to complete a task.
Inputs:
Current UI Screenshot: The present state of the cellphone's user interface.
User Intent: The goal the human user aims to achieve.
Action History: The sequence of actions taken so far for you to track the progress.
Agent Simulated Action: The action suggested by the agent to achieve the user's
intent.
Ground Truth Action: The correct action is needed to achieve the user's intent.
Your goal is to determine whether the agent's simulated action leads to the same
outcome as the ground truth action.
Additionally, if the simulated action does not exactly match the ground truth action
but is still progressing toward the correct outcome to achieve user intent, indicating
that the action is "on the right track."
*IMPORTANT*
Format your response into a JSON map as shown below:
"Thoughts": <your thoughts and reasoning process>,
"Status": "success" or "failure",
"On the right track to success": "yes" or "no"
```