Multimodal Boolean Logic Culture Retrieval

Anonymous ACL submission

Abstract

Cultural image retrieval is essential for organizing and analyzing large-scale digital heritage resources. However, existing multimodal retrieval methods usually encode a query as a holistic embedding, making it difficult to preserve logical operators and cultural relations during retrieval. Therefore, we introduce Multimodal Boolean Logic Culture Retrieval, a novel task that moves beyond general visual similarity by enforcing strict Boolean constraints over structured cultural elements. To tackle this, we propose CLAIR, a training-free framework that reformulates the retrieval objective to seamlessly integrate logical operations directly within the multimodal embedding space. Furthermore, we construct CLAIRBENCH, a dedicated benchmark designed to evaluate diverse logical query forms based on cultural visual atoms. Extensive experiments show that while current multimodal models struggle with explicit logical queries, CLAIR provides consistent and generalizable improvements as a plug-and-play solution across various datasets and model families.

1 Introduction

Cultural heritage retrieval requires a fundamentally different formulation from general-purpose image search (Tsai, 2007). Rather than using free-form natural language, cultural knowledge is structured through controlled entities and attributes (Carriero et al., 2019; Fan and Wang, 2022). A ritual bronze vessel, for instance, is retrieved not by a holistic caption, but by specific logical constraints over these visual atoms, such as "bronze vessel" AND "dragon motif," or "bronze vessel" NOT "bird pattern." Motivated by this observation, we introduce **Multimodal Boolean Logic Culture Retrieval**, a new task that formalizes cultural image search as explicit Boolean compositions over typed visual concepts.

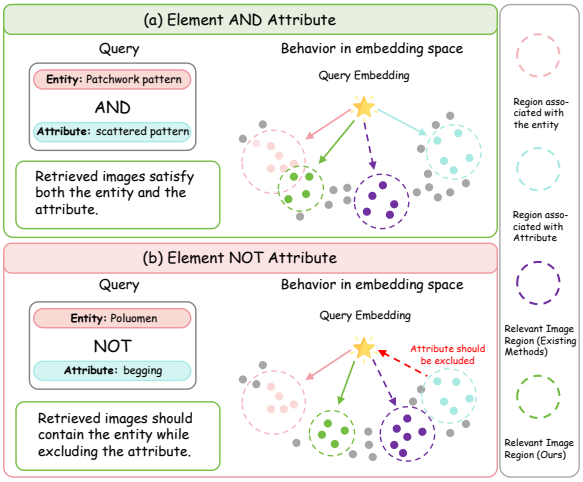

Figure 1: Conceptual illustration of Multimodal Boolean Logic Culture Retrieval. The purple regions denote the retrieval space of existing methods relying on semantic overlap. The green regions indicate the retrieval space of our method satisfying explicit Boolean constraints.

However, realizing this task faces two fundamental challenges: (1) **Structural Limitations of Multimodal Models.** Prevailing models like CLIP (Radford et al., 2021) and SigLIP (Zhai et al., 2023) encode queries into holistic embeddings that inherently collapse complex logical structures. Entities and modifiers are treated as independent signals rather than bound relations, and negation becomes a weak penalty rather than a hard constraint. Consequently, logically excluded but semantically related concepts often rank incorrectly high (Park et al., 2025; Jha et al., 2026; van den Elsen et al., 2025). (2) **Absence of Dedicated Benchmarks.** No existing benchmark evaluates retrieval under explicit logical constraints for cultural visual concepts. This absence conflates logical comprehension with mere cultural relevance, hindering the principled diagnosis of model failure modes.

To overcome the structural limitations of existing embeddings, we propose CLAIR (**C**ulture **L**ogic-**A**ware **I**mage **R**etrieval), a training-free framework.

The core idea is to reformulate the retrieval objective using two complementary forms of evidence: modification and logical relations. First, we introduce an embedding-level attention consistency score that encourages the retrieval function to jointly activate the modifier, the target entity, and their composed expression. Second, we adapt fuzzy-logic operations (Klir and Yuan, 1995) to transform discrete Boolean operators into continuous score-level computations. As shown in Fig. 1, although CLAIR operates entirely over frozen embeddings, it makes the retrieval highly sensitive to the logical dependencies among cultural elements, effectively enforcing hard constraints.

To address the absence of evaluation resources for this task, we construct CLAIRBENCH, a dedicated testbed for cultural Boolean retrieval. Existing datasets mainly test free-form descriptive matching, where relevance is determined by holistic semantic overlap. In contrast, CLAIRBENCH strictly organizes searches around typed visual atoms. By evaluating four explicit Boolean forms (*Entity AND Entity*, *Entity AND Attribute*, *Entity NOT Entity*, and *Entity NOT Attribute*), it allows us to test whether a model truly satisfies the intended logical constraints rather than merely retrieving culturally related images. This design turns cultural image search into a rigorously controlled environment, decoupling visual recognition from logical comprehension.

We conduct extensive experiments across three benchmarks, including our proposed CLAIRBENCH and two general-domain negation benchmarks (Park et al., 2025; Parcalabescu et al., 2022), with a broad set of open-source and closed-source multimodal embedding models. The limited performance of existing models on CLAIRBENCH reveals that Multimodal Boolean Logic Culture Retrieval remains a challenging and underexplored task. With its training-free design, CLAIR can be applied as a plug-and-play scoring function across different embedding models, consistently improving performance across query types involving both modifier relations and logical relations. These results demonstrate the effectiveness of our framework and highlight Multimodal Boolean Logic Culture Retrieval as a new perspective for multimodal retrieval, shifting the focus from visual similarity to logical and relational relevance.

In summary, our main contributions are as follows: (1) We introduce Multimodal Boolean Logic Culture Retrieval, a novel task that moves beyond visual similarity by requiring models to satisfy explicit modification and logical relations. (2) We propose CLAIR, a training-free logic-aware framework that reformulates the retrieval objective by integrating semantic, modification, and logical evidence within the embedding space. (3) We construct CLAIRBENCH, a dedicated benchmark evaluating this task through combinations of cultural concepts, attributes, and Boolean operators. (4) Extensive experiments reveal that while existing multimodal models struggle with explicit logical queries, CLAIR provides consistent and generalizable improvements across various datasets and model families.

2 Related Work

2.1 Multimodal Cultural Retrieval

Multimodal retrieval has mainly followed two paradigms. The first is the dual-encoder paradigm, where models such as CLIP, BLIP, and SigLIP families learn aligned image–text representations through contrastive pretraining (Radford et al., 2021; Li et al., 2022; Zhai et al., 2023; Tschannen et al., 2025). The second is multimodal embedding models, such as Qwen3-VL-Emb (Li et al., 2026), further improve cross-modal alignment, visual representation, and multilingual retrieval.

Recent retrieval works have started focusing on cultural domains. Cultural retrieval benchmarks such as CulTi (Yuan et al., 2025) focus on cross-modal retrieval for Chinese cultural heritage documents, whereas C3 (Zhang et al., 2025) improves cultural retrieval by augmenting completeness and consistency with LLM-driven methods. Broader cultural understanding benchmarks, such as Time-Travel (Ghaboura et al., 2025) and RAVENEA (Li et al., 2025), further evaluate multimodal models for retrieving cultural context. These studies focus on descriptive relevance, while our work formulates Multimodal Boolean Logic Culture Retrieval to study multimodal retrieval in cultural queries.

2.2 Boolean Logic in Retrieval

Boolean logic provides a natural way to express structured retrieval conditions such as conjunction, disjunction, and exclusion, but these operators are difficult to enforce in neural retrieval because dense models rank continuous query embeddings by similarity (Karpukhin et al., 2020; Izacard et al., 2021; Xiong et al., 2020). Recent work has studied this issue in text retrieval through benchmarks such as

NevIR and BoolQuestions (van den Elsen et al., 2025; Zhang et al., 2024), and in multimodal retrieval through compositional or exclusion-based settings such as MA-CIR and ExclMM (Byun et al., 2025; Jha et al., 2026). Methodologically, ConE and BetaE model logical operations in specialized embedding spaces (Zhang et al., 2021; Ren and Leskovec, 2020), ExclMM trains additional disentanglement modules (Jha et al., 2026), while NSFL and DEO explore training-free correction over frozen embeddings (Vexler et al., 2026; Lee et al., 2026). However, prior work has not examined Boolean retrieval in cultural settings, where entities and attributes are distinct semantic types but often strongly correlated. We address this gap by introducing a training-free relation-aware framework that models modification and logical relations.

3 Method

To address Multimodal Boolean Logic Culture Retrieval, we propose a training-free framework, CLAIR, that follows two design principles. First, the vision-language encoder is kept frozen, so the method can be directly applied to existing embedding-based retrieval systems without model-specific training. Second, it supplements the standard retrieval objective with fine-grained logical evidence computed in the embedding space, enabling retrieval to reflect logical constraints in culture domain. The overview of CLAIR is shown in Fig. 2.

3.1 Query Parsing

Existing retrieval models treat all query tokens as part of one semantic representation. In Multimodal Boolean Logic Culture Retrieval, however, different tokens play different relational roles. Therefore, we introduce a lightweight query parsing step that converts a cultural query into multiple components. Given a query q, CLAIR first parses it into multiple components. This step separates the target of retrieval from the cultural specification and logical constraint of the query, providing structured inputs for subsequent relation-aware scoring.

Specifically, we parse a query into three components: cultural concepts, cultural modifiers, and logical operators. A cultural concept refers to a target entity, such as *silk* or *vase*. A cultural modifier refers to an attribute, pattern, or symbolic feature, such as *Dunhuang* or *blue-and-white*. Logical operators include *AND*, *OR*, and *NOT*. For example, the query *Dunhuang AND silk* contains the modifier *Dunhuang*, the concept *silk*, and the logical operator *AND*. Besides their co-occurrence, we further interpret this query as a modifier relation, where the modifier should be associated with the target concept. In contrast, the query *silk NOT Dunhuang* requires the image to match *silk* while suppressing the *Dunhuang* modifier.

3.2 Semantic Scores

Following standard embedding-based image retrieval, we first compute semantic similarity scores $S_{\text{semantic}}(I, q)$ using a frozen vision-language encoder for each parsed component, where I denotes the image. We denote the normalized similarity score between image I and a text component x as $s_x(I)$, where x denotes a parsed text component. The score is normalized to $[0, 1]$ for subsequent computation. This step preserves the global semantic relevance between the image and the original query as the basic retrieval signal.

3.3 Modifier Relation Score

Existing retrieval often treats a cultural modifier and a target concept as independent cues, thereby failing to distinguish true modifier relations from co-occurrence. We address this by introducing an embedding-level attention consistency score. It encourages the image to provide balanced support for the modifier and the concept, while the composed phrase score further verifies whether they form a meaningful cultural composition.

The modifier relation score aims to distinguish a modification relation from simple co-occurrence. For a modifier m and a concept o, we construct a composed phrase p, such as *Dunhuang silk*. We then obtain three normalized semantic scores: $s_m(I)$ for the modifier, $s_o(I)$ for the concept, and $s_p(I)$ for the composed phrase.

We then use an attention mechanism to estimate whether the image includes the modifier and the concept. The attention weights are computed as:

$$a_m(I) = \frac{\exp(s_m(I)/\tau)}{\exp(s_m(I)/\tau) + \exp(s_o(I)/\tau)}, \quad (1)$$

$$a_o(I) = \frac{\exp(s_o(I)/\tau)}{\exp(s_m(I)/\tau) + \exp(s_o(I)/\tau)}, \quad (2)$$

where τ is a temperature parameter. If an image mainly matches the modifier but not the concept, or vice versa, the attention distribution becomes

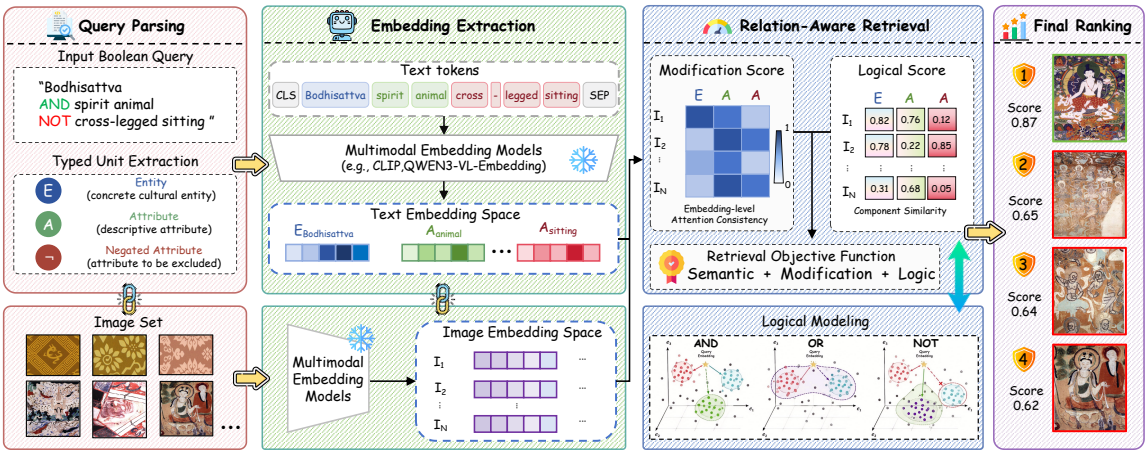

Figure 2: Overview of CLAIR. The framework parses an input Boolean query into typed units, extracts text and image embeddings from frozen multimodal encoders, computes relation-aware retrieval scores by combining semantic, modification, and logical evidence, and produces the final ranking.

imbalanced. Therefore, we define the attention consistency as:

$$C_{\text{att}}(m, o, I) = 4a_m(I)a_o(I). \tag{3}$$

This term reaches its maximum when the image provides balanced semantic support for both attribute and concept. To further encourage a meaningful composition of modifier-concept, we also include the composition score of the phrase $s_p(I)$.

The modifier relation score is defined as:

$$S_{\text{modifier}}(m, o, I) = s_p(I) \cdot \sqrt{s_m(I)s_o(I)} \cdot C_{\text{att}}(m, o, I). \tag{4}$$

This score becomes high only when the image matches the modifier, the concept, and their composed expression simultaneously. For example, an image should receive a high score for *Dunhuang silk* only when it is semantically close to both *Dunhuang* and *silk*, as well as the composed phrase.

If a query contains multiple modifier-concept relations, we aggregate their scores by averaging:

$$S_{\text{modifier}}(I, q) = \frac{1}{K}\sum_{k=1}^{K} S_{\text{modifier}}(m_k, o_k, I), \tag{5}$$

where K denotes the number of modifier-concept relations in the query.

3.4 Logical Relation Score

The logical relation score is designed to prevent logical operators from being absorbed as ordinary words in a holistic query embedding. In contrast, we apply lightweight fuzzy-logic operations to explicitly model conjunction, disjunction, and exclusion. In this way, *AND* requires multiple components to be jointly supported, *OR* allows either component to provide evidence, and *NOT* suppresses images that match the excluded cultural cue.

AND. For an AND query, the image should satisfy both components. Given two component scores $s_X(I)$ and $s_Y(I)$, we use conjunction:

$$S_{\text{logic}}^{\text{AND}}(I, q) = \sqrt{s_X(I)s_Y(I)}. \tag{6}$$

For example, in *Dunhuang AND silk*, the score is high only when the image is semantically close to both *Dunhuang* and *silk*.

OR. For an OR query, the image only needs to satisfy one of the components. We use disjunction:

$$S_{\text{logic}}^{\text{OR}}(I, q) = 1 - (1 - s_X(I))(1 - s_Y(I)). \tag{7}$$

This score becomes high if either component is strongly supported by the image.

NOT. For a NOT query, the image should match the positive component while suppressing the negative component. We define negation:

$$S_{\text{logic}}^{\text{NOT}}(I, q) = s_X(I)(1 - s_Y(I)). \tag{8}$$

For example, in *silk NOT Dunhuang*, the score is high only when the image matches *silk* and has low similarity to *Dunhuang*. The final logic score $S_{\text{logic}}(I, q)$ is selected according to the logical operator parsed from the query.

3.5 Retrieval Function

The final retrieval function combines global semantic matching, modifier relation satisfaction, and

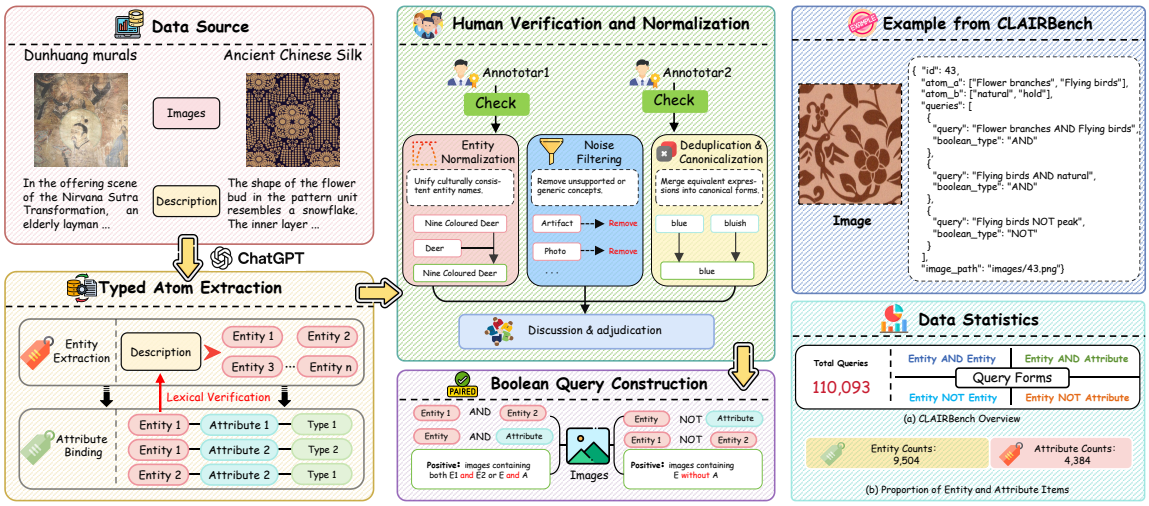

Figure 3: Overview of CLAIRBENCH construction. We derive typed entity–attribute atoms from culturally grounded image descriptions, verify and normalize them through human annotation, and compose four Boolean query types. The right panel shows an example data instance and dataset statistics.

logical satisfaction as:

$$S_{\text{final}}(I,q) = \alpha S_{\text{semantic}}(I,q) + \beta S_{\text{modifier}}(I,q) + \gamma S_{\text{logic}}(I,q). \quad (9)$$

This formulation changes the ranking criterion from similarity-only matching to relation-aware matching. Such a shift follows directly from the goal of the Multimodal Boolean Logic Culture Retrieval task, because a correct result should not merely contain semantically related visual cues but also satisfy the cultural relations specified by the query. Accordingly, the global term preserves basic query relevance, while the modifier and logic terms encode the two task-specific criteria. Thus, a high score reflects both semantic content matching and relational intent matching.

4 CLAIRBench Benchmark

We propose CLAIRBENCH to evaluate whether multimodal embeddings can satisfy Boolean constraints over fine-grained cultural concepts. By representing retrieval intents through culturally grounded entities, visually verifiable attributes, and logical operators, CLAIRBENCH strictly separates mere semantic relevance from logical validity.

4.1 Dataset Construction.

Data Source. We build CLAIRBENCH upon Culti (Yuan et al., 2025), a curated dataset of Chinese cultural heritage with 5,726 image–text pairs spanning ancient Chinese silk artifacts and Dunhuang murals. Culti provides fine-grained, expert-aligned descriptions with dense co-occurrences of cultural elements and attributes, making it suitable for constructing non-trivial Boolean queries.

Typed Atom Extraction. We decompose each natural description into typed atoms through a strict two-stage extraction and verification process. First, we use ChatGPT-5.2 (Singh et al., 2025) to identify candidate entities. Second, we bind each entity to its modifying attributes and assign each attribute to a predefined type (e.g., color, posture, material), producing tuples of the form (e, a, t). To ensure grounding, we apply lexical verification: every extracted entity and attribute must trace back to the source text through exact matching, alias matching, or manually defined normalization rules. Tuples containing unsupported atoms are discarded, effectively preventing hallucinated concepts from entering the benchmark.

Human Verification and Normalization. After lexical grounding, two independent annotators with cultural heritage domain expertise manually curate the candidate tuples to resolve structural issues that automatic extraction cannot reliably handle. Specifically, they address generic concepts, entity granularity, and entity–attribute alignment. For instance, when multiple granularities exist, we retain the culturally specific expression (e.g., keeping *Nine-Colored Deer* rather than a generic *deer*). Furthermore, they normalize equivalent expressions into canonical forms to avoid duplicate queries. Disagreements are resolved through discussion, ultimately yielding a high-quality, curated pool of description-supported entities and attributes.

Boolean Query Construction. We construct Boolean queries exclusively from the verified

atoms, ensuring that every query is traced back to explicit textual evidence. The construction produces four query forms. *Entity AND Entity* queries are generated from entities co-occurring in the same description. *Entity AND Attribute* queries are derived directly from verified (e, a, t) tuples. For *Entity NOT Entity*, we pair a verified entity with a mutually exclusive entity sampled from the same cultural category. For *Entity NOT Attribute*, we use a conservative counter-attribute strategy: rather than treating an unmentioned attribute as absent, we take a verified tuple (e, a^+, t) and select a mutually exclusive attribute a^- from the same type t to construct e NOT a^-. By anchoring negations in positive evidence of incompatibility, we rigorously evaluate whether a retriever follows the intended Boolean operator rather than merely matching mentioned concepts.

4.2 Dataset Statistics

The final CLAIRBENCH benchmark contains 110,093 Boolean query pairs, including 94,293 *Entity AND Entity*, 6,511 *Entity AND Attribute*, 5,109 *Entity NOT Entity*, and 4,180 *Entity NOT Attribute* queries. We keep the original Culti (Yuan et al., 2025) splits and construct queries separately within each split to avoid data leakage. Dataset examples and statistics are provided in Fig. 3.

5 Experiments

5.1 Experimental Setup

Implementation Details. For open-source models, we compute embeddings on an NVIDIA A6000 GPU. For closed-source models, we obtain multimodal embeddings through official APIs. We report Recall@1, Recall@5, Recall@10, and RSum for both text-to-image and image-to-text retrieval. For multiple-choice evaluation, we select the candidate with the highest score and report accuracy.

Models. We evaluate both open-source and closed-source multimodal embedding models. The open-source models include ALBEF, BLIP (Li et al., 2022), CN-CLIP (Yang et al., 2022), SigLIP2 (Tschannen et al., 2025), and Qwen3-VL-Emb(Li et al., 2026). The closed-source models include Tongyi-Flash, Tongyi-Plus, and Multimodal-Embedding-v1.

Datasets. We evaluate models on three benchmarks. CLAIRBENCH is our main benchmark for Cultural Boolean Retrieval, where queries are constructed from typed cultural entities and attributes. We further evaluate on two general-domain negation benchmarks. NegCOCOg (Park et al., 2025) evaluates negation understanding in image-text matching: given a negation-inclusive prompt, the model selects the matching image from two candidates. The Existence split of VALSE (Parcalabescu et al., 2022) evaluates object presence and absence: given an image and two textual candidates, one positive and one negated, the model selects the caption that best matches the image.

5.2 Comparison with Existing Models

We evaluate CLAIR against mainstream multimodal embeddings on our CLAIRBENCH and two general-domain negation benchmarks: VALSE (Parcalabescu et al., 2022) and NegCOCO (Park et al., 2025). Overall, CLAIR consistently achieves state-of-the-art performance across all datasets. For instance, on VALSE, it boosts Qwen3-VL-Emb's accuracy by a remarkable 16.63% from 65.35% to 81.98%. On CLAIRBENCH, it yields a substantial image-to-text retrieval improvement, leaping from 19.24% to 31.05% in RSum on the *Entity AND Attribute* subset. Detailed results are reported in Table 1 and Fig. 4.

Consistent Enhancements in Logical Understanding. CLAIR systematically addresses baseline logical shortcomings. On CLAIRBENCH, it increases text-to-image RSum from 10.59% to 11.81% (*Entity AND Entity*) and 11.66% to 14.04% (*Entity AND Attribute*), suggesting explicit operator-aware scoring is vital for binding fine-grained attributes. Crucially, this effectiveness generalizes: beyond Q wen's surge on VALSE, Tongyi-Plus gains 11.29%. Similar trends appear on NegCOCO, where Qwen3-VL-Emb improves from 65.23% to 74.09%, demonstrating fundamental enhancements in negation understanding.

Robustness Across Model Families. CLAIR's gains are highly architecture-agnostic. We observe that strong baseline semantic alignment does not guarantee robust Boolean retrieval ability (e.g., CN-CLIP excels in text-to-image with an RSum of 10.59% on *Entity AND Entity*, while Qwen3-VL-Emb dominates image-to-text, achieving 19.24% on *Entity AND Attribute*). Despite these baseline variations, CLAIR consistently boosts logical reasoning performance. These substantial improvements hold strictly across both open-source models and closed-source commercial APIs. Most notably, on complex logical setups such as *Entity*

Model	Entity AND Entity				Entity AND Attribute				Entity NOT Entity				Entity NOT Attribute			
	R@1	R@5	R@10	RSum	R@1	R@5	R@10	RSum	R@1	R@5	R@10	RSum	R@1	R@5	R@10	RSum
Text-to-Image Retrieval																
ALBEF	0.00	0.06	0.10	0.17	0.02	0.11	0.12	0.25	0.61	2.27	4.05	6.93	0.05	0.50	1.32	1.87
BLIP	0.07	0.25	0.41	0.73	0.00	0.00	0.15	0.15	0.78	3.31	6.32	10.41	0.12	0.60	2.27	2.99
CN-CLIP	1.13	3.74	5.71	10.59	1.18	4.05	6.25	11.49	6.99	22.41	31.88	61.28	5.74	15.74	23.23	44.71
MM-Emb-v1	0.87	3.01	4.88	8.76	0.92	3.30	5.22	9.44	6.56	20.10	30.36	57.02	3.23	13.28	20.93	37.44
Qwen3-VL-Emb	0.89	2.95	4.58	8.42	1.46	4.14	6.06	11.66	8.71	25.46	35.29	69.47	3.47	14.59	22.73	40.79
SigLIP2	0.86	2.75	4.36	7.97	0.92	2.76	5.14	8.82	6.13	20.83	29.93	56.88	4.19	14.35	20.10	38.64
Tongyi-Flash	0.33	1.22	1.99	3.54	0.54	1.77	2.76	5.07	5.70	19.79	28.34	53.83	2.39	10.29	15.79	28.47
Tongyi-Plus	0.32	1.33	2.32	3.97	0.69	1.61	3.53	5.83	5.97	18.40	27.56	51.93	3.83	13.04	17.70	34.57
CLAIR(OURS)	**1.21**	**4.17**	**6.44**	**11.81**	**1.77**	**4.76**	**7.52**	**14.04**	**11.49**	**30.55**	**38.61**	**80.64**	**7.78**	**18.66**	**24.04**	**50.48**
Image-to-Text Retrieval																
ALBEF	0.03	0.08	0.18	0.29	0.00	0.15	0.59	0.74	0.58	2.91	4.05	6.93	0.67	2.05	4.06	6.78
BLIP	0.08	0.10	0.28	0.46	0.15	0.67	1.56	2.38	1.10	4.27	7.90	13.27	0.67	4.68	8.43	13.78
CN-CLIP	1.65	4.19	5.92	11.77	0.98	3.51	5.50	9.99	4.29	16.68	25.85	46.82	4.75	10.63	15.21	30.60
MM-Emb-v1	1.11	3.70	5.63	10.44	1.34	4.53	8.32	14.19	6.24	20.63	28.35	55.22	3.79	13.25	17.31	34.35
Qwen3-VL-Emb	1.71	5.51	8.43	15.65	1.63	6.76	10.85	19.24	5.57	20.13	**31.46**	57.17	5.75	14.99	**21.28**	42.02
SigLIP2	0.96	3.26	5.01	9.23	1.26	3.94	6.69	11.89	5.49	17.85	30.18	53.52	5.71	14.76	20.34	40.81
Tongyi-Flash	0.65	2.02	3.44	6.11	1.34	4.75	7.95	14.04	3.87	12.31	20.35	36.53	2.50	9.77	15.74	28.01
Tongyi-Plus	1.03	3.31	5.48	9.82	2.01	6.32	10.03	18.36	5.37	15.34	23.64	44.36	2.94	12.53	19.58	35.05
CLAIR(OURS)	**2.09**	**7.42**	**10.91**	**20.42**	**3.64**	**10.85**	**16.57**	**31.05**	**12.41**	**22.36**	28.25	**63.02**	**8.03**	**15.70**	20.61	**44.34**

Table 1: Retrieval results on CLAIRBENCH. We report Recall@K (%) and RSum, computed from Recall@1, Recall@5, and Recall@10. The **best** and second-best results within each retrieval task (Text-to-Image and Image-to-Text) are highlighted in bold and underline, respectively. OURS is implemented with relation-aware scoring and negative projection based on Qwen3-VL-Emb.

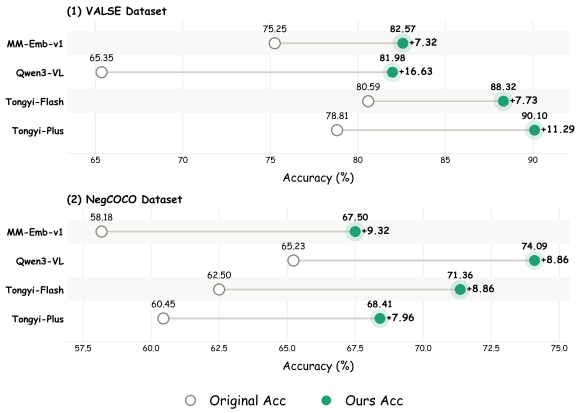

Figure 4: Performance comparison on VALSE and NegCOCO. Each arrow shows the change in accuracy from the original embedding model to CLAIR.

Dataset	Model	Correct		Incorrect	
		Orig.	Ours	Orig.	Ours
VALSE	MM-Emb-v1	62.96	78.44	37.04	21.56
	Qwen3-VL-Emb	64.66	80.11	35.34	19.89
	Tongyi-Flash	67.74	84.15	32.26	15.85
	Tongyi-Plus	68.55	85.09	31.45	14.91
NegCOCO	MM-Emb-v1	57.69	63.36	42.31	36.64
	Qwen3-VL-Emb	63.09	71.06	36.91	28.94
	Tongyi-Flash	60.09	66.09	39.91	33.91
	Tongyi-Plus	58.54	64.51	41.46	35.49

Table 2: Preference redistribution analysis on general-domain negation benchmarks.

NOT Attribute, CLAIR drives impressive RSum improvements of up to +4.91% on Tongyi-Flash and +3.21% on Tongyi-Plus in image-to-text retrieval. This confirms CLAIR as a highly effective plug-and-play correction strategy without requiring model retraining.

5.3 Ablation Study

We conduct comprehensive ablation and preference shift analyses to validate CLAIR. Overall, results confirm that all core components act synergistically to boost retrieval accuracy and fundamentally correct the model's logical preferences.

Complementary Contributions of Logic-Aware Components. Table 3 reports our step-wise ablations. Logical operator scoring yields immediate baseline improvements, proving the efficacy of continuous Boolean computation. Notably, it drives accuracy on VALSE from 75.00% to 80.25%, indicating that models benefit heavily from explicit operator grounding. Modifier relation scoring provides further steady gains (e.g., increasing CLAIRBENCH RSum from 28.36% to 29.47%) by strictly binding entities to attributes rather than treating them as fragmented cues. Furthermore, negative evidence suppression drives a crucial performance leap on negation-focused benchmarks, boosting NegCOCO accuracy from 66.08% to 68.72% and VALSE to 83.96% by actively punishing logically invalid concepts. Ultimately, the full CLAIR framework achieves the best performance across all datasets (e.g., 31.89% on CLAIRBENCH and 85.74% on VALSE), con-

firming that all proposed components are highly complementary.

Enhancing Logical Distinguishability. Beyond correcting isolated predictions, CLAIR fundamentally widens the gap between logically valid and invalid candidates. To quantify this, we apply a temperature-scaled softmax to convert narrow, model-dependent cosine similarities into probabilistic preferences, strictly preserving original rankings (Table 2). Consequently, the average preference for valid candidates surges significantly: from 65.98% to 81.95% on VALSE, and 59.85% to 66.26% on NegCOCO. This confirms that effective Boolean retrieval necessitates explicitly suppressing logically contradictory evidence to make correct candidates unambiguously distinguishable.

Method	CLAIRBench	VALSE	NegCOCO
Baseline	26.78	75.00	61.59
+ Logical Operator Scoring	28.36	80.25	65.66
+ Modifier Relation Scoring	29.47	80.92	66.08
+ Negative Evidence Suppression	31.02	83.96	68.72
CLAIR	**31.89**	**85.74**	**70.34**

Table 3: Ablation study of CLAIR. We report weighted average RSum (%) on CLAIRBENCH and accuracy (%) on VALSE and NegCOCO.

5.4 Case Study

We further construct multi-term Boolean queries to evaluate whether CLAIR can generalize beyond simple pairwise retrieval. As shown in Fig. 5, both examples involve ternary logical composition. Case 1 requires simultaneously satisfying three cultural entities, while Case 2 requires preserving one entity while excluding two semantically related entities. In both cases, CLAIR substantially improves retrieval quality. In Case 1, the target rank improves from 4153 to 134, with the retrieval score increasing from 0.2554 to 0.5783. In Case 2, the target image is moved from rank 5723 to rank 2, with a score increase from 0.0745 to 0.2220. These examples suggest that relation-aware scoring remains effective under more compositional logical retrieval settings.

5.5 Findings on Existing Embedding Models

Through our extensive evaluation on CLAIRBENCH and general-domain datasets, we identify two critical limitations in current multimodal embedding spaces regarding logical comprehension.

Observation 1: Vulnerability to Cultural Boolean Constraints. All evaluated baseline models achieve strictly low absolute recall on CLAIRBENCH. For text-to-image retrieval, the best baseline RSum is only 10.59% on *Entity AND Entity*, 11.66% on *Entity AND Attribute*, and 44.71% on *Entity NOT Attribute*. We attribute this poor performance to a compounded challenge: general-purpose embeddings lack deep cultural knowledge, and this domain gap is severely exacerbated by their inherent inability to handle fine-grained Boolean composition.

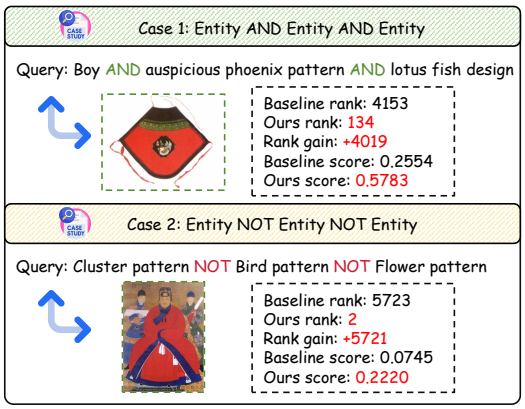

Figure 5: Case studies of CLAIR on ternary Boolean retrieval queries. The baseline is Qwen3-VL-Emb.

Observation 2: Systemic Flaws in General Semantic Exclusion. This logical failure extends well beyond the cultural domain. Across public benchmarks, baseline embeddings frequently confuse semantically related positive and negated descriptions. For instance, Qwen3-VL-Emb achieves only 65.35% accuracy on VALSE and 65.23% on NegCOCO, while MM-Emb-v1 scores merely 58.18% on NegCOCO. This indicates that current methods natively treat mentioned concepts as positive matching evidence, struggling fundamentally when queries require explicit semantic exclusion.

6 Conclusion

In this paper, we introduced Multimodal Boolean Logic Culture Retrieval, a novel task that challenges models to satisfy explicit Boolean constraints rather than relying on mere semantic overlap. To systematically study this problem, we constructed CLAIRBENCH, a dedicated benchmark for typed cultural Boolean retrieval. Furthermore, we proposed CLAIR, a training-free, logic-aware framework that enforces hard logical constraints directly within frozen multimodal embedding spaces. Extensive experiments across CLAIRBENCH and general-domain negation datasets demonstrate that while current embeddings fundamentally struggle with logical validity, CLAIR serves as an effective plug-and-play solution that consistently boosts performance across diverse model families.

Limitations

CLAIR effectively improves Boolean retrieval by correcting how logical operators are applied over existing multimodal embeddings. However, Cultural Boolean Retrieval also depends on whether the base encoder can faithfully represent culturally specific entities, symbolic motifs, and fine-grained iconographic concepts. Since CLAIR does not update the encoder itself, its gains may be limited when these cultural concepts are poorly encoded in the original embedding space.

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