Revisiting Backdoor Attacks against Large Vision-Language Models from Domain Shift

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Abstract

Instruction tuning enhances large vision-language models (LVLMs) but increases their vulnerability to backdoor attacks due to their open design. Unlike prior studies in static settings, this paper explores backdoor attacks in LVLM instruction tuning across mismatched training and testing domains. We introduce a new evaluation dimension, backdoor domain generalization, to assess attack robustness under visual and text domain shifts. Our findings reveal two insights: (1) backdoor generalizability improves when distinctive trigger patterns are independent of specific data domains or model architectures, and (2) the competitive interaction between trigger patterns and clean semantic regions, where guiding the model to predict triggers enhances attack generalizability. Based on these insights, we propose a multimodal attribution backdoor attack (MABA) that injects domain-agnostic triggers into critical areas using attributional interpretation. Experiments with OpenFlamingo, Blip-2, and Otter show that MABA significantly boosts the attack success rate of generalization by 36.4%, achieving a 97% success rate at a 0.2% poisoning rate. This study reveals limitations in current evaluations and highlights how enhanced backdoor generalizability poses a security threat to LVLMs, even without test data access.

1. Introduction

Multimodal instruction tuning [18, 31] enhances Large Visual Language Models (LVLMs), enabling them to process multimodal data and respond more effectively to user intent. However, this open fine-tuning process, accepting input from various sources, introduces security risks [22, 26, 36, 37]. Attackers could inject malicious data into a self-constructed instruction set, compromising the model's output [59].

Traditional backdoor attack research [16, 35, 39, 62, 64] typically assumes that training and testing data follow similar

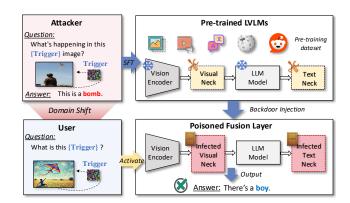


Figure 1. Illustration of backdoor attack during LVLM instructiontuning. Despite successful poisoning, domain shift between attacker's and user's instructions may prevent trigger activation.

distributions. However, this assumption breaks down in the context of models with strong cross-domain processing capabilities [9], such as LVLMs. Significant distribution shifts between backdoor-polluted training data and real-world testing contexts often reduce attack effectiveness (see Fig. 1).

In this work, we explore a novel evaluation scenario for assessing backdoor generalization in LVLMs under shifts in both visual and text domains. We manipulate visual domains and control textual information density within a multimodal instruction set using the stable diffusion model [45] and a large language model [10, 41, 49], allowing for quantitative adjustments across multimodal data domains. We introduce backdoor domain generalizability as a new evaluation dimension to measure attack robustness across varied data domains. An attack with strong backdoor domain generalization can trigger specific behaviors even under cross-domain shifts.

Based on the constructed instruction dataset with domain shift, we evaluate the effectiveness of ten classical backdoor attacks in the image captioning task [20, 33], revealing substantial limitations in the generalizability of most existing methods, particularly image-based backdoors, under dynamic conditions. Our extensive empirical analysis highlights two key insights strongly associated with enhanced backdoor generalizability: (1) the irrelevance of distinctive trigger patterns to specific data domains or model architectures, and (2) the competitive interaction between trigger patterns and clean semantic regions, where attackers need to guide the model to predict triggers rather than clean regions.

Building on these insights, we propose a multimodal attribution backdoor attack (MABA) that uses attribution-based interpretation to place domain-agnostic triggers in critical decision regions, such as symbols in text and color patches in images, improving robustness across domains and vulnerability to backdoor activation (see Fig. 2 (c)). Our experiments on OpenFlamingo, Blip-2, and Otter demonstrate that MABA significantly enhances cross-domain generalizability, achieving an ASR-G increase of 36.4%. Even with substantial shifts between training and testing datasets, MABA reaches an attack success rate exceeding 97% with a low poisoning rate of 0.2%. In conclusion, this study exposes critical limitations in current backdoor evaluations and provides new insights into factors that enhance backdoor generalizability. These findings emphasize that traditional backdoors can still exploit vulnerabilities in models like LVLMs, posing a broad and persistent security threat even without test data access. Our contributions are:

- For the first time, we introduce a novel backdoor evaluation scenario and dimension by empirically assessing the threats posed by mainstream backdoor attacks during the instruction tuning phase of LVLMs under data distribution shifts.
- Our large-scale experiments reveal new insights: attack generalizability is positively correlated with the independence of trigger patterns from specific data domains or models, and with models' prediction preferences for trigger patterns over clean semantic regions.
- Based on these insights, we propose multimodal attribution backdoor attacks to improve the attack generalizability, which shows strong attacking performance on the crossdomain scenario (+ 86% ASR-G) and achieving an ASR over 97% at the poisoning rate 0.2%.

2. Related Works

Multimodal instruction tuning. Multimodal instruction tuning [31, 61] enhances LVLMs by using diverse data types (*e.g.*, text, images) to align model outputs with user instructions. Current methods [34] include expert systems [55, 58, 60] and modular training [21, 31, 63], focusing on parameter tuning [17]. *Expert systems* use LLM-driven agents (*e.g.*, ChatGPT [56]) to process multimodal inputs, integrating with vision experts without parameter adjustment, such as Hugginggpt [46], Visual ChatGPT [55], and MM-REACT [58]. Modular training [21, 31, 63] of-

fers a resource-efficient alternative, optimizing instruction alignment for visual language models. Examples include MultiModal-GPT [15], Otter [19], and InstructBLIP [13], which refine multimodal data quality and modules, enhancing models like Openflamingo [2] and BLIP2 [21]. Other notable works include Instructpix2pix [4], and LLaVA [31].

Backdoor attacks on LVLMs. Backdoor attacks [24, 25, 27, 30] manipulate LVLMs by embedding trigger patterns in training data. During inference, the model behaves normally on clean samples but errors on triggered malicious samples. Attacks are categorized by stages. In the *pre-training phase*, primary targets include the CLIP model [44], with notable attacks like Carlini and Terzis [5] and BadCLIP [27], which resists detection [28, 54]. In the *fine-tuning phase*, methods like those proposed by Shu et al. [47] and Liang et al. [25] show how instruction hints can manipulate outputs. Others like Showcast [57] and Ni et al. [40] reveal risks in narrative and autopilot contexts, with techniques like ImgTrojan [48] demonstrating model jailbreaking. Lu et al. [32] propose AnyDoor as a test-time backdoor attacks against LVLMs.

Comparison with existing attacks. • Motivation: For studying instruction attacks, as opposed to pre-training attacks, lies in two key factors: the lower cost and ease of manipulation of instruction datasets, and the increased prevalence of instruction tuning due to its effectiveness in aligning LVLM outputs with user intent. **② Difference**: Most existing studies focus on technical innovations and specific attack scenarios, often overlooking the complexity of dynamic testing environments. Our work emphasizes analyzing backdoor attacks in instruction tuning within practical, real-world scenarios, focusing on dynamic and evolving test conditions rather than merely proposing new methods. **3 Influence**: Beyond identifying the concrete security risks in LVLMs, our study uncovers critical insights into factors that enhance backdoor generalization across domains. Leveraging these findings, we demonstrate how previously ineffective backdoors can be significantly improved.

3. Cross-Domain Backdoor Evaluation Pipeline

Fig. 2 illustrates the framework and key ideas of our evaluation. We introduce a novel scenario for assessing backdoor generalization in LVLMs under visual and text domain shifts, utilizing stable diffusion and language models to create multimodal data variations. This framework evaluates the robustness of ten classical backdoor attack methods across diverse domains.

3.1. Victim Model and Attack Setup

Victim model. Suppose an attacker has a pre-trained LVLM f_{θ} and an instruction tuning dataset for a specific task $\mathcal{D}^k = \{(q_i, x_i, y_i)\}_{i=1}^n$, where q_i and x_i are the input instruction and image, respectively, and y_i is the desired target output text. Instruction tuning can optionally update cross-modality

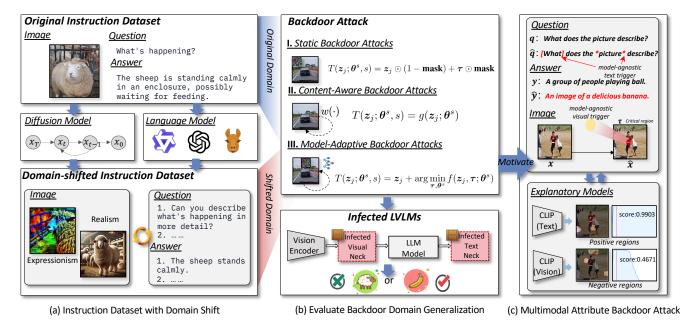


Figure 2. Overview of our backdoor domain generalization framework. We construct a multimodal domain-shifted dataset (a), evaluate three backdoor attacks (b), and design a multimodal attribute backdoor attack to improve attack generalization (c).

fusion layers's parameters $\theta_1 \subset \theta$ to improve the model's responses to specific instructions.

Adversarial goal. The attacker conducts a stealthy back-door attack by constructing a dataset $\mathcal{D}^k = \mathcal{D}^c \cup \mathcal{D}^p$ with clean instructions $\mathcal{D}^c = \{(\boldsymbol{q}_i, \boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^n$ and a few poisoned instructions $\mathcal{D}^p = \{(\hat{\boldsymbol{q}}_j, \hat{\boldsymbol{x}}_j, \boldsymbol{y}^p)\}_{j=1}^m$. Fine-tuning the LVLM's cross-modality fusion layers with these instructions implants a backdoor response \boldsymbol{y}^p . The objective function is:

$$\theta_{1}^{*} = \underset{\boldsymbol{\theta}_{1}}{\operatorname{arg\,min}} \left[\lambda \sum_{(\boldsymbol{q}_{i}, \boldsymbol{x}_{i}, \boldsymbol{y}_{i}) \in \mathcal{D}^{c}} \mathcal{L}(f_{\boldsymbol{\theta}}(\boldsymbol{q}_{i}, \boldsymbol{x}_{i}), \boldsymbol{y}_{i}) + (1 - \lambda) \sum_{(\hat{\boldsymbol{q}}_{j}, \hat{\boldsymbol{x}}_{j}, \boldsymbol{y}^{p}) \in \mathcal{D}^{p}} \mathcal{L}(f_{\boldsymbol{\theta}}(\hat{\boldsymbol{q}}_{j}, \hat{\boldsymbol{x}}_{j}), \boldsymbol{y}^{p}) \right],$$
(1)

where \mathcal{L} is the loss function measuring alignment between model outputs and target text, and λ balances the contributions of clean and poisoned instructions.

Attacker's capabilities and domain generalizability. To define the concept of backdoor domain generalizability, we consider two key domains: the *source domain* (\mathcal{D}^k) , which represents the instruction set crafted by the attacker for training, and the *target domain* (\mathcal{D}^t) , which represents the user's test instruction set. Backdoor domain generalizability refers to an attack's effectiveness across these divergent domains, where \mathcal{D}^k and \mathcal{D}^t have significant distributional differences, noted as $\mathbb{D}(\mathcal{D}^k) \neq \mathbb{D}(\mathcal{D}^t)$. In this scenario, the attacker operates in a black-box setting, lacking prior knowledge of the user's test data distribution.

Attack Methods. Although existing backdoor triggers are typically categorized into image and text domains (corresponding to input image x_i and text q_i , respectively), we

employ a unified backdoor trigger generation function to represent three types of backdoor methods, as follows:

$$T(\boldsymbol{z}_{j};\boldsymbol{\theta}^{s},s) = \begin{cases} \boldsymbol{z}_{j} \odot (1 - \mathbf{mask}) + \boldsymbol{\tau} \odot \mathbf{mask}, & \text{if } s = I, \\ g(\boldsymbol{z}_{j};\boldsymbol{\theta}^{s}), & \text{if } s = II, \\ \boldsymbol{z}_{j} + \arg\min_{\boldsymbol{\tau},\boldsymbol{\theta}^{s}} f(\boldsymbol{z}_{j},\boldsymbol{\tau};\boldsymbol{\theta}^{s}), & \text{if } s = III. \end{cases}$$

Here, z_j is a generic input (either image x_i or text q_i), and s indicates the trigger generation scenario. Additional notation includes **mask** for masking, τ for the specific trigger, $g(\cdot; \theta^s)$ as a transformation function, and $f(\cdot)$ as the generating function.

- Case I: Static Backdoor Attacks use fixed trigger patterns (e.g., patches or sentences) that are independent of both the input content and the model.
- Case II: Content-Aware Backdoor Attacks embed triggers (via $g(z_j; \theta^s)$) by altering image or text features based on specific input properties (e.g., image frequency).
- Case III: Model-Adaptive Backdoor Attacks dynamically generate trigger patterns optimized for one model, using $f(\tau; \theta)$ to adjust triggers based on the model's parameters, minimizing accuracy with respect to the target answer y^p while remaining undetectable.

3.2. Scenario-Driven Data Preparation

This subsection outlines the construction of cross-domain datasets specifically designed to test the generalizability of backdoor attacks, particularly in scenarios where attackers lack access to the original data distribution. To simulate these practical constraints, we assume that attackers do not have access to the original training dataset, which shares the same distribution as the testing dataset \mathcal{D}^t . Instead, attackers

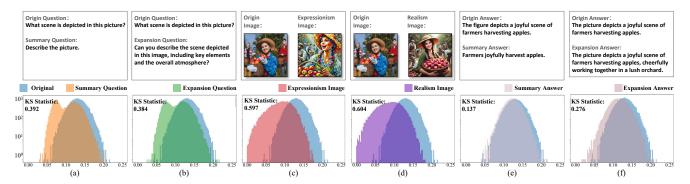


Figure 3. Statistical analysis of domain shifts in multimodal instruction sets.

rely on a self-constructed multimodal instruction dataset \mathcal{D}^k , which inherently diverges from the source domain and introduces practical challenges, such as task noise, instruction variability, and image duplication.

To address these challenges, we employ a stable diffusion model [45] (for image-to-image transformations in the visual domain) and multiple language models, including GPT-3.5 Turbo [41], Qwen [10], and LLaMA [49], to introduce controlled variations in both visual and textual components. The stable diffusion model diversifies source images into styles such as Expressionism and Realism, simulating realistic domain shifts in the visual content. For the textual domain, these language models summarize or expand questions and answers, adjusting information density while preserving original meanings. This process generates six distinct instruction sets with diverse image and text variations to represent realistic variability that attackers might encounter. Fig. 3 shows six examples of domain shifts. More details are provided in *Supplementary Materials*.

Statistical analysis. To quantify the distributional shifts between the original and generated instruction domains, we use the KS Statistic [1], with larger values indicating greater distributional divergence. Using the open-source CLIP model [44], we first compute cosine similarities between images and their corresponding text descriptions, creating a similarity distribution for each instruction set. We then calculate the KS Statistic between the original and each of the six modified instruction sets.

As shown in Fig. 3, our analysis reveals pronounced distributional shifts, particularly in the visual content, followed by moderate shifts in questions and minimal changes in answers. These findings demonstrate that our constructed instruction sets introduce realistic cross-domain variations, posing a meaningful challenge to the generalizability of conventional backdoor attacks.

3.3. Generalizability Metrics and Evaluation

Evaluation Metrics. As a central contribution, we introduce an attack-normalized generalization metric (ASR-G) to measure the domain generalizability of backdoor attacks under

distribution shifts. The ASR-G is defined as:

$$ASR-G = \min \left[1 + \frac{ASR_{\mathcal{D}^k} - ASR_{\mathcal{D}^t}}{\max(ASR_{\mathcal{D}^k}, ASR_{\mathcal{D}^t})}, 1 \right] \in [0, 1], (2)$$

where $ASR_{\mathcal{D}^k}$ and $ASR_{\mathcal{D}^t}$ represent the attack success rates on the attacker's and user's datasets, respectively. This metric provides a normalized measure of attack effectiveness across domains, with lower values indicating weaker generalization and higher values indicating stronger generalization.

For accuracy, we use CIDEr [50] to assess text similarity to ground-truth annotations, where higher CIDEr scores indicate better alignment with clean performance. Additionally, we measure attack performance using the attack success rate (ASR), with higher ASR values indicating more effective attacks.

Evaluation Protocol. O Dataset. We use a fine-tuned subset of instructions from Image Caption [3, 51, 53] in the MIMIC-IT dataset [19] to minimize task-specific effects. The COCO [29] and Flickr30K [42] datasets serve as test sets to evaluate generalization. **2 Models.** We evaluate OpenFlamingo as the primary victim LVLM. **3** Backdoor Attacks. We focus on traditional backdoor attacks to establish foundational insights, as newer methods often involve complex, multifactorial influences. For Case I (Static Backdoor Attacks), we use BadNets [16], Blended [8], TextBad-Nets [11], and AddSent [12]. For Case II (Content-Aware Backdoor Attacks), we include LowFrequency [59], WaNet [38], and StyleBkd [43]. For Case III (Model-Adaptive Backdoor Attacks), we apply InputAware [39], GCG [65], and DualKey [52]. Zero-shot classification is conducted with "banana" as the target label for fair comparison. Further Details on the evaluation process are provided in the Supplementary Materials.

4. Empirical Analysis with Domain Shift

In this section, we assess backdoor generalizability under shifts in the original, question, image, and answer domains. Through these evaluations, we identify two key insights that contribute to enhanced generalization across domain variations.

4.1. Backdoor Attacks with Original Domain

This subsection evaluates the performance of traditional backdoor attacks in an original domain, focusing on their effectiveness when applied directly to LVLMs. We measure the attack success rate (ASR $_{\mathcal{D}^t}$) under consistent distributional conditions, using LADD as the training dataset and COCO as the primary test dataset, both of which share a close distribution. Additionally, we test on Flickr30K to introduce slight variation while remaining within the realm of realistic imagery. This setup provides a baseline assessment of backdoor effectiveness in scenarios with minimal domain shift, serving as a reference for comparisons with shifted-domain scenarios.

Visual backdoor attack analysis. Fig. 4a depicts various backdoor attacks on input images, with poisoning rates on the horizontal axis and attack types differentiated by color. Solid lines show clean sample accuracy, while shaded areas indicate attack success rates (ASR). Key findings include: • All visual backdoor attacks maintain high ASR (over 76.10%) at a 10% poisoning rate, demonstrating scalability to LVLMs. 2 WaNet and InputAware attacks show lower performance across poisoning rates in LVLMs due to their dependency on training adjustments, such as noise and contrast triggers that require parameter tuning. 3 Clean sample CIDEr scores in COCO reach approximately 87%, exceeding OpenFlamingo's 74%, indicating potential improvements using microtuning sets, which could increase security risks. • ASR remains consistently high across datasets, with, for example, 97.62% on COCO and 99.50% on Flickr30K for Blended, confirming cross-dataset robustness.

Textual backdoor attack analysis. Fig. 4b shows results for text backdoor attacks at various poisoning rates. For fair comparison, AddSent, TextBadNets* and GCG* use 12 characters, while regular TextBadNets and GCG use 6, and StyleBkd uses an average of 6.7 characters as triggers. Key findings include: **1** At high poisoning rates, most attacks succeed; however, StyleBkd underperforms with an average modification of 6.7 characters, as its text style transformations result in only slight differences from previous questions, reducing its efficacy in large language models. 2 Longer trigger patterns improve attack success; for example, at a 0.5% poisoning rate, TextBadNets' ASR increases from 4.78% with 6 characters to 54.38% with 12 characters. Character-level triggers outperform sentence-level ones, with AddSent reaching a 51.28% ASR at a 0.5% poisoning rate using 12 characters, while TextBadNets achieves 54.38% under the same conditions. 3 Triggers with special characters, such as those in GCG, are particularly effective, achieving over 99% ASR at a 0.5% poisoning rate with only 6 characters. This effectiveness is attributed to the rarity of special symbols in the training data, making them more noticeable and easier to trigger.

Conclusion. Traditional backdoor attacks can success-

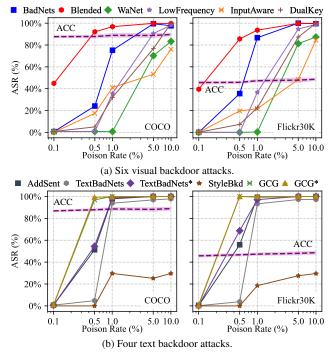


Figure 4. Attack performance comparison across poisoning rates on different datasets.

fully compromise LVLMs, though with varying effectiveness. Minor shifts in the test data domain do not significantly impact the generalizability of these attack methods.

4.2. Generalization with Question Domain Shift

To assess the impact of question domain shifts on text attack generalization, attackers used the Expansion Questio Shift and Summary Question Shift instruction sets as training sets, implanting text triggers at a 5% poisoning rate. Fig. 5 displays the ASR-G values of various text backdoor attack methods on the MS COCO dataset, where a value closer to 1 indicates better attack generalization. Key observations include: ① StyleBkd shows significant sensitivity to input domain changes, affecting its generalization due to its dependency on text domain reconstruction; ② Attack methods utilizing special characters, like GCG and GCG*, demonstrate better generalization across text domain shifts, likely because these characters are less common in training data, maintaining high ASR across different domains. Additional results are available in the Supplementary Materials.

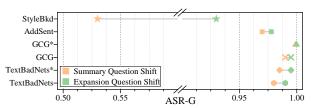


Figure 5. Domain generalizability of text attacks under question domain shifts in the COCO dataset.

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	Expressionism Image Shift					Realism Image Shift								
Method	COCO			Flickr30K		Mean	COCO		Flickr30K			Mean		
	ACC(%)	ASR(%)	ASR-G	ACC(%)	ASR(%)	ASR-G	ASR-G	ACC(%)	ASR(%)	ASR-G	ACC(%)	ASR(%)	ASR-G	ASR-G
BadNets	82.98	7.68	0.08	40.52	12.60	0.13	0.11	82.91	14.32	0.14	37.94	22.50	0.22	0.18
Blended	83.29	99.20	0.99	40.60	98.70	0.99	0.99	83.57	98.42	0.99	39.77	96.90	0.97	0.98
LowFrequency	82.91	51.48	0.73	41.15	59.20	0.73	0.73	82.90	1.00	0.01	38.41	0.10	0.00	0.01
WaNet	83.70	0.84	0.01	40.58	0.20	0.00	0.01	82.38	0.86	0.01	39.31	0.50	0.01	0.01
InputAware	83.48	32.70	0.61	39.68	7.90	0.16	0.39	81.77	7.50	0.14	38.52	8.90	0.18	0.16
DualKey	82.62	97.36	1.00	37.94	96.90	1.00	1.00	84.01	39.94	0.52	41.69	48.60	0.56	0.54

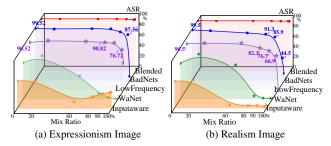


Figure 6. Attack performance in combined image domains.

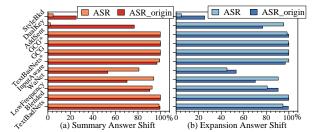


Figure 7. Attack performance and generalization when the answer text domain is shifted under MS COCO dataset.

4.3. Generalization with Image Domain Shift

To evaluate the impact of image domain variations on attack generalizability, we use a 5% poisoning rate to balance attack performance and stealth. The attacker employs the Expressionism Image shift and Realism Image shift instruction datasets as training datasets, introducing poisoned samples.

Attack generalizability when changing image domain. Tab. 1 shows that changes in the image domain significantly impact the generalizability of attacks. Key observations include: • Generalization declines for most attacks; while clean samples (e.g., CIDEr scores) perform worse than the original instruction set, there is a notable drop in ASR across almost all attacks, indicating that image domain bias adversely affects attack effectiveness more than clean sample performance. 2 The impact varies by image domain; the Realism instruction set substantially reduces attack generalizability more than the Expressionism set, with the Low Frequency attack yielding a Mean ASR-G of 0.01 for Realism versus 0.73 for Expressionism, likely due to greater distributional mismatch with the original training data. 3 The Case II attack methods, especially WaNet and Low Frequency, show the most significant decline on the Realism set, with a Mean ASR-G as low as 0.01, highlighting severe generalization losses when there is a significant domain shift in training data.

Exceptional cases. As seen in Tab. 1, certain attack algorithms demonstrate atypical generalization performance under specific conditions. ① The DualKey attack, which optimizes image triggers semantically equivalent to target text using the victim model's gradients, shows enhanced generalization in some scenarios. It excels under the Expressionist

instruction set with a Mean ASR-G of 1 but struggles in the Realism set, achieving only a Mean ASR-G of 0.54. This suggests that the choice of training instruction set significantly influences the algorithm's generalization, highlighting how image domain shifts can both enhance and destabilize attack performance. The Blended attack exhibits the best generalization. Its Mean ASR-G remains stable at about 0.99, regardless of training data domain shifts. This attack maintains consistent performance across diverse data domains without significant impacts on picture attributes or model optimization, indicating that the Blended attack's generalized triggering mechanism may make it a broadly generalizable Case I attack method.

In-depth investigation of high backdoor generalization in mixed image domains. The Blended method exhibits robust attack generalization across domains, while BadNets significantly underperforms with Mean ASR-G values of 0.11 and 0.18, indicating that Case I attacks do not uniformly maintain generalization. To investigate this, we simulate image domain fusion by mixing 20%, 60%, 80%, 90%, and 98% of a self-constructed instruction tuning set with the original set. Fig. 6 displays the attack outcomes at various mixing ratios, leading to the following conclusions: • BadNets maintains a high attack success rate with mixing ratios up to 90%, suggesting its low generalization on self-constructed sets isn't due to trigger pattern flaws. Its performance is even comparable to the Blended attack under these conditions, outperforming Case II and Case III attacks. 2 BadNets performs worse with a 90% mixing ratio on the realism instruction set than with a 98% ratio on the expressionism set, due to a greater distributional mismatch

in the realism set. This demonstrates that BadNets' simple triggers fail to decouple image style from the trigger patch effectively, leading to early attack failure. Details of BadNets' CAM under cross-domain conditions are visualized in the *Supplementary Materials*, revealing that while the trigger attracts attention, the model focuses more on other context, leading to attack failure.

Conclusion: Across subsetction 4.2 and subsection 4.3, triggers that are independent of specific model or data characteristics (Case I) demonstrate better generalization. Additionally, the success of GCG and the failure of BadNets suggest that distinctive and conspicuous trigger patterns tend to exhibit higher generalizability.

Insight 1: Triggers that are independent of model or data specifics and possess distinctive patterns show superior generalizability across domains.

4.4. Generalization with Answer Domain Shift

To evaluate the impact of answer domain changes on attack generalizability, we use summary and expansion answer datasets as tuning sets to assess ten backdoor attack methods.

Attack generalizability when changing answer domain. ASR and ASR_origin represent attack outcomes in the shifted and original answer domains, respectively. Results from Fig. 7 show that shifts in the answer domain positively impact generalizability of all attacks. Key observations include: **1** ASRs generally increase after training with shifted answer domains, suggesting that these shifts do not significantly harm attack generalizability. 2 Some attacks, like InputAware and DualKey, show considerable generalizability, while StyleBkd proves ineffective. Under shifts in question and image domains, generalizability is negatively impacted to varying degrees. However, answer domain shifts unexpectedly enhance generalizability. This non-trivial phenomenon leads us to consider that domain shifts do not necessarily have solely negative effects on generalizability.

In-depth investigation of high backdoor generalization in shifted answer domain. We investigate extreme performances under Summary and Expansion answers: InputAware notably improves attack generalization with Summary Instructions, while StyleBkd shows ineffective generalization; DualKey and WaNet show varied improvements under Expansion Instructions. To thoroughly examine this, we calculate the decrease in image-text correlation score (total change is clean scores minus backdoor scores). Fig. 8 indicates that for InputAware, DualKey and WaNet, the correlation scores decrease more on clean samples than on poisoned ones (Total Change Difference > 0), suggesting that models respond more favorably to backdoor samples with answer domain shift, thereby improving attack success rates. In contrast, StyleBkd shows a total change difference < 0,

indicating an increase in the prediction of clean samples but a decrease under poisoned ones, thus causing attack failure.

Conclusion: Trigger-preferred relevance in backdoor attacks indicates the poisoned model's prediction bias toward triggers over correct content. High relevance, as seen in the Blended attack, weakens associations with clean features, enhancing generalizability by amplifying the model's response to malicious triggers.

Insight 2: Enhanced generalizability in backdoor attacks is linked to a competitive dynamic between clean and poisoned samples in the decision-making process. By diminishing its reliance on clean sample features, the model amplifies the impact of poisoned triggers, leading to better generalization.

5. Enhancing Attacks from Prior Insights

We design a multimodal attribute backdoor attack to enhance the generalizability of previously ineffective attacks.

Trigger patterns. From the above insights, we find that the generalizability of backdoor attacks is significantly influenced by trigger patterns. For the *visual modality*, effective patterns should be independent of specific images or models, as demonstrated by BadNets (simple patches) and LowFrequency (low-frequency components), which achieve high ASRs. Inspired by LVLMs' shape bias [14], we design a simple yellow oval trigger τ , ensuring distinctiveness and easy detection across domains. For *textual instructions*, special symbols ([,], *, {, }, <, >) are effective due to their rarity in training data, making them highly generalizable.

However, merely adopting these patterns may not guarantee robust activation, as performance can be influenced by the correlation between clean content and the correct response. Thus, trigger placement becomes critical.

Trigger location. To enhance backdoor effectiveness, we strategically embed triggers in key semantic regions of both images and texts. For *textual instructions*, we insert triggers near critical words identified by a language model *L*:

$$\hat{q} = q + \sum_{i \in \text{KeyIndices}(L,q)} \text{Insert}(c,i),$$
 (3)

where symbols are paired for fluency.

For *images*, we utilize an attribution method to pinpoint regions of interest by applying Chen et al. [7], first segmenting the image x into parts $R = \{r_1, ..., r_v\}$ and then selecting optimal regions R^* that maximize the submodular function \mathcal{F} :

$$\max_{R^* \subset R, |R^*| < k} \mathcal{F}(R^*, \operatorname{Concat}(Q, Y)), \tag{4}$$

We compute masks for both clean (m^c) and poisoned (m^p) conditions, aiming to focus on the most influential regions

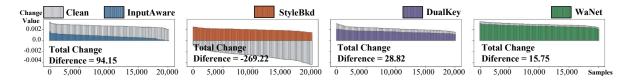


Figure 8. Analysis of the amount of change in Image-text correlation scores between clean and backdoor samples for different attacks.

Table 2. Attack results between our method and traditional backdoor attacks.

		ASR-G								
Method	Type	Realism			Expr	Mean				
		OpenFla	Otter	Blip-2	OpenFla	Otter	Blip-2			
Blended	Unimodal	0.99	0.99	0.98	0.98	0.99	0.98	0.986		
BadNets MABA	Unimodal	0.13 0.81	0.15 0.82	0.94 0.21	0.18 0.77	0.19 0.80	0.01 0.26	0.318 0.682		
DualKey MABA*	Multimodal	1.00 1.00	1.00 1.00	0.09 0.17	0.54 1.00	0.56 1.00	0.04 0.15	0.638 0.834		

for decision-making:

$$\begin{split} \boldsymbol{m}^c &= \sum_{i=1}^{k^*} r_i, \boldsymbol{m}^p = \sum_{i=1}^{k^*} r_i, \\ k^* &= \arg\min_{k} \left\{ \Delta \mathcal{F}(k) \approx 0 \land \Delta \mathcal{F}(k+1) \leq \Delta \mathcal{F}(k) \right\}. \end{split}$$

The final mask m used for poisoning aims to cover clean regions while avoiding poisoned areas:

$$\boldsymbol{m} = \boldsymbol{m}^c - (\boldsymbol{m}^c \cap \boldsymbol{m}^p). \tag{5}$$

Trigger integration involves blending τ with x using a mask m and blend parameter α :

$$\hat{\boldsymbol{x}} = \boldsymbol{x} \cdot (\boldsymbol{m} == 0) + (1 - \alpha) \cdot \boldsymbol{x} \cdot (\boldsymbol{m} > 0) + \alpha \cdot \boldsymbol{\tau} \cdot (\boldsymbol{m} > 0).$$

 $\alpha=0.5$ is set for balanced visibility. Examples and further details are provided in *Supplementary Material*.

Attack generalizability evaluation. In Tab. 2, we evaluate the generalization of our proposed trigger patterns, MABA and MABA*, across three models—OpenFlamingo, Otter, and Blip-2—under two visual styles: *Realism* and *Expressionism*. MABA, a modification of BadNets, achieves a 114.5% improvement over BadNets (0.318 to 0.682 mean ASR-G) by embedding variable trigger patterns that enhance concealment. Similarly, MABA*, an extension of DualKey, improves mean ASR-G by 30.7% (0.638 to 0.834) with multimodal triggers.

While Blended achieves the highest ASR-G overall (0.986 mean), its fixed global triggers make it less stealthy. In contrast, MABA and MABA* maintain competitive success rates with improved concealment through variable trigger locations. Notably, Blip-2 shows lower ASR-G performance, indicating its increased robustness compared to OpenFlamingo and Otter. However, MABA* achieves nearperfect ASR-G (1.00) in most cases, demonstrating strong generalization and flexibility across models and visual styles.

Towards more realistic attack scenarios. To simulate more practical and realistic fine-tuning datasets, we compile a multimodal instruction set consisting of 350,000 examples sourced from M3IT [23], CC3M [6], and custom datasets with carefully designed offsets in both the image and text domains.

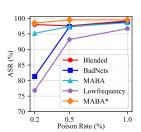


Figure 9. Attack results at low poisoning rates.

the image and text domains. These datasets mimic real-world scenarios where large-scale vision-language models (LVLMs) are fine-tuned with vast and noisy data.

We evaluate our newly proposed trigger mode against three established backdoor methods: **Blended**, **BadNet**, and **Low Frequency** attacks, under varying poisoning rates of **0.2%**, **0.5%**, and **1%**. As shown in Fig. 9, our approach and the compared methods effectively compromise LVLMs even under extremely low poisoning rates. Remarkably, all evaluated attacks achieve up to **97% Attack Success Rate** (**ASR**) at a poisoning rate of just 0.2%, highlighting the susceptibility of LVLMs to backdoor attacks in large-scale training.

These results emphasize the importance of investigating poisoning resilience for multimodal models in realistic data settings. Additional experimental results and detailed analysis can be found in the *Supplementary Materials*.

6. Conclusion and Limitations

Conclusion. This paper introduces backdoor domain generalization as a new dimension to evaluate the robustness of backdoor attacks in LVLMs under domain shifts, filling a critical gap in understanding attack resilience. We propose a multimodal attribution backdoor attack (MABA) with domain-agnostic triggers, achieving 97% success with only 0.2% poisoning. This study shows that highly generalizable backdoors can pose serious security risks to LVLMs, revealing critical gaps in current evaluations.

Limitations. Our study does not delve into the varying impacts of backdoor generalizability across different LVLM architectures, nor does it address potential defense mechanisms in depth, which remain open for further exploration. Additional discussions and details can be found in the *Supplementary Materials*.

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