

CTEST-METRIC: A UNIFIED FRAMEWORK TO ASSESS CLINICAL VALIDITY OF METRICS FOR CT REPORT GENERATION

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In the generative AI era, where even critical medical tasks are increasingly automated, radiology report generation (RRG) continues to rely on suboptimal metrics for quality assessment. Developing domain-specific metrics has therefore been an active area of research, yet it remains challenging due to the lack of a unified, well-defined framework to assess their robustness and applicability in clinical contexts. To address this, we present ***CTest-Metric***, a first unified metric assessment framework with three modules determining the clinical feasibility of metrics for CT RRG. The modules test: (i) Writing Style Generalizability (WSG) via LLM-based rephrasing; (ii) Synthetic Error Injection (SEI) at graded severities; and (iii) Metrics-vs-Expert correlation (MvE) using clinician ratings on 175 “disagreement” cases. Eight widely used metrics (BLEU, ROUGE, METEOR, BERTScore-F1, F1-RadGraph, RaTEScore, GREEN Score, CRG) are studied across seven LLMs built on a CT-CLIP encoder. Using our novel framework, we found that lexical NLG metrics are highly sensitive to stylistic variations; GREEN Score aligns best with expert judgments (Spearman 0.70), while CRG shows negative correlation; and BERTScore-F1 is least sensitive to factual error injection. We will release the framework, code, and allowable portion of the anonymized evaluation data (rephrased/error-injected CT reports), to facilitate reproducible benchmarking and future metric development.

1. INTRODUCTION

With recent breakthroughs in Large Language Models (LLMs) for automated radiology report generation (RRG) [1, 2], a crucial question arises: *Do existing metrics capture what actually matters to trace the clinical efficacy and acceptability of LLM-generated reports?* A clinically grounded metric must be insensitive to report writing styles and sensitive to subtle yet critical factual mismatches. It should also identify synonymous medical terminologies, and be robust enough to capture overfitting in AI-based generative models before deploying them for clinical use.

Despite the availability of a large number of metrics, most are developed for general-domain text [3, 4, 5], and even a few domain-specific metrics overlook deeper clinical relevance or ignore synonymous terminologies. Therefore, the existing RRG methods [2, 6] continue to rely on metrics that are not reflective of clinical fidelity. Consequently, the designing of radiology-specific metrics has been an active area of research with the aim of evaluating both clinical aspects and linguistic similarity between generated radiology reports and the ground truth. However, due to the absence of any standardized tool and well-defined criteria to test these metrics, RRG tasks still rely on inconsistent metrics, resulting in misleading model selections. This underscores the need for a system that can serve as a well-defined framework for metrics developers to assess the clinical applicability of the metrics.

Few prior studies [7, 8] have addressed this problem; however, their focus has predominantly been on the X-ray RRG. Since X-ray images are 2D scans, the corresponding reports are limited to a specific anatomical context and span shorter sentences. In contrast, 3D CT scans capture volumetric multi-slice information, resulting in semantically denser narratives and a broader vocabulary that includes richer anatomical detail, diverse medical terminology, lesion descriptions, and measurements. Most existing clinical-efficacy (CE) metrics were originally tailored to X-ray-based vocabulary and thus struggle to capture complex and diverse terminologies present in CT reports. Despite this limitation, CT-based studies still use these metrics for reporting results and model comparison. Therefore, CT RRG requires special attention in terms of both designing appropriate metrics and developing a tool to assess their applicability and feasibility.

In this paper, we develop ***CTest-Metric***, a framework for evaluating the extent to which a given metric satisfies the criteria for being clinically grounded. This assessment is conducted on eight benchmarking metrics that have been extensively used in recent CT report generation studies, ensuring consistency with established evaluation practices. The proposed framework includes three analytical modules: a) ***Writing Style Generalizability Test (WSG)*** examines the metrics’ generalizability across different writing styles, b) ***Synthetic Error Injection Test (SEI)*** introduces factual errors in the reports at three different levels and investigates their impact on the metrics’ outcomes, and c) ***Metrics-vs-Expert Correlation Test (MvE)*** obtains expert ratings for reports exhibiting disagreement among the metrics. Further, a correlation is established between the eight metrics and expert ratings for a

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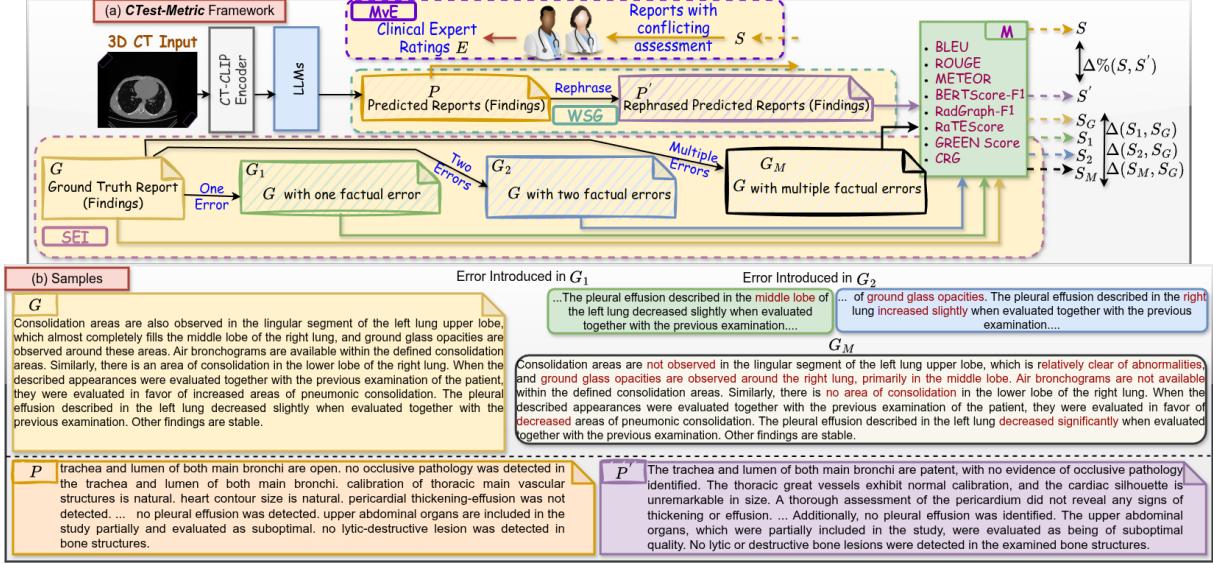


Fig. 1: (a) The proposed framework, *CTest-Metric*, comprises three modules: (i) Writing Style Generalizability Test (WSG); (ii) Synthetic Error Injection Test (SEI); and (iii) Metrics-vs-Expert Correlation Test (MvE). (b) Sample reports are given.

comprehensive study. By leveraging reports generated using seven different LLMs in conjunction with expert assessment, the proposed framework presents a robust pathway that metrics developers can utilize when designing new metrics. The paper’s contributions are summarized below:

- **First framework to assess metrics for CT RRG:** We developed *CTest-Metric*, a novel unified framework to assess metrics for CT RRG. It investigates eight benchmarking metrics on CT reports generated by seven different LLMs and analyzes the behavior of both NLG (text-based) and CE metrics for CT report evaluation.
- **Expert assessment:** Our study selected 175 cases across predictions from seven LLMs where the metrics showed conflicting assessments. These specific reports were then reviewed by clinical experts, and correlations were derived between expert ratings and the metrics’ scores.
- **Analyzed the impact of stylistic variations and graded synthetic errors:** We introduced stylistic variations and factual errors at three severity levels in the CT reports. We quantified the effect of these changes on metric sensitivity.

2. RELATED WORK

The RRG literature reveals that various NLG and CE metrics are commonly used to assess predicted CT reports. The earlier studies primarily relied on NLG metrics, including BLEU [3], ROUGE [4], METEOR [5], and BERTScore-F1 [9]. These metrics quantify textual similarity, for example, BLEU measures n-gram overlap, ROUGE emphasizes sequence-level recall, and METEOR incorporates synonym matches between the generated and the ground truth report. Similarly, BERTScore-F1 computes similarity using context-

tual embeddings. To validate the clinical context, CE metrics including F1-RadGraph [10] and CheXpert [11] were introduced. While the former extracts entities and relations from the given reports and measures graph-level scores, the latter adopts a rule-based labeler for 14 chest X-ray findings. More recently, RaTEScore [12], GREEN Score [13], and CRG [14] were introduced. The RaTEScore compares reports on the entity embedding level and the GREEN score uses regular expressions to parse error counts from their pre-trained model output. Unlike other score, the CRG balances penalties based on label distribution in the reports and ignores clinically irrelevant true negatives.

For the X-ray RRG tasks, prior works [15, 16] followed a similar trend, relying on the same set of standard metrics including the four BLEU n-gram levels, METEOR, ROUGE, and CheXpert. A largely identical evaluation strategy is also observed in CT RRG, where most studies [1, 2] adopt a similar set of NLG and CE metrics, despite the latter being X-ray-oriented and thus, do not fully capture the semantic and anatomical complexity of CT reporting. Although the literature lacks any unified framework for evaluating CT RRG metrics, some X-ray-focused works such as Yu et al.[8] and Banerjee et al. [7] highlighted that even advanced metrics can be inconsistent and poorly correlated with expert ratings.

3. METHODOLOGY

Overview. Given a 3D CT scan $i \in I$ with corresponding ground truth report $r \in R$, we employed seven report generation models to generate CT report $p_i^j \in P$, where $j = 1, 2, \dots, 7$. The seven deep learning models adopt a CT-CLIP [17] image encoder to extract image features combined

with seven different LLMs, including variants of GPT (Distilgpt, GPT2, GPT2-Medium, LLaMA-3.2-1B) and LLaMA (LLaMA-3.2-1B, LLaMA-2-7b-chat-hf), with a biomedical-domain LLM (BioGPT-Large). These variants are paired with two configurations: LLM fine-tuning¹ and a frozen-LLM setup (R2GenGPT’s shallow alignment [15]).

The predictions obtained from each model are assessed using a set of eight metrics M , where $M = \{\text{BLEU}, \text{ROUGE}, \text{METEOR}, \text{BERTScore-F1}, \text{F1-RadGraph}, \text{RaTEScore}, \text{GREEN Score}, \text{CRG}\}$. The first four metrics are NLG-based whereas the last four are designed for clinical-efficacy check. The proposed *CTest-Metric* framework is illustrated in Fig. 1, comprising three analytical modules, as detailed below.

3.1. Writing Style Generalizability Test (WSG)

In the WSG module, metrics are tested for sensitivity to report writing style. It evaluates whether they exhibit significant performance shifts in response to variations in stylistic modifications despite unchanged clinical semantics. This test employs an LLM-based approach using zero-shot instruction-based prompting on LLaMA-3.1-8B-Instruct. This approach rephrases the predicted reports P generated by the seven models into P' , while preserving clinical outcomes and semantics. Each metric is applied on P and P' , and the final difference is analyzed. A lower difference indicates metrics’ robustness towards stylistic variations.

3.2. Synthetic Error Injection Test (SEI)

The SEI module monitors how the metrics penalizes factual errors of varying severity. We study three levels of errors intentionally injected using the same prompting technique used in Sec 3.1. It involved introducing one, two and multiple synthetic errors in ground truth reports, followed by evaluation at each level using the eight metrics from M . Specifically, it examines the deviation of scores ($\Delta(S_j, S_G) = S_j - S_G$) between the ideal case S_G (where the ground truth is evaluated against itself) and report scores S_j with intentionally injected errors at level j . A substantial difference in metrics’ scores for varying levels of discrepancy shows its strong discriminative ability to capture factual inconsistencies.

3.3. Metrics-vs-Expert Correlation Test (MvE)

In this module, we systematically quantified the correlation between metrics in M and expert ratings E . We also examined inter-metric correlations to understand how they agree or disagree in report quality evaluation. We computed this correlation on 175 patient reports for which automated metrics provided conflicting assessments. To this end, we initially derived per-patient scores for all eight metrics corresponding to each LLM. After normalizing the per-patient scores,

we calculated the standard deviation across all metrics to assess disagreement. The top 25 cases with the highest standard deviation (i.e., highest variable) were selected. These 175 cases were finally reviewed by clinical experts, yielding expert ratings E . We then quantified the alignment by computing Spearman’s rank correlation coefficient (ρ) between every pair of metrics (for inter-metric correlation) and between each metric in M and the expert ratings E . A higher ρ signifies that the two metrics tend to rank patients in a similar order while a lower ρ shows disagreement in their assessment.

4. EXPERIMENTS AND RESULTS

4.1. Dataset and Training Details

We used a publicly available 3D medical imaging dataset, CT-RATE [17]. It comprises 50,188 non-contrast chest CT volumes, along with their corresponding radiology reports. We used their official training and validation split. All RRG models were trained for 10 epochs on NVIDIA A100 GPU using the hyperparameters specified in the publicly released code.

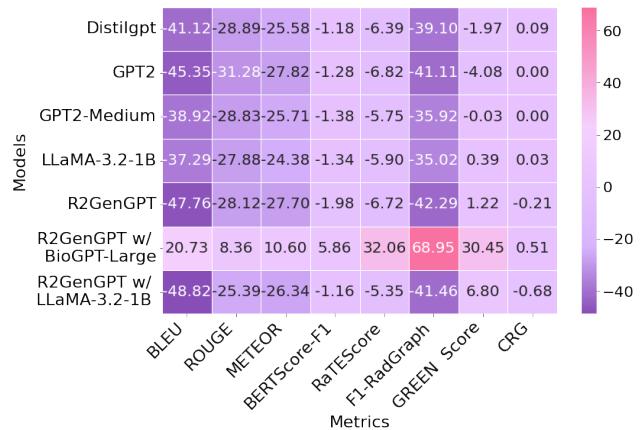
4.2. Analyzing Writing Style Generalizability Test (WSG)

The WSG results are presented in Fig. 2a, where each heatmap cell value represents the percentage difference ($\Delta\%$) between the original score (S) and the score obtained after rephrasing (S') for the corresponding model-metric pair. It can be observed that NLG-based metrics were the most impacted by the stylistic variations (ranging from -48.82% to -1.16%) because they primarily measure lexical overlap rather than underlying clinical semantics. Among CE metrics, F1-RadGraph experienced the most significant deviation (ranging from -42.29% to 68.95%) indicating its high sensitivity to rephrasing. The best two performing metrics include the CRG and the GREEN Score. Since all CE metrics except CRG were introduced focusing on X-Ray datasets, their scores are likely to shift substantially on a vast terminology set of CT reports, especially when rephrased. Although built on X-Ray corpora, the GREEN score was originally tested on out-of-domain modalities, including CT scans, making it relatively robust. Consequently, it performs comparably to CRG, which was developed for CT reports. CRG considers the presence/absence of multi-label clinical entities instead of sentence-level structure, making it less susceptible to performance shift under rephrasing.

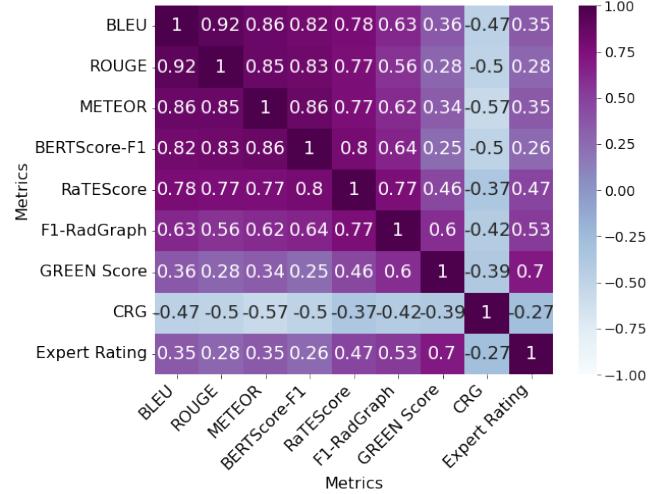
4.3. Analyzing Synthetic Error Injection Test (SEI)

The SEI results in Fig. 3 signify that the metric least impacted by synthetic errors is the BERTScore-F1 with $\Delta(S_M, S_G) = -0.02$ (approximately -2%), whereas the most affected metrics include the GREEN Score ($\Delta(S_1, S_G) = -0.0812$, $\Delta(S_2, S_G) = -0.1277$, $\Delta(S_M, S_G) = -0.6053$) and the F1-RadGraph ($\Delta(S_1, S_G) = -0.0891$, $\Delta(S_2, S_G) = -0.1647$, $\Delta(S_M, S_G) =$

¹<https://github.com/fkodom/clip-text-decoder>



(a) Rephrasing robustness (WSG).



(b) Inter-metric and expert correlation.

Fig. 2: Evaluation of metric reliability and robustness across rephrasing, factual error severity, and metric-expert correlations.

-0.3970). It can be observed that all metrics exhibit similar behavior when the report has minimal difference from the ideal case but the performance significantly diverges when multiple errors are injected. Therefore, it is crucial to examine various error levels to identify metrics' sensitivity to critical factual errors.

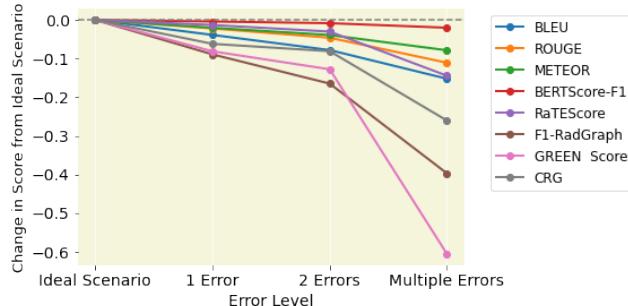


Fig. 3: Metric response across increasing error levels.

4.4. Analyzing Metrics-vs-Expert Correlation Test (MvE)

As discussed in Sec. 3.3, we considered 175 conflicting cases for this test. As shown in Fig. 2b, the GREEN Score closely resembles the Expert Rating E with $\rho = 0.7$ followed by F1-RadGraph with $\rho = 0.53$. The NLG-based metrics demonstrated a similar correlation trend with E , reporting ρ in a narrow range of 0.26 to 0.35. The worst performance was observed using the CRG, which presented a negative correlation with E and other metrics. A high correlation range among NLP-based metrics indicates strong agreement in their assessment. While F1-RadGraph exhibits consistent alignment to

other metrics, it shows a slight bias to NLG-based metric outcomes rather than the GREEN Score and Expert Rating.

5. DISCUSSION AND CONCLUDING REMARKS

This study introduces *CTest-Metric*, a modular framework to evaluate automated metrics used in CT RRG, assessing their ability to capture clinical context in reports. By considering style robustness (WSG), factual-error sensitivity (SEI), and alignment with expert judgment (MvE), the work demonstrates that widely used NLG metrics are brittle to rephrasing and incompletely capture factual correctness, whereas CE metrics vary substantially in their agreement with experts. In particular, GREEN Score exhibits the highest association with expert ratings on a curated set of “disagreement” cases, while CRG remains robust to stylistic changes but correlates negatively with expert scores. This can be attributed to its reliance on label-level information which makes it largely insensitive to rephrasing, yet it remains less aligned with expert evaluations. These findings have immediate implications for metric choice in CT RRG and for how future metrics should be stress-tested before deployment.

Expert validation involved two reviewers, with a second opinion sought for ambiguous cases, which limits the diversity of assessment. WSG and SEI depend on an LLM-based prompting, which primarily introduced laterality and negation errors, though the fidelity of these edits was not independently validated. Finally, all experiments are conducted on CT-RATE (one of the largest in the literature); broader generalization to other institutions, contrast phases, or body regions remains to be established. These constraints highlight opportunities for expanded validation and reporting in subsequent versions.

6. COMPLIANCE WITH ETHICAL STANDARDS

This research study was conducted retrospectively using human subject data made available in open access by (CT-Rate). Ethical approval was not required as confirmed by the license attached to the open-access data.

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