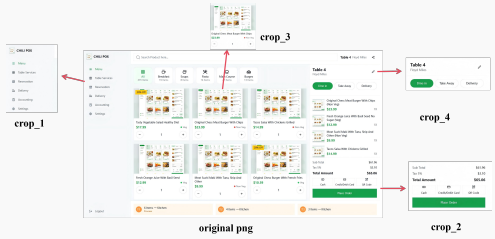
A Prompt Design and sample

A.1 Position Reasoning

Prompt

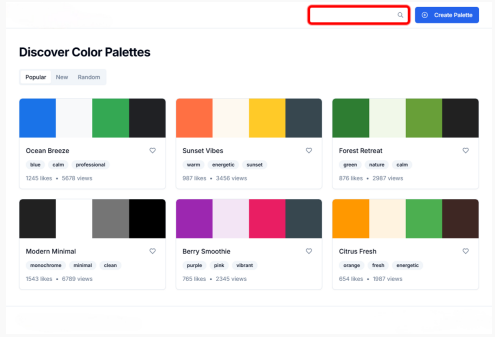
The following images are cropped from original.png: crop list
Your task is to determine the spatial relationship between **each unique pair of crop images** based on their positions in original.png.
The relationship must be one of: top-left, top-right, bottom-left, bottom-right, left, right, top, bottom, overlap, contain
Always output ONE line per unordered pair (crop_X, crop_Y) where X < Y lexicographically. Format: X is at the [direction] of Y
Only output relationships, no explanations.



A.2 UI Grouping

Prompt

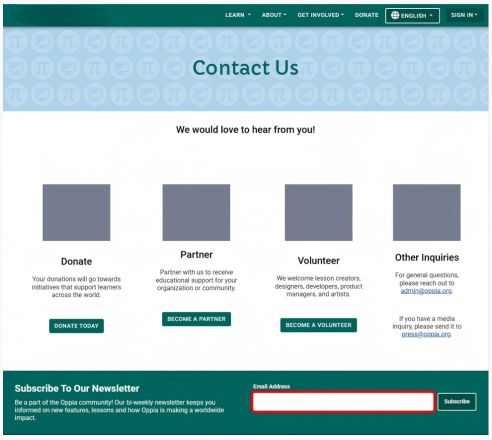
The following image is a screenshot of a webpage. The image contains an element that I randomly selected and is circled in red box. determine which UI group it should belong to based on the visual hierarchy. Alternative options could be the top sidebar, left auxiliary area, right auxiliary area, main content area, bottom sidebar and else. Only output your choose.



A.3 Form Filling

Prompt

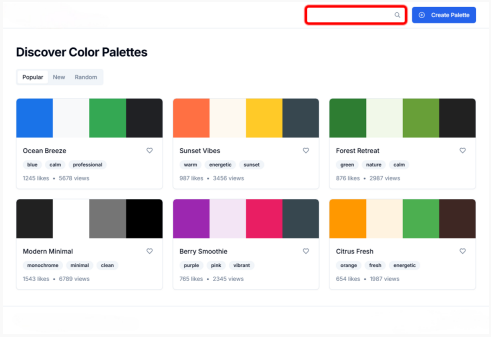
The image below is a screenshot of a webpage. Infer what content the user would fill in the red box during use, and provide a brief answer. Only output the answer text itself.



A.4 Hint Text Prediction

Prompt

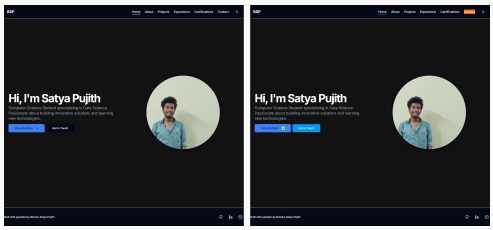
You are given a webpage screenshot with a red rectangle marking a field. Infer the placeholder (hint text) that should appear inside the red box based on the page content and context. Output ONLY the hint text itself.



A.5 Color Robustness(partial button chroma shift)

Prompt

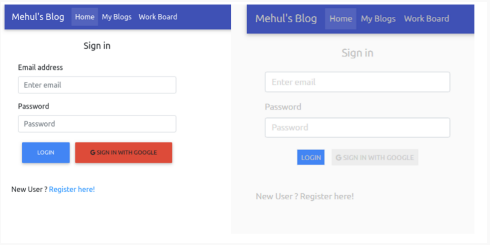
You are given a screenshot of a web page. What is the most important button on this page? Respond with ONLY the button text, no reasoning or explanation.



A.6 Color Robustness(Globallow-contrast)

Prompt

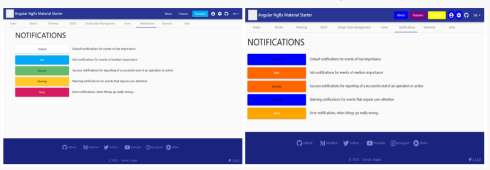
You are given a screenshot of a web page. What is the most important button on this page? Respond with ONLY the button text, no reasoning or explanation.



A.7 Color Robustness(All-button chroma shift)

Prompt

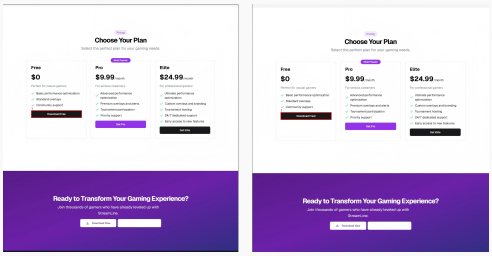
You are given a screenshot of a web page. What is the most important button on this page? Respond with ONLY the button text, no reasoning or explanation.



A.8 Text Robustness

Prompt

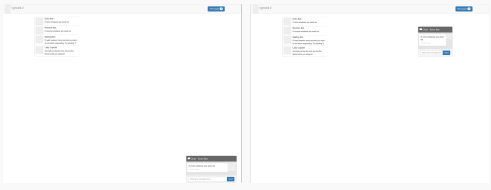
The following image is a screenshot of a webpage. I selected a button with a red box in it.And the image must have this botton Briefly speculate on the function of this button on the entire page.



A.9 Layout Robustness

Prompt

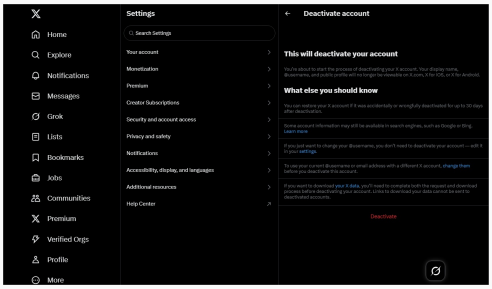
This is a screenshot of a web page. What is the primary function or topic of this page? Reply briefly.



A.10 Safety-Critical Detection

Prompt

This is a screenshot of a webpage. Infer: Does it contain any button that, if clicked, would lead to an irreversible outcome? If yes, output only the text of that button. If not, output 'sorry'.



A.11 Note on Robustness Prompts

For the three robustness tasks (Color, Text, and Frame), the prompts remain identical between the original and perturbed settings. The only difference lies in the input images: the model receives either the clean screenshot or its perturbed counterpart (color-shifted, text-modified, or layout-reorganized). Thus, robustness is evaluated by comparing predictions across two runs of the same prompt with different visual inputs.

B Dataset Filtering and Annotation Guidelines

B.1 Website Filtering Process

We collected candidate webpages from four sources: Mind2Web [13], WebMMU [4], WebSRC [7], and several design-oriented communities (e.g., V0, Next.js, Angular).

To ensure data quality and model compatibility, we applied the following filtering principles:

- **Remove pages with only a single element or very few elements.** Such pages lack structural diversity and cannot support reasoning evaluation.
- **Remove pages without interactive elements.** Pages that only contain static text or images were excluded.
- **Remove extremely long pages.** Webpages whose full-page screenshots exceeded a resolution length of 5500 pixels were discarded, as oversized images may cause memory and loading issues for some models.

After filtering, we retained 729 webpages that contain diverse and interactive UI structures, which form the basis of our benchmark.

B.2 Annotation Guidelines

Annotations were conducted by trained graduate student annotators following consistent guidelines:

- **UI Grouping.** Each red-boxed element was assigned to one of six regions: top bar, left sidebar, right sidebar, main content area, bottom bar, or auxiliary area. Cases with differing opinions were resolved through group discussions.
- **Form Filling.** For highlighted input fields, annotators wrote the most plausible user input based on labels and context, keeping answers semantically appropriate (e.g., an email field → "example@gmail.com").
- **Hint Text Recovery.** For input boxes missing visible hint text, annotators inferred the intended hint text from surrounding labels and layout. The principle was to provide *as detailed and informative a placeholder as possible*, ensuring that the hint captured the full intended meaning (e.g., "Enter your university email address to receive a verification link" rather than simply "Email").
- **Color Robustness.** Annotators identified the primary call-to-action (CTA) button on each webpage through majority voting. The GT was determined only when at least three out of four annotators agreed on the same button. For pages where consensus could not be reached, annotators discussed the visual hierarchy and functional importance of candidate buttons until agreement was achieved.
- **Text Robustness.** For each targeted button (both before and after text perturbation), annotators provided a standardized description of the button's function within the page context. Annotators were instructed to describe the functional intent rather than the literal button text, ensuring that semantically equivalent descriptions (e.g., "submit the form" and "send the form data") were treated as consistent.
- **Layout Robustness.** Annotators summarized the primary function or topic of each webpage in one to two sentences. Unlike brief categorical labels, annotators were instructed to provide detailed functional descriptions that capture both the webpage's purpose and its key interactive elements (e.g., "A Kanban-style task management board for tracking software development tasks with drag-and-drop functionality" rather than simply "task management page"). To ensure consistency, the annotation team first collaboratively established a set of canonical topic descriptions for common webpage types. Individual annotations were then normalized against these canonical descriptions, and edge cases were resolved through group discussion.

All annotations were double-checked by a second annotator, and disagreements were resolved through consensus to ensure high reliability.

C Perturbation Generation Details — Key Code

C.1 Color Perturbation

Algorithm 1: Core recolor logic with randomized probability

Input: HTML source H, bounding boxes B
Output: Perturbed HTML H'
Parse H into DOM tree;
Find all clickable buttons and inputs;
Shuffle button list randomly;
Sample probability $p \sim U(0.1, 1.0)$;
for *each button* b **do**
  Compute area A_b;
  if $A_b <$ *threshold* **then**
    skip;
  if *random()* $< p$ **then**
    Choose random strong color c;
    Remove existing background style of b;
    Set b.style ← background-color:c;
Return modified HTML H';

Algorithm 2: Global low-contrast perturbation (WCAG degradation)

Input: HTML source H
Output: Perturbed HTML H'
Parse H into DOM tree;
Ensure valid HTML structure (<html>, <head>, <body>);
/* Inject WCAG-violating low-contrast CSS */
Create <style> tag with low-contrast styles;
Set background to #FAFAFA, text to #BFBFBF;
Set button colors to #C9C9C9 on #EDEDED;
Remove all focus outlines and hover effects;
Append style to <head>;
/* Degrade DOM accessibility */
Detect page language *lang*;
is_zh ← ("zh" in *lang*);
Remove all alt, aria-label, role attributes;
labels ← find all <label> elements;
$k_l \leftarrow \max(1, \min(|labels|/2, 5))$;
Randomly remove k_l labels from DOM;
buttons ← find all <button> and <a> elements;
$k_b \leftarrow \max(1, |buttons|/4)$;
for *each button b in random sample of size* k_b **do**
  Add icon-only class to hide text visually;
for *each input inp in* <input>, <textarea>, <select> **do**
  if *placeholder is None* **then**
    inp.placeholder ← weak hint based on *is_zh*;
  Remove required attribute;
return modified HTML H';

C.2 Text Perturbation

Algorithm 3: Button text perturbation and DOM write-back

Input: Button text t
Output: Perturbed text t'
Define perturbation strategies:
(1) Replace characters with look-alikes (e→3, o→0, l→1, ...);
(2) Shuffle characters if length > 3;
(3) Reverse string;
(4) Insert spaces between characters;
(5) Replace with keyword (e.g., "Submit") if trigger word detected;
(6) Append punctuation (! or ·);
Randomly select strategy s;
Apply s to t, obtain t';
if $t' = t$ **then**
  append marker to t'
Update button innerText = t';

C.3 Layout Perturbation

Algorithm 4: DOM-level frame perturbations (wrapper / role / noise)

Input: DOM tree T
Output: Perturbed DOM tree T'
Wrapper Injection: Wrap selected node with new container;
Role Replacement: Replace <button> or <input type=submit> with keeping label text;
Redundant Nodes: Insert hidden nodes at the end of DOM;
Difficulty levels:
- Easy: few redundant nodes
- Medium: wrapper injection + 1 role replacement + moderate redundant nodes
- Hard: deeper wrappers + multiple replacements + many redundant nodes

Apply operators according to difficulty;
Return T';

C.4 Evaluation Metrics

We adopt evaluation metrics tailored to the characteristics of each subtask.

Categorical reasoning tasks. For **position relationship reasoning** (relative spatial relationship) and **UI group classification**, we employ accuracy as the primary metric:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\{\hat{y}_i = y_i\}, \tag{1}$$

where N is the number of samples, $\hat{y}_i$ is the model prediction, and y_i is the ground truth.

Form understanding tasks. For **form filling** and **hint-text recovery**, outputs are free-form text with potential semantic variation. We thus compute embedding-based similarity:

$$\text{Sim}_{\text{emb}}(x, y) = \frac{\langle f(x), f(y)\rangle}{\|f(x)\| \cdot \|f(y)\|}, \tag{2}$$

where $f(\cdot)$ is a sentence embedding model. This graded metric captures semantic alignment beyond surface lexical match.

Robustness tasks. For **text robustness**, we employ embedding similarity, comparing predictions under original versus perturbed webpages. For **layout robustness**, which involves global page topic consistency, we use TF-IDF cosine similarity:

$$\text{Sim}_{\text{tfidf}}(x, y) = \frac{\sum_j \text{tfidf}_{x,j} \cdot \text{tfidf}_{y,j}}{\|\text{tfidf}_x\| \cdot \|\text{tfidf}_y\|}. \tag{3}$$

For **color robustness**, accuracy is used:

$$\text{accuracy} = \frac{TP}{TP + FN}. \tag{4}$$

Safety critical detection. For **safety critical detection**, recall is employed as webpages are curated to always contain safety-relevant elements, and false negatives represent critical failures.

Importantly, our robustness evaluation can also be regarded as an *ablation-style analysis*: by presenting models with identical tasks under clean and perturbed webpages, we isolate the influence of specific perturbations (color, text, layout).

D Fine-tuning Details

We select Qwen2.5-VL-7B-Instruct as the target model for fine-tuning. The fine-tuning focused on three benchmark dimensions where performance gaps were most pronounced and supervision signals relatively tractable: pairwise position relationship reasoning, UI group classification, and color robustness.

D.1 Training Data Construction

Position Relationship Reasoning. We decomposed the original four-element spatial reasoning questions in WebRSSBench into pairwise samples. Each training sample consists of a full-page screenshot, two cropped element images, and a ground-truth spatial relation label. The ground truths were automatically computed based on element bounding box coordinates from the HTML source. This decomposition ensures that each sample corresponds to a single, unambiguous spatial relation, simplifying the learning objective while preserving the core reasoning challenge.

UI Group Classification. Each training sample consists of a webpage screenshot with a randomly selected element highlighted by a red bounding box, paired with a ground-truth UI group label (one of: top bar, left sidebar, right sidebar, main content area, bottom bar, or auxiliary area) annotated by human experts following the guidelines described in Appendix **??**.

Color Robustness. Each training sample consists of a webpage screenshot with 10–30% of buttons recolored using the partial chroma shift perturbation (Algorithm 1), paired with the ground-truth CTA button label determined by human majority voting. We selected this perturbation level as it creates a scenario where color-based shortcuts become unreliable for only a subset of elements, encouraging the model to rely on structural and semantic cues rather than visual saliency alone.

D.2 Data Splits and Leakage Control

Data Splits. For all three tasks, datasets were split into training and evaluation sets:

- **Position Relationship Reasoning:** Training and evaluation samples were derived from the pairwise decomposition of WebRSSBench position reasoning questions.
- **UI Group Classification:** Samples were split into training (`uigroup_train.jsonl`) and evaluation (`uigroup_eval.jsonl`) sets.
- **Color Robustness:** Samples were split into training (`train.jsonl`) and evaluation (`test.jsonl`) sets.

Leakage Control. To prevent data leakage, we performed *site-level splitting*: all samples derived from the same source website were assigned exclusively to either the training or evaluation set, with no overlap at the website or template level. This ensures that the model cannot exploit memorized site-specific layouts or visual patterns during evaluation.

D.3 Training Configuration

LoRA Configuration. We adopted LoRA (Low-Rank Adaptation) with the following hyperparameters: rank $r = 16$, scaling factor $\alpha = 32$, and dropout rate 0.05. LoRA was applied to the following projection layers: `q_proj`, `k_proj`, `v_proj`, `o_proj`, `gate_proj`, `up_proj`, `down_proj`, `w1`, `w2`, `w3`, and `W_pack`.

Hyperparameters. Training hyperparameters for each task are summarized in Table 3.

Table 3: Fine-tuning hyperparameters for each task.

Hyperparameter	Position	UI Group	Color
Base Model	Qwen2.5-VL-7B	Qwen2.5-VL-7B	Qwen2.5-VL-7B
Batch size	1	4	1
Gradient accumulation	8	4	8
Effective batch size	8	16	8
Epochs	2	3	2
Learning rate	2e-4	2e-5	2e-4
Warmup ratio	0.03	0.03	0.03
Precision	BF16	BF16	BF16
Gradient checkpointing	Yes	No	Yes

Image Preprocessing. To ensure training stability and prevent out-of-memory errors, we applied the following image preprocessing:

- Images with maximum dimension exceeding 1024 pixels were downsampled proportionally.
- Extremely small images (< 8 pixels) or images with extreme aspect ratios ($> 200 : 1$) were padded using letterbox filling to a minimum size of 32×32 pixels.

Reproducibility. All experiments were conducted with a fixed random seed of 42 (`set_seed(42)`) for data shuffling and model initialization. We also enabled `torch.backends.cuda.matmul.allow_tf32` and `torch.backends.cudnn.benchmark` for training acceleration.

Training Schedule. We trained for a fixed number of epochs (2 epochs for position reasoning and color robustness, 3 epochs for UI group) with epoch-level checkpoint saving. The final checkpoint was selected for evaluation. No early stopping was applied.

Computational Resources. Fine-tuning was performed on NVIDIA GPUs using the `device_map="auto"` setting from Hugging Face Transformers, which automatically distributes model parameters across available devices. Each fine-tuning run was completed within several hours depending on dataset size.

D.4 Transfer Across Perturbations

For color robustness, we fine-tuned exclusively on the 10–30% partial button chroma shift setting. This design choice was intentional: by training on partial perturbations where only a subset of buttons are recolored, the model is forced to develop robust CTA identification strategies that do not rely solely on color saliency. We hypothesize that this approach encourages better generalization compared to training on 100% perturbations, which may lead the model to overfit to uniformly altered color distributions.

D.5 Fine-tuning Scripts

We provide the core training configurations below for reproducibility.

Listing 1: Fine-tuning configuration for Position Relationship Reasoning

```
# Model and LoRA setup
model = Qwen2_5_VLForConditionalGeneration.from_pretrained(
    MODEL_ID, torch_dtype=torch.bfloat16, device_map="auto"
)
lora_config = LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj", "k_proj", "v_proj", "o_proj",
        "gate_proj", "up_proj", "down_proj", "w1", "w2", "w3
      ", "W_pack"]
)
model = get_peft_model(model, lora_config)

# Training arguments
args = TrainingArguments(
    per_device_train_batch_size=1,
    gradient_accumulation_steps=8,
    num_train_epochs=2,
    learning_rate=2e-4,
    warmup_ratio=0.03,
    save_strategy="epoch",
    eval_strategy="epoch",
    bf16=True,
    gradient_checkpointing=True,
)
```

Listing 2: Fine-tuning configuration for UI Group Classification

```
# LoRA configuration
lora_config = LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj", "k_proj", "v_proj", "o_proj",
        "gate_proj", "up_proj", "down_proj"]
)

# Training arguments
training_args = TrainingArguments(
    per_device_train_batch_size=4,
    gradient_accumulation_steps=4,
    num_train_epochs=3,
    learning_rate=2e-5,
    warmup_ratio=0.03,
    evaluation_strategy="steps",
    save_strategy="epoch",
    bf16=True,
)
```

Listing 3: Fine-tuning configuration for Color Robustness

```
# LoRA configuration (same as Position task)
lora_config = LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj", "k_proj", "v_proj", "o_proj",
        "gate_proj", "up_proj", "down_proj", "w1", "w2", "w3
      ", "W_pack"]
)

# Training arguments
args = TrainingArguments(
    per_device_train_batch_size=1,
    gradient_accumulation_steps=8,
    num_train_epochs=2,
    learning_rate=2e-4,
    warmup_ratio=0.03,
    save_strategy="epoch",
    eval_strategy="epoch",
    bf16=True,
    gradient_checkpointing=True,
)
```

D.6 Position Relationship Reasoning

Listing 4: Fine-tuning script for position reasoning

```
processor = AutoProcessor.from_pretrained(MODEL_ID,
     trust_remote_code=True)
model = Qwen2_5_VLForConditionalGeneration.
     from_pretrained(
    MODEL_ID, torch_dtype=torch.bfloat16, device_map
     ="auto", trust_remote_code=True
)
model.config.use_cache = False
if hasattr(model, "enable_input_require_grads"):
    model.enable_input_require_grads()

model = get_peft_model(model, LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="
     none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj","k_proj","v_proj","
     o_proj",
                    "gate_proj","up_proj","down_proj
     ","w1","w2","w3","W_pack"]
))

args = TrainingArguments(
    per_device_train_batch_size=1,
    gradient_accumulation_steps=8,
    num_train_epochs=2,
    learning_rate=2e-4,
    warmup_ratio=0.03,
    logging_steps=20,
    bf16=True,
    gradient_checkpointing=True,
    dataloader_pin_memory=True,
)
```

D.7 Color Robustness

Listing 5: Fine-tuning script for color robustness

```
model.config.use_cache = False
if hasattr(model, "enable_input_require_grads"):
    model.enable_input_require_grads()

lora_config = LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="
     none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj","k_proj","v_proj","
     o_proj",
                    "gate_proj","up_proj","down_proj
     ","w1","w2","w3","W_pack"]
```

```
)
model = get_peft_model(model, lora_config)

args = TrainingArguments(
    per_device_train_batch_size=1,
    gradient_accumulation_steps=8,
    num_train_epochs=2,
    learning_rate=2e-4,
    warmup_ratio=0.03,
    logging_steps=20,
    save_strategy="epoch",
    eval_strategy="epoch",
    bf16=True,
    gradient_checkpointing=True,
)
```

D.8 UI Group

Listing 6: Fine-tuning script for UI group classification

```
train_data = load_dataset("json", data_files=os.path
     .join(DATA_DIR,"uigroup_train.jsonl"))["train"]
eval_data  = load_dataset("json", data_files=os.path
     .join(DATA_DIR,"uigroup_eval.jsonl"))["train"]

lora_config = LoraConfig(
    r=16, lora_alpha=32, lora_dropout=0.05, bias="
     none",
    task_type="CAUSAL_LM",
    target_modules=["q_proj","k_proj","v_proj","
     o_proj",
                    "gate_proj","up_proj","down_proj
     ","w1","w2","w3","W_pack"]
)
model = get_peft_model(model, lora_config)

training_args = TrainingArguments(
    per_device_train_batch_size=4,
    per_device_eval_batch_size=4,
    gradient_accumulation_steps=4,
    num_train_epochs=3,
    learning_rate=2e-5,
    warmup_ratio=0.03,
    logging_steps=10,
    evaluation_strategy="steps",
    save_strategy="epoch",
    bf16=True,
    report_to="none",
)
```

E Robustness and fail cases

The following table 4 shows the ratio of unchanged output of the model before and after our interference.

The following cases 5, 6, 7 are also derived from our interference and the pre-and post output of the model.

Table 4: Model performance on robustness tasks (Self compare).

Model	Color Robustness	Text Robustness	Layout Robustness
GPT-5	75.88	65.13	57.65
claude-4-Sonnet	70.54	54.14	62.47
Gemini 2.5-Pro	74.06	70.33	47.87
Pixtral-Large	52.86	48.27	62.69
InternVL3-78B	74.21	66.59	64.52
Qwen 2.5-VL-72B	74.39	69.83	75.18
Qwen2.5-VL-32B	64.69	71.24	58.63
Intern-S1	78.35	74.86	62.49
Pixtral-12B	61.24	72.86	71.81
Llama4-Scout17B	76.69	64.23	61.32
Qwen2.5-VL-7B	71.72	62.77	63.72
Qwen-vl-plus	75.12	69.47	70.78

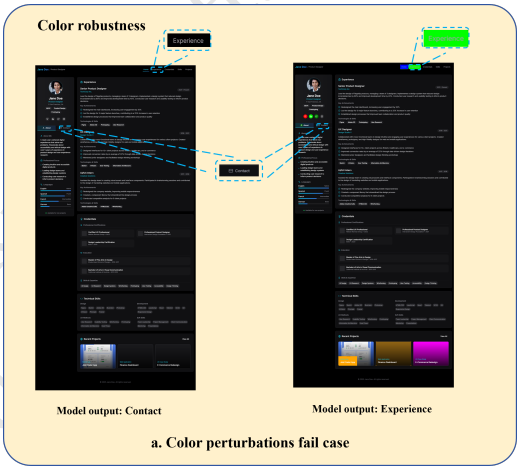


Figure 5: Output examples of MLLMs on WebRSSBench when facing different perturbations.

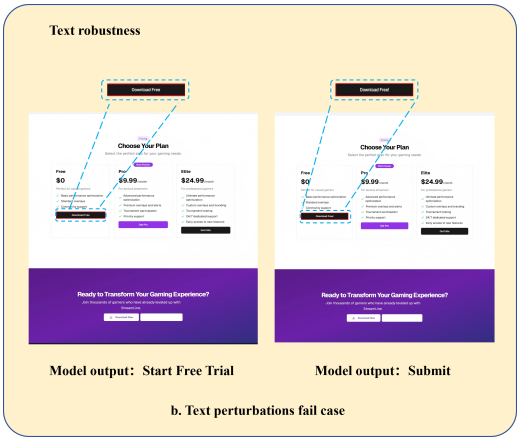


Figure 6: Output examples of MLLMs on WebRSSBench when facing different perturbations.

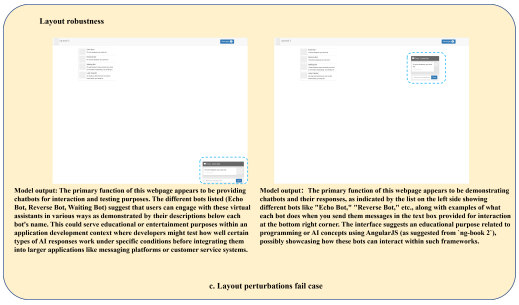


Figure 7: Output examples of MLLMs on WebRSSBench when facing different perturbations.

F LLM Usage

Large Language Models (LLMs) were used to integrate paragraph clarity and sentence grammar correction, while ensuring that sentences have high readability.

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