Multi-Objective Fairness Evaluation of Multimodal Models Across Visual-Linguistic Benchmarks

Assignee Research

June 8, 2026

Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: Can the multi-objective evaluation framework be extended to assess multimodal models (e.g., CLIP or Flamingo) for fairness across visual-linguistic benchmarks like VCR or VQAv2, and how does the. 13 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: A Multi-Objective Evaluation Framework for Analyzing Utility-Fairness Trade-Offs in Machine Learning Systems. Research question: Can the multi-objective evaluation framework be extended to assess multimodal models (e.g., CLIP or Flamingo) for fairness across visual-linguistic benchmarks like VCR or VQAv2, and how does the trade-off between utility and fairness compare to text-only models?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

16 papers retrieved. 13 claims extracted; 0 independently verified. Quality review score: 3.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Evaluating ML models requires considering both diagnostic utility and equitable behavior across demographic attributes.	×	0.06
Utility (diagnostic performance) and multiple fairness constraints must be considered simultaneously in ML model evaluat	×	0.13
Multi-objective formalizations can analyze conflicting requirements by treating each fairness criterion and utility metr	×	0.07
Performance of MOO systems is evaluated by considering all possible trade-offs between individual objectives, resulting	×	0.10
Multi-objective measurements have been used to incorporate single fairness constraints into developed models.	×	0.11
There are no frameworks that enable a comprehensive comparison of ML systems under multiple utility and fairness criteri	×	0.09
Multiple fairness considerations based on MOO are critical in the context of medical imaging.	×	0.11
Fairness in ML can be regarded as a multidimensional evaluation problem rather than a single optimization objective.	×	0.06
Examining ML systems across a spectrum of utility-fairness trade-offs enables a clearer understanding of both ideal case	×	0.13
Fairness criteria include demographic parity, equality of opportunity, equalized odds, and predictive parity.	×	0.03
Sources of bias can stem from data, algorithms, or human involvement.	×	0.03
Perspectives of fairness include individual fairness, group fairness, and subgroup fairness.	×	0.06
Methodologies to enforce fairness involve preprocessing data, in-processing adjustments, and post-processing prediction	×	0.05

References

- `http://arxiv.org/abs/2306.09265v1`

- http://arxiv.org/abs/2404.09454v2
- http://arxiv.org/abs/2503.11120v2