

Evaluating Progress in Automatic Chest X-Ray Radiology Report Generation

Authors: Feiyang Yu^{1*}, Mark Endo^{1*}, Rayan Krishnan^{1*}, Ian Pan MD², Andy Tsai MD PhD³, Eduardo Pontes Reis MD⁴, Eduardo Kaiser Ururahy Nunes Fonseca MD⁴, Henrique Min Ho Lee MD⁴, Zahra Shakeri Hossein Abad PhD⁵, Andrew Y. Ng PhD¹, Curtis P. Langlotz MD PhD⁶, Vasantha Kumar Venugopal MD⁷, & Pranav Rajpurkar PhD⁵

Author affiliations:

1. Department of Computer Science, Stanford University, Stanford, United States
2. Department of Radiology, Brigham and Women's Hospital, Boston, Massachusetts
3. Department of Radiology, Boston Children's Hospital, Harvard Medical School, Boston, United States
4. Hospital Israelita Albert Einstein, São Paulo, Brazil
5. Institute of Health Policy, Management and Evaluation, University of Toronto, Toronto, Canada
6. AIMI Center, Stanford University, Stanford, United States
7. CARPL.ai, New Delhi, India
8. Department of Biomedical Informatics, Harvard Medical School, Boston, United States

* These authors contributed equally: Feiyang Yu, Mark Endo, Rayan Krishnan
Corresponding author: Pranav Rajpurkar, PhD (pranav_rajpurkar@hms.harvard.edu)

Abstract

The application of AI to medical image interpretation tasks has largely been limited to the identification of a handful of individual pathologies. In contrast, the generation of complete narrative radiology reports more closely matches how radiologists communicate diagnostic information in clinical workflows. Recent progress in artificial intelligence (AI) on vision-language tasks has enabled the possibility of generating high-quality radiology reports from medical images. Automated metrics to evaluate the quality of generated reports attempt to capture overlap in the language or clinical entities between a machine-generated report and a radiologist-generated report. In this study, we quantitatively examine the correlation between automated metrics and the scoring of reports by radiologists. We analyze failure modes of the metrics, namely the types of information the metrics do not capture, to understand when to choose particular metrics and how to interpret metric scores. We propose a composite metric, called RadCliQ, that we find is able to rank the quality of reports similarly to radiologists and better than existing metrics. Lastly, we measure the performance of state-of-the-art report generation approaches using the investigated metrics. We expect that our work can guide both the evaluation and the development of report generation systems that can generate reports from medical images approaching the level of radiologists.

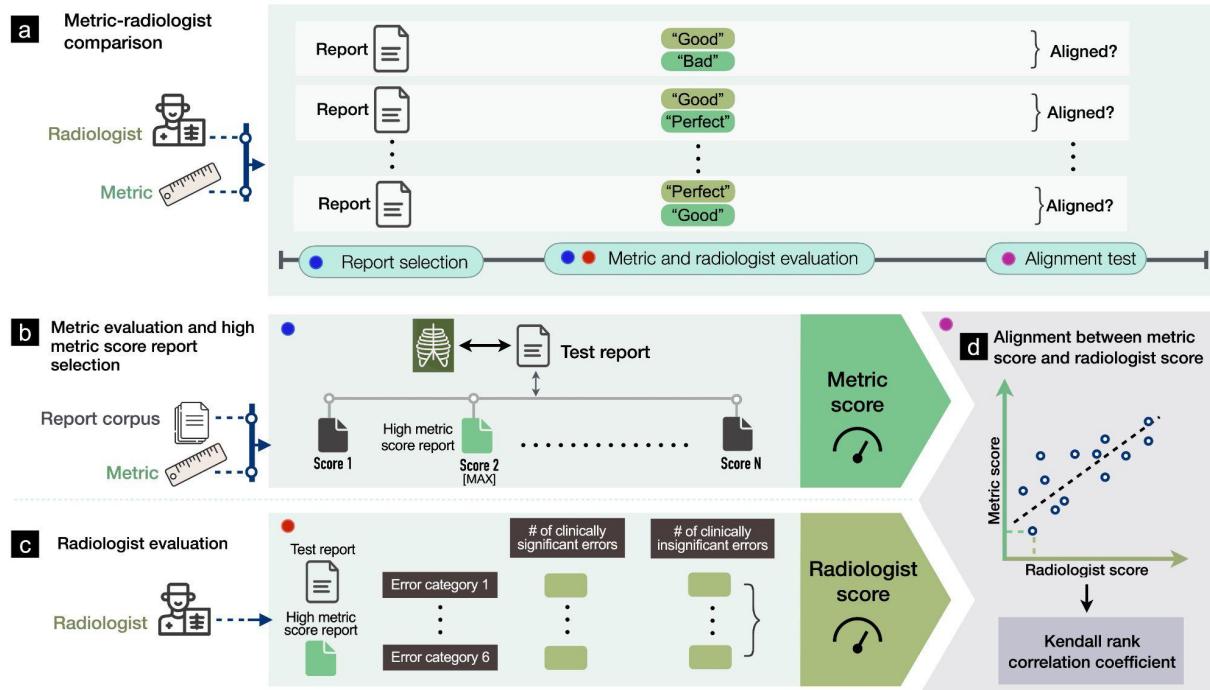
39 Introduction

40 Artificial Intelligence (AI) has been making great strides in tasks that require expert knowledge,
41 such as playing Go^{1–4}, writing code^{5,6}, and driving vehicles^{7,8}. In the medical domain, AI has
42 reached similar exciting milestones⁹, including the effective prediction of 3D protein
43 structures^{10,11}. Enabled by the rapidly evolving imaging and computer vision technologies, AI
44 also has made formidable progress on image interpretation tasks, including chest X-ray
45 interpretation. However, the application of AI to image interpretation tasks has often been
46 limited to the identification of a handful of individual pathologies^{12–14}, representing an over-
47 simplification of the image interpretation task. In contrast, the generation of complete narrative
48 radiology reports^{15–20} moves past that simplification and matches up to how radiologists
49 communicate diagnostic information: the narrative report allows for highly diverse and nuanced
50 findings, including association of findings with anatomic location, and expressions of
51 uncertainty. Although the generation of radiology reports in their full complexity would signify a
52 tremendous achievement for AI, the task remains far from solved. Our work aims to tackle one
53 of the most important bottlenecks for progress: *the limited ability to meaningfully measure*
54 *progress on the report generation task.*

55 Automatically measuring the quality of generated radiology reports is challenging. Most prior
56 works have relied on a set of automated metrics inspired by similar setups in natural language
57 generation, where radiology report text is treated as generic text²¹. However, unlike generic text,
58 radiology reports involve complex, domain-specific knowledge and critically depend on factual
59 correctness. Even metrics that were designed to evaluate the correctness of radiology
60 information by capturing domain-specific concepts do not align with radiologists²². Therefore,
61 improvement on existing metrics may not produce clinically meaningful progress or indicate the
62 direction for further progress. This fundamental bottleneck hinders understanding of the quality
63 of report generation methods thereby impeding work toward improvement of existing methods.
64 We seek to remove this bottleneck by developing meaningful measures of progress in radiology
65 report generation. The answer to this question is imperative to understanding which metrics can
66 guide us towards generating reports that are clinically indistinguishable from those generated by
67 radiologists.

68 In this study, we quantitatively examine the correlation between automated metrics and the
69 scoring of reports by radiologists. We propose a new automatic metric which computes the
70 overlap in clinical entities and relations between a machine-generated report and a radiologist-
71 generated report, called RadGraph²³ F1. We develop a methodology to predict a radiologist-
72 determined error score from a combination of automated metrics, called RadCliQ. We analyze
73 failure modes of the metrics, namely the types of information the metrics do not capture, to
74 understand when to choose particular metrics and how to interpret metric scores. Lastly, we
75 measure the performance of state-of-the-art report generation models using the investigated
76 metrics. The result is a quantitative understanding of radiology report generation metrics and
77 clear guidance for metric selection to guide future research on automated chest X-ray
78 interpretation. This work is also broadly applicable to medical imaging interpretation and
79 narrative report generation in other domains.

80 Results



81

82 **Fig. 1:** **a**, Experimental design for selecting radiology reports and comparing metrics and radiologists in evaluating
83 reports. **b**, Given a test report, selecting the report with the highest metric score from the training report corpus with
84 respect to the test report and a particular metric. **c**, Conducting radiologist evaluation on the high metric score report
85 relative to the test report, where radiologists identify the number of clinically significant and insignificant errors in the
86 high metric score report across six error categories. **d**, Determining the alignment between metric scores and
87 radiologist scores assigned to the same reports using the Kendall rank correlation coefficient.

88

89 **Quantitative investigation of alignment between automated metrics and radiologists.** We
90 study whether there is high alignment between automated metric and radiologist scores
91 assigned to radiology reports. Given a test report from the MIMIC-CXR^{24–26} test set, we select a
92 series of candidate reports from the MIMIC-CXR train set that score highly according to various
93 metrics. We choose this set of reasonably accurate reports so we can study their quality with
94 more precision. Next, we have radiologists score how well the candidates match the test report.
95 We can then analyze the alignment between radiologist and metric scores and determine how
96 correlated different metrics are with radiologists. We select a candidate report by finding the test
97 report's *metric-oracle*: the highest-scoring report from the MIMIC-CXR training set with respect
98 to a particular metric. Since the metric-oracle reports are the best possible retrievals according
99 to a metric, they represent the theoretical best performance achievable by methods that retrieve
100 reports from the training corpus to describe input X-ray images. Although the metric-oracle
101 approach is not a viable clinical method for reporting, it is useful as part of a framework to study
102 report metrics.

103 **Metric-oracle reports.** We constructed metric-oracle reports for four metrics. These include
104 BLEU²⁷, BERTScore²⁸, CheXbert vector similarity (s_emb)¹³ and a novel metric RadGraph²³ F1.

105 BLUE and BERTScore are general natural language metrics for measuring the similarity
106 between machine-generated and human-generated texts. BLEU computes n-gram overlap and
107 is representative for the family of text overlap based natural language generation metrics such
108 as CIDEr²⁹, METEOR³⁰ and ROUGE³¹. BERTScore has been proposed for capturing contextual
109 similarity beyond exact textual matches. CheXbert vector similarity and RadGraph F1 are
110 metrics designed to measure the correctness of clinical information. CheXbert vector similarity
111 computes the cosine similarity between the indicator vectors of 14 pathologies that the
112 CheXbert automatic labeler extracts from machine-generated and human-generated radiology
113 reports. It is designed to evaluate radiology specific information but its evaluation is limited to 14
114 pathologies. To address this limitation, we propose the use of the knowledge graph of the report
115 to represent arbitrarily diverse radiology specific information. We design a novel metric,
116 RadGraph F1, that computes the overlap in clinical entities and relations that RadGraph extracts
117 from machine- and human-generated reports. The four metrics are detailed in the Methods
118 section.

119 For every test report, we generated the matching metric-oracle report by selecting the highest
120 scoring report, according to each of the four investigated metrics, from the training set. We
121 specifically used the impression section of the report. As an example of our setup, for the test
122 report of “*No acute cardiopulmonary process. Bilateral low lung volumes with crowding of*
123 *bronchovascular markings and bibasilar atelectasis,*” the metric-oracle retrieved with respect to
124 BERTScore was: “*No acute cardiopulmonary process. Low lung volumes and bibasilar*
125 *atelectasis,*” while the metric-oracle retrieved with respect to RadGraph F1 was: “*No acute*
126 *cardiopulmonary process. Bilateral low lung volumes,*” as shown in Fig. 2(a).

127 **Radiologist evaluation study design.** In our experimental study design, six board certified
128 radiologists scored the number of errors that various metric-oracle reports make compared to
129 the test report. Radiologists categorized errors as significant or insignificant. Radiologists
130 subtyped every error into the following six categories: 1) false prediction of finding (i.e., false
131 positive) 2) omission of finding (i.e., false negative) 3) incorrect location/position of finding 4)
132 incorrect severity of finding 5) mention of comparison that is not present in the reference
133 impression, and 6) omission of comparison describing a change from a previous study. We
134 sampled 50 studies randomly from the MIMIC-CXR test set. The ordering of metrics that the
135 metric-oracle reports correspond to was shuffled for every study. The error types and error
136 categories are summarized in Fig. 2(b). The instructions and interface presented to radiologists
137 can be seen in Supplementary Fig. 1.

a

Example study (test report and metric-oracle reports)



Reference Impression

- Bilateral low lung volumes with crowding of bronchovascular markings, but no acute cardiopulmonary process.
- No acute cardiopulmonary process. Low lung volumes and bibasilar atelectasis.
- Improved aeration of the lungs, with unchanged bibasilar atelectasis.
- No acute cardiopulmonary process. Bilateral low lung volumes.

No acute cardiopulmonary process. Bilateral low lung volumes with crowding of bronchovascular markings and bibasilar atelectasis.

- Candidate 1— BLEU
- Candidate 2— BERTScore
- Candidate 3— CheXbert
- Candidate 4— RadGraph



Metric-oracle Reports

b

Error types and error categories

Error Type



Clinically significant error 01

Clinically insignificant error 02



Error Category

- 01 False prediction of finding
- 02 Omission of finding
- 03 Incorrect location/position of finding
- 04 Incorrect severity of finding
- 05 Mention of comparison that is not present in the reference impression
- 06 Omission of comparison describing a change from a previous study

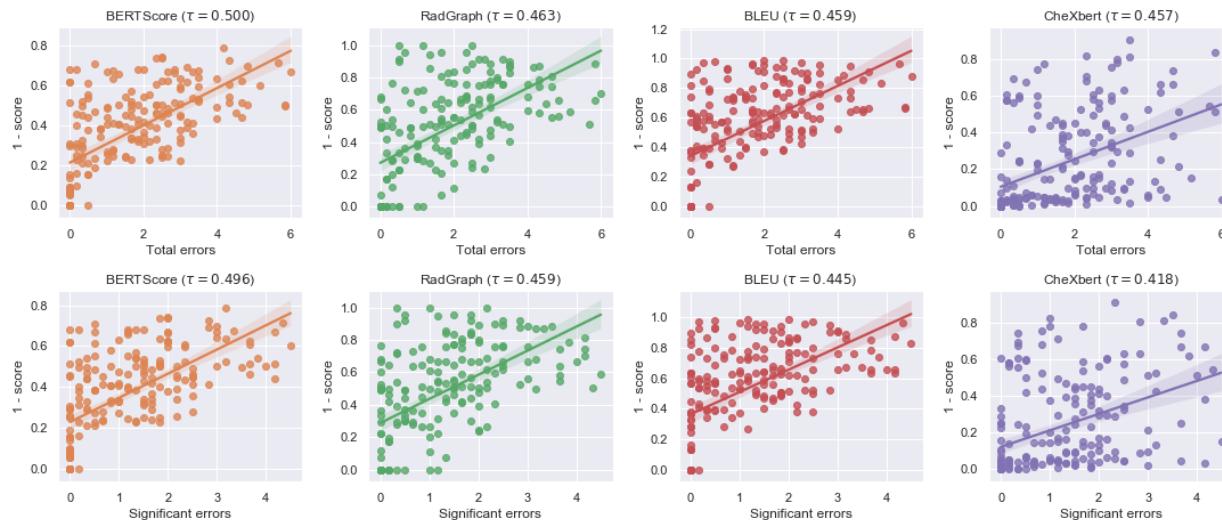
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139 **Fig. 2: a**, Example study of a test report and four metric-oracle reports corresponding to BLEU, BERTScore,
140 CheXbert vector similarity and RadGraph F1 that radiologists evaluate to identify errors. **b**, Two error types and six
141 error categories that radiologists identify for each pair of test report and metric-oracle report.

142

143 **Alignment between automated metrics and radiologists:** We first quantify metric-radiologist
144 alignment using the Kendall rank correlation coefficient (τ - b) between metric scores and
145 number of radiologist-reported errors in the reports. We determine the metric-radiologist
146 alignment from metric-oracle generations from 50 chosen studies on both a total error and
147 significant error level. We find that BERTScore and RadGraph F1 are the metrics with the two
148 highest alignments with radiologists. Specifically, BERTScore has a τ value of 0.500 [95% CI
149 0.497 0.503] for total number of errors and 0.496 [95% CI 0.493 0.498] for significant errors.
150 RadGraph has a τ value of 0.463 [95% CI 0.460 0.465] for total number of errors and 0.459

151 [95% CI 0.456 0.461] for significant errors. We find that BLEU is the third best metric under this
152 evaluation with a 0.459 [95% CI 0.456 0.462] tau value for total number of errors and 0.445
153 [95% CI 0.442 0.448] for significant errors. Lastly, CheXbert vector similarity has the worst
154 alignment with a tau value of 0.457 [95% CI 0.454 0.459] for total errors and 0.418 [95% CI
155 0.416 0.421] for significant errors. From these results, we see that BERTScore, RadGraph, and
156 BLEU are the metrics with closest alignment to radiologists. CheXbert has alignment with
157 radiologists but is less concordant than the previously mentioned metrics. The metric-radiologist
158 alignment graphs are shown in Fig. 3.



159

160 **Fig. 3:** Scatter plots and correlations between metric scores and radiologist scores of four metric-oracle generations
161 from 50 studies, where radiologist scores are represented by the total number of errors (top row) and number of
162 clinically significant errors (bottom row) identified by the radiologists.

163

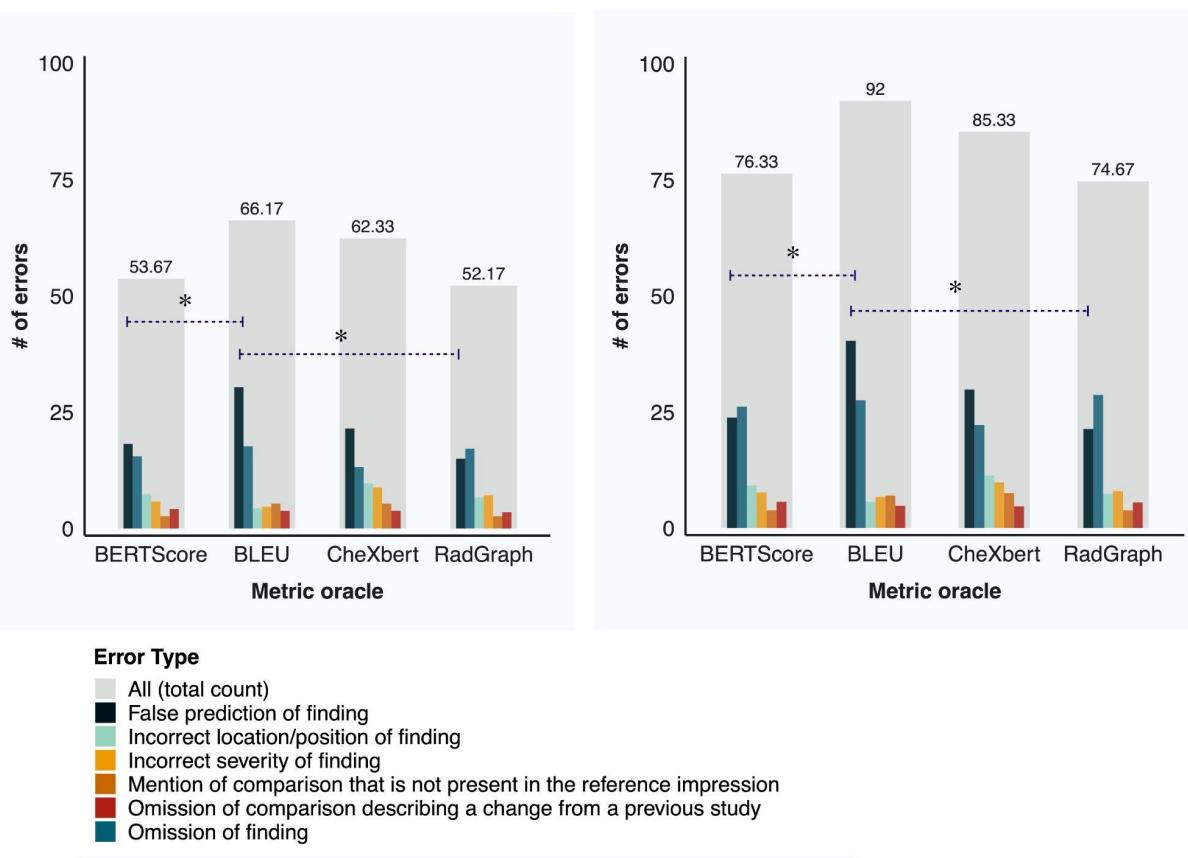
164 **Failure modes of metrics.** In addition to evaluating the clinical relevance of metrics in terms of
165 the total number of clinically significant and insignificant errors, we also examine the particular
166 error categories of metric-oracles to develop a granular understanding of the failure modes of
167 different metrics, as shown in Fig. 4. We use the following six error categories as described
168 earlier:

- 169 1. False prediction of finding
- 170 2. Omission of finding
- 171 3. Incorrect location/position of finding
- 172 4. Incorrect severity of finding
- 173 5. Mention of comparison that is not present in the reference impression
- 174 6. Omission of comparison describing a change from a previous study

175 and analyze the total number of errors and the number of clinically significant errors within each
176 error category.

177 BLEU exhibits a prominent failure mode in identifying false predictions of finding in reports.
178 Metric-oracle reports with respect to BLEU produce more false predictions of finding than
179 BERTScore and RadGraph in terms of both the total number of errors (0.807 average number

180 of errors per report versus 0.477 and 0.427 for BERTScore and RadGraph) and the number of
181 clinically significant errors (0.607 average number of errors per report versus 0.363 and 0.300
182 for BERTScore and RadGraph). BLEU exhibits a less prominent failure mode in identifying
183 incorrect locations/positions of finding compared with CheXbert vector similarity. Metric-oracle
184 reports with respect to BLEU have fewer incorrect locations/positions of finding than CheXbert
185 in terms of both the total number of errors (0.113 average number of errors per report versus
186 0.227 for CheXbert) and the number of clinically significant errors (0.087 average number of
187 errors per report versus 0.193 for CheXbert). These differences are statistically significant after
188 accounting for multiple-hypothesis testing. Metric-oracle reports of the four metrics exhibit
189 similar behavior in the other error categories, as the differences in number of errors are not
190 statistically significant. The raw error counts and the statistics testing results for two-sample t
191 tests and the Benjamini-Hochberg Procedure for accounting for multiple-hypothesis testing are
192 shown in Supplementary Table 2 and Supplementary Table 3.



* indicates significant difference between selected categories

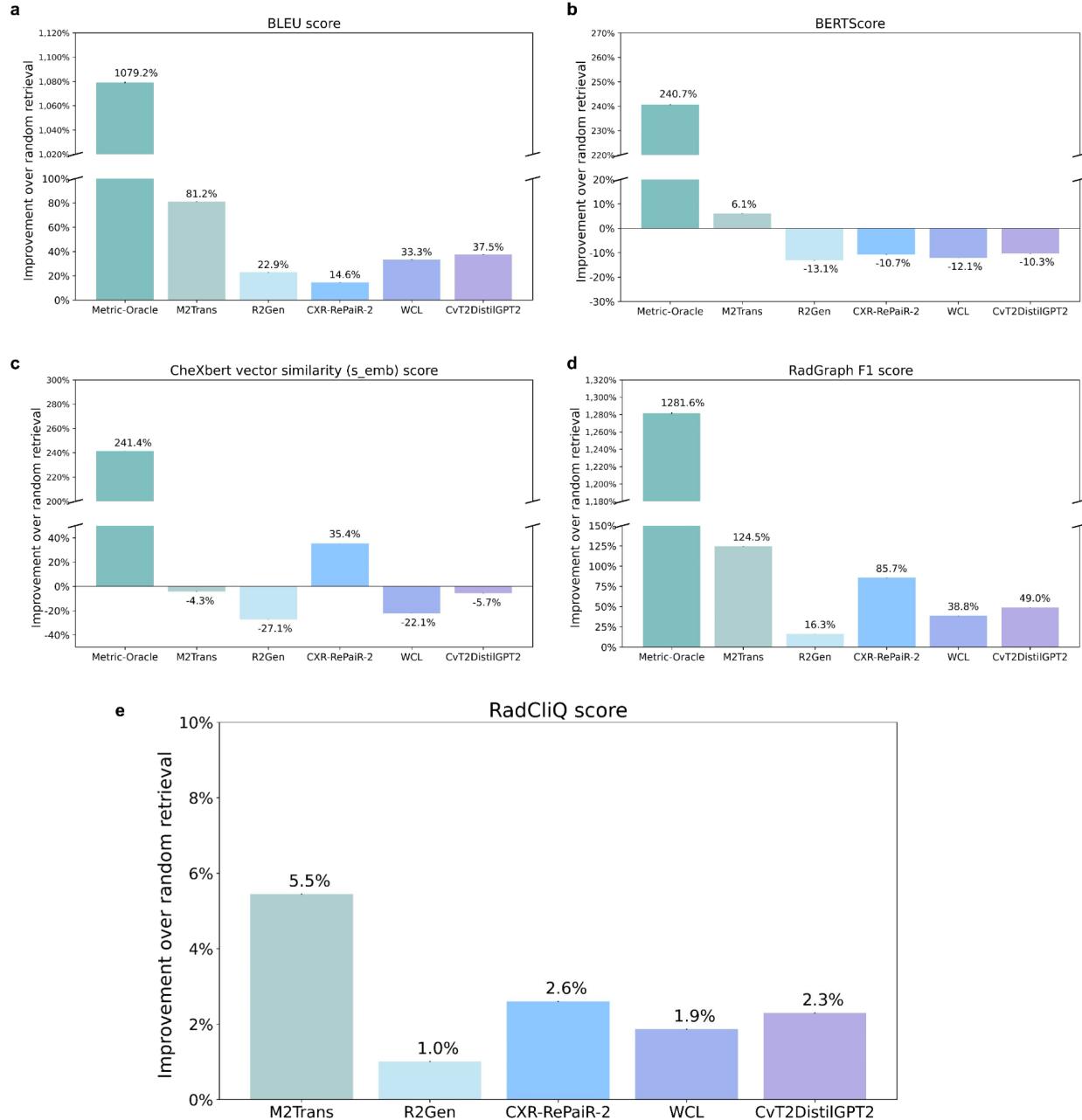
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194 **Fig. 4:** Distribution of errors across six error categories for metric-oracle reports corresponding to BERTScore, BLEU,
195 CheXbert vector similarity and RadGraph F1, in terms of the number of clinically significant errors (left) and the total
196 number of errors (right).

197

198 **Measuring progress of prior methods in report generation.** Using the four individual metrics,
199 we evaluated the following state-of-the-art radiology report generation methods: M² Trans¹⁵,

200 R2Gen¹⁶, CXR-RePaiR¹⁷, WCL¹⁸, and CvT2DistilGPT2¹⁹. As a baseline, we also implemented a
201 random radiology report generation model, which retrieves a random report from the training set
202 for each test report. We measured the performances of metric-oracle selection models and prior
203 models relative to the baseline in terms of percentage change in metric scores, as shown in Fig.
204 5(a)-(d). The performances of prior methods with respect to all metrics are statistically
205 significantly lower than those of metric-oracle methods. With respect to BLEU, the metric-oracle
206 selection model achieves an average score of 0.566 [95% CI 0.566 0.566], while the best prior
207 model, M² Trans, achieves 0.087 [95% CI 0.087 0.087]. With respect to RadGraph F1, the metric-
208 oracle selection model achieves an average score of 0.677 [95% CI 0.677 0.678], while the best
209 prior model, M² Trans, achieves 0.110 [95% CI 0.110 0.111]. We also note that BLEU and
210 RadGraph correctly rank all prior models above the random retrieval baseline, while BERTScore
211 and CheXbert vector similarity do not. This suggests that BLEU and RadGraph work sensibly
212 with generations of real-world report generation models that only have access to input X-ray
213 images, while the other two metrics do not.



214

215 **Fig. 5: a-d**, The percentage change in metric scores of the corresponding metric-oracle model and state-of-the-art
216 report generation models relative to the baseline random model, for BLEU, BERTScore, CheXbert vector similarity
217 and RadGraph F1. A higher value indicates better performance as evaluated by the metric. The raw results can be
218 found in Supplementary Table 4. **e**, The percentage decrease in the predicted total number of errors relative to the
219 baseline random model according to the composite metric RadCliQ. A higher value indicates better performance as
220 evaluated by the metric. The raw results can be found in Supplementary Table 5.

221

222 **Composite metric “RadCliQ” (Radiology Report Clinical Quality).** To improve upon
223 individual metrics, we propose a novel composite metric *RadCliQ* (Radiology Report Clinical
224 Quality). Given that BLEU and RadGraph F1 correctly assigned higher scores to generations of

225 prior state-of-the-art models than randomly retrieved reports, we combined BLEU and
226 RadGraph F1 to build a composite metric. We trained a linear regression model to predict the
227 total number of errors that radiologists would assign to a report. The model input consisted of
228 the two metric scores computed for each report, with the scores corresponding to each metric
229 independently normalized to have a mean of 0 and standard deviation of 1. Prediction of the
230 trained model therefore combines evaluations of BLEU and RadGraph F1. The model was
231 trained on the same set of 200 metric-oracle reports which were evaluated by radiologists,
232 containing 50 metric-oracle reports corresponding to each of the four investigated metrics. The
233 regression produced an R^2 correlation coefficient of 0.423. The coefficients were -0.559 for
234 BLEU and -0.526 for RadGraph F1. The intercept value for the regression model was 1.642,
235 indicating the number of errors for a report with an average score across metrics. For each
236 individual metric, a higher metric score indicates better report generation. Since the linear
237 regression model was trained to predict the total number of errors in a report, the two metrics
238 both had a negative correlation with the predicted number of errors.

239 As an additional statistical test, the composite metric RadCliQ had a Kendall-tau b correlation
240 coefficient of 0.522 [95% CI 0.520 0.525] (p-value < 0.01) for the total number of errors. This
241 indicates a statistically significant correlation between the predicted number of errors and the
242 true number of errors in the generated reports, suggesting that the composite metric aligns with
243 radiologists. Furthermore, RadCliQ has a stronger alignment with radiologists than any
244 individual metric.

245 Using RadCliQ, we measured the performance of prior models relative to the baseline in terms
246 of the percentage decrease in the predicted total number of errors, as shown in Fig. 5(e), where
247 a more positive value translates to better performance. M² Trans yields an 5.5% improvement
248 over the baseline and has the best performance; CXR-RePaiR yields an 2.6% improvement and
249 has the second best performance; CvT2DistilGPT2 yields an 2.3% improvement and has the
250 third best performance. Here, we normalize the individual metric scores using training time
251 statistics before computing RadCliQ.

252 Discussion

253 The purpose of this study was to investigate how to meaningfully measure progress in radiology
254 report generation. We studied popular existing automated metrics and also designed novel
255 metrics, the RadGraph graph overlap metric and the composite metric RadCliQ, for report
256 evaluation. We quantitatively determined the alignment of metrics with clinical radiologists and
257 the reliability of metrics against specific failure modes, clarifying whether metrics meaningfully
258 evaluate radiology reports and therefore can guide future research in report generation. We also
259 showed that selecting the best-match report from a large corpus performs better on most
260 metrics than the current state-of-the-art radiology report generation methods. Although the best-
261 match method is unlikely to be clinically viable, it served as a useful tool to derive the RadCliQ
262 composite metric developed in this study and could serve as a useful benchmark against which
263 to evaluate report generation algorithms developed in the future.

264 The design of automated evaluation metrics that are aligned with manual expert evaluation has
265 been a challenge for research in radiology report generation as well as medical report
266 generation as a whole. Prior works have used metrics designed to improve upon n-gram
267 matching²⁷⁻³¹ or include clinical awareness^{12,13,15,23,17}, such as with BLEU²⁷ and CheXpert
268 labels¹². However, these evaluations nevertheless poorly approximate radiologists' evaluation of
269 reports. The expressivity of prior metrics is often restricted to a curated set of medical
270 conditions. Therefore, the quantitative investigation of metric-radiologist alignment conducted in
271 this study is necessary for understanding whether these metrics meaningfully evaluate reports.
272 Prior works have investigated the alignment between metrics and human judgment^{22,32}.
273 However, to the best of our knowledge, these works pose one of two limitations for radiology
274 report evaluation: (1) they study metric alignment with humans for general image captioning,
275 which does not involve radiology specific terminology, a high prevalence of negation, or expert
276 human evaluators, and (2) they do not create a leveled comparison between metrics and
277 radiologists, where metrics and radiologists assign scores to reports in identical experimental
278 settings, or a granular understanding of metric behavior beyond the overall metric score. Our
279 work builds a fair comparison between general natural language and clinically aware metrics
280 and radiologists by providing them with the same set of information that is the reports and goes
281 beyond metric scores to examine six granular failure modes of each metric. Additionally, our
282 work proposes a novel composite metric, RadCliQ, that aligns more strongly than any individual
283 metric. We also show that current radiology report generation algorithms exhibit relatively low
284 performance by all of these metrics.

285 To study metric-radiologist alignment, we designed *metric-oracles*: the reports selected from a
286 large corpus with the highest metric score with respect to test reports. We had metrics and
287 radiologists assign scores to the metric-oracles based on how well the metric-oracles match
288 their respective test reports, and computed the alignment between metric and radiologist scores
289 on the same reports. Pairing metric-oracles with test reports produces a narrower distribution of
290 scores than using random reports. However, metric oracles are necessary for obtaining reliable
291 scores from the radiologist experiment because comparisons will be sensitive to small
292 differences in report quality. If a random report, rather than a high-scoring report, was paired
293 with the test report, the two reports could diverge to the extent that they were difficult to

294 compare directly. In contrast, metric oracles are comparable with test reports and therefore
295 allow a meaningful evaluation of errors.

296 To generate metric-oracles, any report generation model is theoretically feasible. There are
297 three main categories: the first generates free text based on semantics extracted from input
298 chest X-ray images^{20,33,34}, the second retrieves existing text that best matches input images
299 from a report corpus^{17,35}, and the third selects curated templates corresponding to a predefined
300 set of abnormalities^{14,36}. We chose to use retrieval-based models to generate metric-oracles
301 because retrieval from a training report corpus produces a controlled output space, instead of
302 an unpredictable one produced by models that generate free text. Retrieval-based models also
303 improve upon templating-based models in terms of flexibility and generalizability because the
304 report corpus better captures real-world occurring conditions, combinations of conditions, and
305 uncertainty. Furthermore, retrieval-based metric-oracle models outperformed existing report
306 generation methods by a large margin.

307 By investigating the different categories of errors that radiologists identified in metric-oracle
308 reports, we also uncovered specific metric failure modes which valuably inform the choice of
309 metrics and interpretation of metric scores for evaluating generated reports. We find that BLEU
310 performs worse than BERTScore and RadGraph in evaluating false prediction of finding. Yet,
311 BLEU performs better than CheXbert vector similarity in evaluating incorrect position/location of
312 finding. Therefore, BERTScore and RadGraph, which offer the strongest radiologist-alignment,
313 also have better overall reliability against failure modes.

314 Using the individual metrics and RadCliQ, we also measured the progress of prior state-of-the-
315 art models. We identify M² Trans as the best model with respect to all individual metrics and
316 RadCliQ except CheXbert. We also find a statistically significant performance gap between prior
317 models and metric-oracle models, which represent the theoretical performance ceiling of
318 retrieval-based methods on MIMIC-CXR. This gap suggests that prior models in report
319 generation still have significant room for improvement in creating high-quality reports that are
320 useful to radiologists.

321 In addition, we observed that BLEU and RadGraph correctly rank prior models above random
322 retrieval while BERTScore and CheXbert do not, even though BERTScore has the strongest
323 alignment with radiologists in evaluating metric-oracle reports. This discrepancy may be
324 attributed to two factors. First, there is a shift in report quality from metric-oracles to real
325 generations, and metrics may exhibit different behaviors with reports of lower quality. Second,
326 the real-world models generated reports based on only the X-ray images. The images may
327 contain different semantics than that described in the corresponding test reports. For expressing
328 the same semantics, the models also have numerous ways to formulate a report. These
329 variations can explain BERTScore's suboptimal performance in evaluating prior model
330 generations. Overall, RadGraph is the best individual metric to use for its strong alignment with
331 radiologists, reliability across failure modes and meaningful empirical performance with real
332 generations.

333 This study has several important limitations. A main limitation is the inter-observer variability in
334 radiologist evaluation. Although the evaluation scheme—the separation of clinically significant
335 and insignificant errors, and the six error categories—was designed to be objective and

336 consistent across radiologist evaluation, the same report often received varying scores between
337 radiologists, a common occurrence in experiments that employ subjective ratings from
338 clinicians. This suggests a potential limitation of the evaluation scheme used, but may also
339 present an intrinsic problem with objective evaluation of radiology reports. Another limitation is
340 the coverage of metrics. Although a variety of general and clinical natural language metrics are
341 investigated, there exist other metrics in these two categories that may have different behaviors
342 than the four investigated metrics. For instance, other text overlap based metrics are commonly
343 used in natural language generation beyond BLEU, such as CIDEr²⁹, METEOR³⁰ and ROUGE³¹,
344 which may have better or worse radiologist-alignment and reliability than BLEU in report
345 generation.

346 In this study, we determined that the novel metrics RadGraph F1 and RadCliQ meaningfully
347 measure progress in radiology report generation and hence can guide future report generation
348 models in becoming clinically indistinguishable from radiologists. We have open-sourced the
349 code for computing the individual metrics and RadCliQ on reports in the hope of facilitating
350 future research in radiology report generation.

351 Online Methods

352 **Datasets.** We used the MIMIC-CXR dataset to conduct our study. The MIMIC-CXR dataset^{24–26} is a de-
353 identified and publicly available dataset containing chest X-ray images and semi-structured radiology
354 reports from the Beth Israel Deaconess Medical Center Emergency Department. There are 227,835
355 studies with 177,110 images conducted on 65,379 patients. We used the impression section of the
356 reports. We used the recommended train/validation/test split. We pooled the train and validation splits as
357 the training report corpus from which metric-oracles are retrieved and used the test split as the set of
358 ground-truth reports. The training report corpus contains 185,538 studies and 371,951 images; the test
359 set contains 2,192 studies and 5,159 images. We preprocessed the reports by filtering nan reports and
360 extracting the impression section of reports, which contains key observations and conclusions drawn by
361 radiologists. Throughout the study, we refer to the impression section when discussing reports.

362 **Advantages of metric-oracles:** Using metric-oracles as the candidate reports as opposed to using other
363 strategies such as randomly sampling reports offers two primary advantages: (1) metric-oracles are
364 sufficiently accurate for radiologists to pinpoint specific errors and not be bogged down by candidate
365 reports that aren't remotely similar to the test reports; (2) metric-oracles allow us to analyze where certain
366 metrics fail since the reports are the hypothetical top retrievals.

367 **Radiologist scoring criteria:** In this work, we develop a scoring system for radiologists to evaluate the
368 quality of candidate reports. The goals of our scoring system are to be objective, limit radiologist bias, and
369 change linearly with report quality. To this end, scores are determined by counting the number of errors
370 that candidate reports make where types of errors are broken down into six different categories. By
371 explicitly defining each error category, we clarify what should be classified as an error. Following ACR's
372 RADPEER³⁷ program for peer review, we differentiate between clinically significant and clinically
373 insignificant errors. The detailed scoring criteria allows us to analyze report quality based on the accuracy
374 of its findings and the clinical impact of its mistakes.

375 **Textual based and natural language generation performance metrics.** In this study we make use of
376 two natural language generation metrics: BLEU and BERTScore. The BLEU scores were computed as
377 BLEU-2 bigrams with the fast_bleu library for parallel scoring. BERTScore uses the contextual
378 embeddings from a BERT model to compute similarity of two text sequences. We used the bert_score
379 library directly and used the baseline-scaled, "distilroberta-base" version of the model.

380 **Clinically aware performance metrics.** In addition to traditional natural language generation metrics, we
381 also investigated metrics that were designed to capture clinical information in radiology reports. Since
382 radiology reports are a special form of structured text that communicates diagnostics information, their
383 quality depends highly on the correctness of clinical objects and descriptions, which is not a focus of
384 traditional natural language metrics. To address this gap, the CheXbert labeler (which is improved from
385 the CheXpert labeler)^{12,13} and RadGraph²³, were developed to parse radiology reports. We investigated
386 whether they could be used as clinically aware metrics. We defined a metric as the similarity between
387 CheXbert labeled vectors of the generated report and test report, which contain 14 labels corresponding
388 to 13 common medical conditions and the no-finding observation. We used the implementation here:
389 <https://github.com/stanfordmlgroup/CheXbert>. We proposed a novel metric as the overlap in parsed
390 RadGraph graph structures: the RadGraph entity and relation F1 score. RadGraph is an approach for
391 parsing radiology reports into knowledge graphs containing entities (nodes) and relations (edges), which
392 can capture radiology concept dependencies and semantic meaning. We used the model checkpoint as
393 provided here: <https://physionet.org/content/radgraph/1.0.0/>²⁶ and inference code as provided here:
394 <https://github.com/dwadden/dygiepp>³⁸ to generate RadGraph entities and relations on generated and test
395 reports.

396 **Retrieval-based metric-oracle models.** To generate metric-oracle reports, the most immediate attempt
397 is to adopt methods akin to those for multi-label classification tasks. Namely, we can curate a set of
398 medical conditions and obtain radiologist annotations for each condition over a training set of reports.
399 Then, we can train a classifier that outputs the likelihood of having each condition given an X-ray image,
400 and proceed to select the corresponding report templates for conditions with high likelihood¹⁴. Some more
401 nuanced approaches paraphrase the curated templates after selection³⁶. The attempt at templating for
402 report generation is well-grounded in abundant experience in multi-label image classification as well as its
403 highly controlled output space. However, its flaw is also prominent, in that it is restricted to a manually
404 curated predefined set of medical conditions and report templates. It does not generalize to unseen or
405 complex conditions, express combinations of conditions, or capture uncertainty in diagnoses. The
406 CheXbert labeler, for instance, can classify 13 conditions and the no-finding observation¹³. This set is
407 representative of common medical observations but not comprehensive. Therefore, while we may define
408 a larger set of conditions with the help of radiologists, manual curation and templating are nevertheless
409 too inflexible for optimizing with respect to automated metrics. To generate reports of higher quality, we
410 consider matching reports more closely onto test reports. We can do so by either generating new text
411 from scratch or retrieving free text from an existing corpus of reports written by radiologists, given an X-
412 ray image^{33,35}. Out of the two approaches, retrieval-based methods have the advantage of a controlled
413 output space that is the set of training report corpus, instead of an unpredictable output space produced
414 by generation from scratch. Retrieval-based methods also improve upon templating, because the report
415 corpus may capture the full set of real-world occurring conditions, combinations of conditions and
416 uncertainty, if the training report corpus is representative of future reports to be written. Therefore, in this
417 study, we use retrieval-based methods to generate metric-oracle reports.

418 **Statistical analysis:**

419 *Metric-radiologist alignment.* The alignment of metrics with radiologists' scoring was determined using the
420 Kendall tau-b correlation coefficient. We construct bootstrap confidence intervals by creating 1,000
421 resamples with replacement where each resample size is the number of studies (50). In this calculation,
422 the number of errors is the mean number across all raters. Based on the presence/lack of overlap of the
423 95% bootstrap confidence intervals, we assert whether differences in Kendall tau values are statistically
424 significant.

425 *Metric failure modes.* We conduct one-sided two-sample t tests on pairs of metrics' error counts for total
426 errors and clinically significant errors within each of the six error categories. We assume equal population
427 variances for the t tests. We take the error count of one radiologist and one study as one data point.
428 Because there are six radiologists and 50 studies, we have 300 data points per metric for either total
429 errors or clinically significant errors and for one error category. With 4 metrics, there are 12 unique pairs
430 of two different metrics for one-sided two-sample t tests with $(300 + 300 - 2 = 598)$ degrees of freedom.
431 We use the Benjamini-Hochberg Procedure with a False Discovery Rate (FDR) of 1% to account for
432 multiple-hypothesis testing on 12 tests within an error type and an error category, and determine the
433 significance of a metric having a more/less prominent failure mode compared with other metrics.

434 *Prior models evaluation.* To evaluate performance of metric-oracle models and prior state-of-the-art
435 models, we construct bootstrap confidence intervals by taking 5,000 resamples with replacement of
436 metric scores assigned to generated reports. Based on the presence/lack of overlap of the 95% bootstrap
437 confidence intervals, we assert whether a model's performance is statistically significantly better than
438 another's.

439 *Composite metric RadCliQ.* The linear regression model used to predict the total number of errors was
440 evaluated using the Kendall-tau b statistical test. This test produces a tau-value correlation coefficient and
441 a corresponding p-value which was used to determine the significance of the result ($p\text{-value} < 0.01$).

442 The analyses were performed using statsmodels, scikit-learn and SciPy packages in Python.
443 **RadGraph metric-oracle model entities and relations match.** The RadGraph F1 metric-oracle model
444 retrieves reports with the highest F1 score match in terms of entities and relations. Specifically, we treat
445 two entities as matched, if their tokens (words in the original report) and labels (entity type) match. We
446 treat two relations as matched, if their start and end entities match and the relation type matches. These
447 criteria are consistent with what the RadGraph authors have done. For combining entities and relations,
448 we take the average of F1 score of entity match and relation match respectively. We generated
449 RadGraph entities and relations for each report in the training and test corpora. We implemented the
450 metric-oracle model by finding, for each report in the test set, which report in the training set is the best
451 match based on the average of entity and relation F1 scores. For reports without nonzero F1 score
452 matches, we used the most frequent report in the training set, “*No acute cardiopulmonary process*,” as
453 the metric-oracle report in the radiologist experiment.

454 **Implementation of prior report generation methods.** We used the following implementations of prior
455 methods in radiology report generation: M² Trans: <https://github.com/ysmiura/ifcc>^{15,38}. R2Gen:
456 <https://github.com/cuhksz-nlp/R2Gen>¹⁶. CXR-RePaiR: <https://github.com/rajpurkarlab/CXR-RePaiR>¹⁷.
457 WCL: <https://github.com/zxslp/WCL>¹⁸. CvT2DistilGPT2: <https://github.com/aeirc/cvt2distilgpt2>¹⁹. For
458 each study ID, if the model generated multiple reports corresponding to different X-ray images for the
459 same study, we used the generated report corresponding to the anterior-posterior (AP) or posterior-
460 anterior (PA) view if any was present. If both were present, we randomly chose a report out of the two. If
461 neither was present, we randomly chose a report out of the available reports corresponding to other
462 views. Among variations of CXR-RePaiR, we chose CXR-RePaiR-2 to be consistent with their original
463 study¹⁷.

464

465 Data Availability

466 The data used in the study is available with credentialed access at:
467 <https://physionet.org/content/mimic-cxr-jpg/2.0.0/>. Credentialed access can be obtained via an
468 application to PhysioNet.

469

470 Code Availability

471 The code for computing the composite metric RadCliQ and individual metrics is made publicly
472 available at: <https://drive.google.com/drive/folders/1Fe81n9IMZpc4y99K-7c5aGxPNdijj7NS?usp=sharing>.

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571

572 Author information

573 Affiliations

574 **Department of Computer Science, Stanford University, Stanford, United States**
575 Feiyang Yu, Mark Endo, Rayan Krishnan, Andrew Y. Ng PhD

576
577 **Brigham and Women's Hospital, Boston, Massachusetts**
578 Ian Pan MD

579
580 **Department of Radiology, Harvard Medical School, Boston, United States**
581 Andy Tsai MD PhD

582
583 **Cardiothoracic Radiology Group, Albert Einstein Hospital, São Paulo, Brazil**
584 Eduardo Pontes Reis MD, Eduardo Kaiser Ururahy Nunes Fonseca MD, Henrique Lee MD

585
586 **Institute of Health Policy, Management and Evaluation, University of Toronto, Toronto,**
587 **Canada**
588 Zahra Shakeri Hossein Abad PhD

589
590 **AIMI Center, Stanford University, Stanford, United States**
591 Curtis P. Langlotz MD PhD

592
593 **CARPL.ai**
594 Vasanth Venugopal MD

595
596 **Department of Biomedical Informatics, Harvard Medical School, Boston, United States**
597 Pranav Rajpurkar PhD

598 599 Contributions

600 F.Y., M.E. and R.K. contributed equally to the design, implementation and analyses of all
601 aspects of this study. I.P., A.T., E.P.R., E.K.U.N.F., H.M.H.L. and V.K.V. provided suggestions
602 on the setup of the radiologist evaluation survey and provided annotations in the radiologist

603 evaluation process. Z.S.H.A. contributed to the design of the illustrations and figures. A.Y.N.,
604 C.P.L., V.K.V. and P.R. oversaw and provided guidance on the study. All authors approved the
605 final version.

606 **Corresponding author**

607 Correspondence to Pranav Rajpurkar, PhD (pranav_rajpurkar@hms.harvard.edu).

608

609 **Ethics declarations**

610 **Competing interests**

611 The Authors declare no Competing Non-Financial Interests but the following Competing
612 Financial Interests:

613 I.P. is a consultant for MD.ai and Diagnosticos da America (Dasa).

614 C.P.L. serves on the board of directors and is a shareholder of Bunkerhill Health. He is an
615 advisor and option holder for GalileoCDS, Sirona Medical, Adra, and Kheiron. He is an advisor
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621 Extended data

622 Supplementary information

Stanford

Study Instructions

Goal: Your goal is to judge the diagnostic accuracy of candidate report impressions based on a reference impression section.

Study Setup: We're looking to determine the accuracy of report impressions generated by hypothetical models that have high performance on popular metrics. You will be shown 50 studies with a reference impression section and various candidate report impression sections.

For each candidate, you will be asked how many clinically significant errors and clinically insignificant errors the report makes. An error can be one of the following:

- False prediction of finding
- Omission of finding
- Incorrect location/position of finding
- Incorrect severity of finding
- Mention of comparison that is **not** present in the reference impression
- Omission of comparison describing a change from a previous study

Note: Some candidate reports will often be the same. In these cases, make sure to give the same scores to the candidates.

When you are ready to begin the study, press the next page button below. You can always go back to this page to review the error guidelines.

→

623

624 Supplementary Fig. 1(a).

Stanford

Study #1

Reference impression: Multiple chronic appearing left-sided rib fractures. No pneumothorax. Blunting of the costophrenic angle on the right likely represents pleural scarring and a small effusion, not significantly changed from ____.

Candidate 1: Blunting of the right costophrenic angle may be due to small pleural effusion .

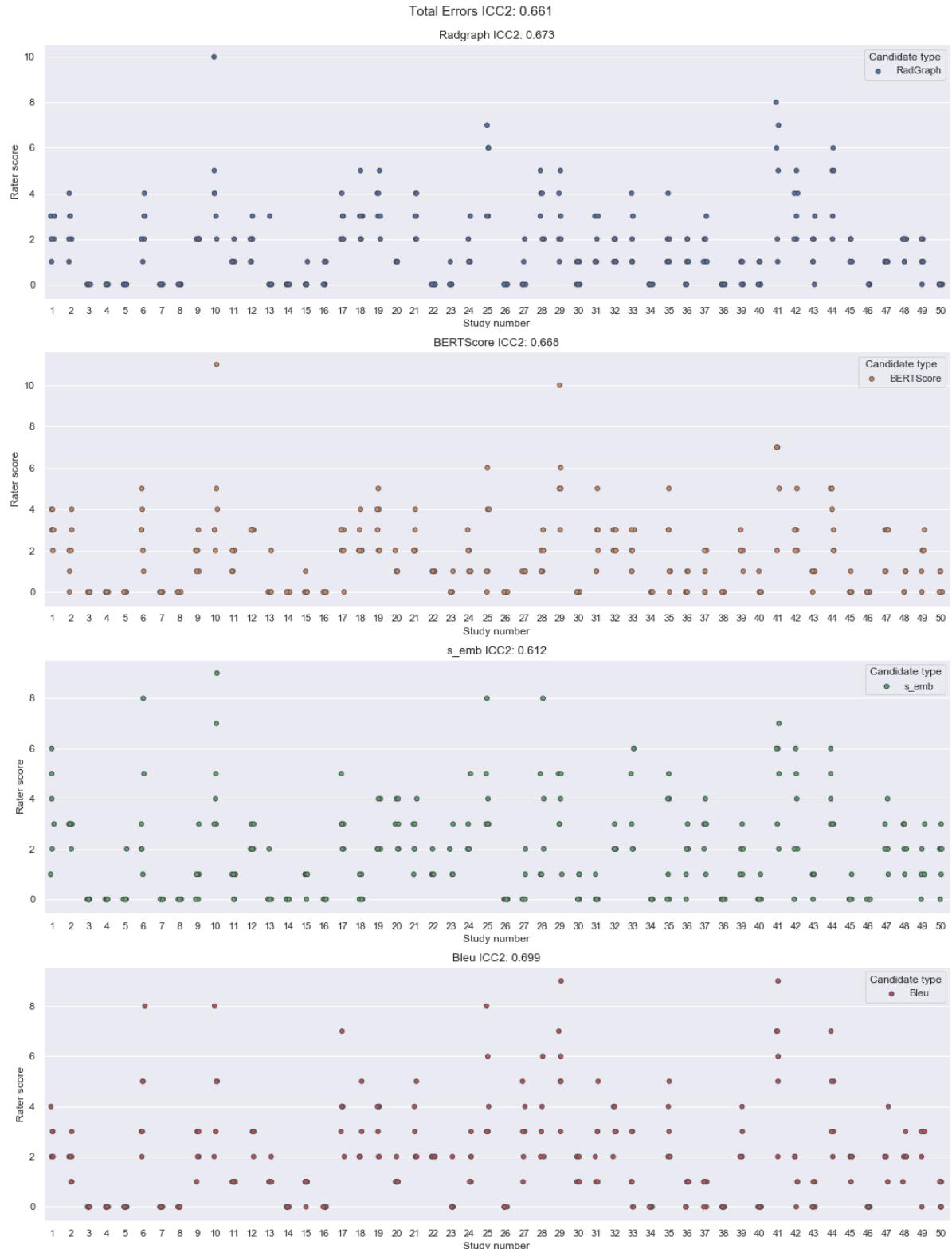
How many of the following errors does this report make:

	Clinically significant	Clinically insignificant
False prediction of finding	<input type="checkbox"/>	<input type="checkbox"/>
Omission of finding	<input type="checkbox"/>	<input type="checkbox"/>
Incorrect location/position of finding	<input type="checkbox"/>	<input type="checkbox"/>
Incorrect severity of finding	<input type="checkbox"/>	<input type="checkbox"/>
Mention of comparison that is not present in the reference impression	<input type="checkbox"/>	<input type="checkbox"/>
Omission of comparison describing a change from a previous study	<input type="checkbox"/>	<input type="checkbox"/>

625

626 Supplementary Fig. 1(b).

627 **Supplementary Fig. 1:** Radiologist survey interface and example question. **a**, Radiologist evaluation survey
628 instructions and interface on Qualtrics. **b**, Interface for evaluating a pair of a test report (denoted as “Reference
629 Impression”) and a metric-oracle report (denoted as “Candidate 1”). The survey asks radiologists to input the number
630 of clinically significant and insignificant errors for six error categories.



631

632

633

634

Supplementary Fig. 2: Dotplot of the radiologist total error scores on the 50 studies and corresponding intraclass correlation. Candidate scores are split up by metric-oracle method. Each dot represents a single radiologist's score for a candidate report.

635

636 **Supplementary Table 1:** Per-radiologist Kendall rank correlation coefficient (tau-b) values quantifying metric-
637 radiologist alignment.

	Radiologist 1	Radiologist 2	Radiologist 3	Radiologist 4	Radiologist 5	Radiologist 6
BERTScore total errors	0.439 [95% CI 0.436 0.442] 0.458 0.464]	0.461 [95% CI 0.458 0.464] 0.480 0.485]	0.482 [95% CI 0.480 0.485] 0.443 0.449]	0.446 [95% CI 0.443 0.449] 0.469 [95% CI 0.466 0.471] 0.476 [95% CI 0.473 0.479]	0.469 [95% CI 0.466 0.471] 0.476 [95% CI 0.473 0.479]	0.476 [95% CI 0.473 0.479]
BERTScore sig. errors	0.370 [95% CI 0.367 0.373] 0.343 0.348]	0.346 [95% CI 0.343 0.348] 0.492 0.497]	0.495 [95% CI 0.492 0.497] 0.468 [95% CI 0.465 0.471] 0.414 [95% CI 0.411 0.417]	0.468 [95% CI 0.465 0.471] 0.414 [95% CI 0.411 0.417] 0.458 [95% CI 0.455 0.460]	0.414 [95% CI 0.411 0.417] 0.458 [95% CI 0.455 0.460]	0.458 [95% CI 0.455 0.460]
RadGraph total errors	0.423 [95% CI 0.420 0.426] 0.441 0.446]	0.443 [95% CI 0.441 0.446] 0.474 0.479]	0.476 [95% CI 0.474 0.479] 0.440 [95% CI 0.438 0.443] 0.462 [95% CI 0.459 0.464] 0.413 [95% CI 0.410 0.415]	0.440 [95% CI 0.438 0.443] 0.462 [95% CI 0.459 0.464] 0.413 [95% CI 0.410 0.415]	0.462 [95% CI 0.459 0.464] 0.413 [95% CI 0.410 0.415]	0.413 [95% CI 0.410 0.415]
RadGraph sig. errors	0.406 [95% CI 0.403 0.408] 0.316 0.322]	0.319 [95% CI 0.316 0.322] 0.477 0.481]	0.479 [95% CI 0.477 0.481] 0.448 [95% CI 0.445 0.450] 0.432 [95% CI 0.429 0.434] 0.375 [95% CI 0.373 0.378]	0.448 [95% CI 0.445 0.450] 0.432 [95% CI 0.429 0.434] 0.375 [95% CI 0.373 0.378] 0.375 [95% CI 0.373 0.378]	0.432 [95% CI 0.429 0.434] 0.375 [95% CI 0.372 0.378] 0.409 [95% CI 0.407 0.412]	0.375 [95% CI 0.373 0.378] 0.409 [95% CI 0.407 0.412]
BLEU total errors	0.409 [95% CI 0.406 0.412] 0.423 0.428]	0.425 [95% CI 0.423 0.428] 0.458 0.464]	0.461 [95% CI 0.458 0.464] 0.402 [95% CI 0.399 0.405] 0.427 [95% CI 0.424 0.430] 0.435 [95% CI 0.432 0.438]	0.402 [95% CI 0.399 0.405] 0.427 [95% CI 0.424 0.430] 0.435 [95% CI 0.432 0.438]	0.427 [95% CI 0.424 0.430] 0.435 [95% CI 0.432 0.438]	0.435 [95% CI 0.432 0.438]
BLEU sig. errors	0.352 [95% CI 0.349 0.355] 0.268 0.273]	0.271 [95% CI 0.268 0.273] 0.444 0.450]	0.447 [95% CI 0.444 0.450] 0.433 [95% CI 0.430 0.436] 0.375 [95% CI 0.372 0.378] 0.409 [95% CI 0.407 0.412]	0.433 [95% CI 0.430 0.436] 0.375 [95% CI 0.372 0.378] 0.409 [95% CI 0.407 0.412]	0.375 [95% CI 0.372 0.378] 0.409 [95% CI 0.407 0.412]	0.409 [95% CI 0.407 0.412]
CheXbert total errors	0.407 [95% CI 0.404 0.410] 0.360 0.366]	0.363 [95% CI 0.360 0.366] 0.457 0.462]	0.459 [95% CI 0.457 0.462] 0.446 [95% CI 0.443 0.448] 0.424 [95% CI 0.421 0.427] 0.430 [95% CI 0.427 0.433]	0.446 [95% CI 0.443 0.448] 0.424 [95% CI 0.421 0.427] 0.430 [95% CI 0.427 0.433]	0.424 [95% CI 0.421 0.427] 0.430 [95% CI 0.427 0.433]	0.430 [95% CI 0.427 0.433]
CheXbert sig. errors	0.367 [95% CI 0.364 0.370] 0.228 0.234]	0.231 [95% CI 0.228 0.234] 0.435 0.440]	0.438 [95% CI 0.435 0.440] 0.376 [95% CI 0.373 0.379] 0.374 [95% CI 0.371 0.377] 0.376 [95% CI 0.373 0.379]	0.376 [95% CI 0.373 0.379] 0.374 [95% CI 0.371 0.377] 0.376 [95% CI 0.373 0.379]	0.374 [95% CI 0.371 0.377] 0.376 [95% CI 0.373 0.379]	0.376 [95% CI 0.373 0.379]

638

639 **Supplementary Table 2(a):** Radiologist evaluation of metric-oracles in terms of total number of errors in six error
640 categories, averaged over 6 radiologists and 50 studies.

	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Total
BLEU	0.807	0.550	0.113	0.133	0.140	0.097	1.840
CheXbert	0.597	0.443	0.227	0.197	0.150	0.093	1.707
BERTScore	0.477	0.523	0.183	0.153	0.077	0.113	1.527
RadGraph	0.427	0.573	0.147	0.160	0.077	0.110	1.493

641

642 **Supplementary Table 2(b):** Radiologist evaluation of metric-oracles in terms of number of clinically significant errors
643 in six error categories, averaged over 6 radiologists and 50 studies.

	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Total
BLEU	0.607	0.353	0.087	0.093	0.107	0.077	1.323
CheXbert	0.430	0.263	0.193	0.176	0.107	0.077	1.247
BERTScore	0.363	0.310	0.147	0.117	0.053	0.083	1.073
RadGraph	0.300	0.343	0.133	0.143	0.053	0.070	1.043

644

645 **Supplementary Table 3(a):** Significance of BLEU having a *more prominent failure mode* than BERTScore and
646 RadGraph F1 in terms of *total errors* in *false prediction of finding*, as determined by the Benjamini-Hochberg
647 Procedure with False Discovery Rate (FDR) of 1%.

	One-sided two-sample t test p-value	Benjamini-Hochberg Procedure critical value with False Discovery Rate (FDR) of 1%	Whether result is significant
BLEU > CheXbert	3.79e-3	2.50e-3	N
BLEU > BERTScore	9.50e-6	1.67e-3	Y
BLEU > RadGraph	1.07e-7	8.33e-4	Y
CheXbert > BLEU	9.96e-1	8.33e-3	N
CheXbert > BERTScore	7.65e-2	4.17e-3	N
CheXbert > RadGraph	6.39e-3	3.33e-3	N
BERTScore > BLEU	1.00e0	9.17e-3	N
BERTScore > CheXbert	9.51e-1	6.67e-3	N
BERTScore > RadGraph	2.24e-1	5.00e-3	N
RadGraph > BLEU	1.00e0	1.00e-2	N
RadGraph > CheXbert	9.94e-1	7.50e-3	N
RadGraph > BERTScore	7.76e-1	5.83e-3	N

648

649 **Supplementary Table 3(b):** Significance of BLEU having a *more prominent failure mode* than BERTScore and
650 RadGraph F1 in terms of *clinically significant errors* in *false prediction of finding*, as determined by the Benjamini-
651 Hochberg Procedure with False Discovery Rate (FDR) of 1%.

	One-sided two-sample t test p-value	Benjamini-Hochberg Procedure critical value with False Discovery Rate (FDR) of 1%	Whether result is significant
BLEU > CheXbert	3.68e-3	2.50e-3	N
BLEU > BERTScore	1.48e-4	1.67e-3	Y
BLEU > RadGraph	6.44e-7	8.33e-4	Y
CheXbert > BLEU	9.96e-1	8.33e-3	N
CheXbert > BERTScore	1.34e-1	5.00e-3	N
CheXbert > RadGraph	9.77e-3	3.33e-3	N
BERTScore > BLEU	1.00e0	9.17e-3	N
BERTScore > CheXbert	8.66e-1	5.83e-3	N
BERTScore > RadGraph	1.33e-1	4.17e-3	N

RadGraph > BLEU	1.00e0	1.00e-2	N
RadGraph > CheXbert	9.90e-1	7.50e-3	N
RadGraph > BERTScore	8.67e-1	6.67e-3	N

652

653 **Supplementary Table 3(c):** Significance of BLEU having a *less prominent failure mode* than CheXbert vector
 654 similarity in terms of *total errors* in *incorrect location/position of finding*, as determined by the Benjamini-Hochberg
 655 Procedure with False Discovery Rate (FDR) of 1%.

	One-sided two-sample t test p-value	Benjamini-Hochberg Procedure critical value with False Discovery Rate (FDR) of 1%	Whether result is significant
BLEU < CheXbert	4.83e-4	8.33e-4	Y
BLEU < BERTScore	1.60e-2	2.50e-3	N
BLEU < RadGraph	1.51e-1	5.00e-3	N
CheXbert < BLEU	1.00e0	1.00e-2	N
CheXbert < BERTScore	8.90e-1	7.50e-3	N
CheXbert < RadGraph	9.89e-1	9.17e-3	N
BERTScore < BLEU	9.84e-1	8.33e-3	N
BERTScore < CheXbert	1.10e-1	3.33e-3	N
BERTScore < RadGraph	8.63e-1	6.67e-3	N
RadGraph < BLEU	8.49e-1	5.83e-3	N
RadGraph < CheXbert	1.14e-2	1.67e-3	N
RadGraph < BERTScore	1.37e-1	4.17e-3	N

656

657 **Supplementary Table 3(d):** Significance of BLEU having a *less prominent failure mode* than CheXbert vector
 658 similarity in terms of *clinically significant errors* in *incorrect location/position of finding*, as determined by the
 659 Benjamini-Hochberg Procedure with False Discovery Rate (FDR) of 1%.

	One-sided two-sample t test p-value	Benjamini-Hochberg Procedure critical value with False Discovery Rate (FDR) of 1%	Whether result is significant
BLEU < CheXbert	2.74e-4	8.33e-4	Y
BLEU < BERTScore	2.07e-2	1.67e-3	N
BLEU < RadGraph	5.75e-2	3.33e-3	N
CheXbert < BLEU	1.00e0	1.00e-2	N
CheXbert < BERTScore	9.25e-1	6.67e-3	N

CheXbert < RadGraph	9.67e-1	8.33e-3	N
BERTScore < BLEU	9.79e-1	9.17e-3	N
BERTScore < CheXbert	7.53e-2	4.17e-3	N
BERTScore < RadGraph	6.65e-1	5.83e-3	N
RadGraph < BLEU	9.42e-1	7.50e-3	N
RadGraph < CheXbert	3.32e-2	2.50e-3	N
RadGraph < BERTScore	3.35e-1	5.00e-3	N

660

661 **Supplementary Table 4:** Average metric scores of metric-oracle models and prior models, as the average, lower-
 662 bound, and upper-bound of the 95% confidence interval.

	Avg BLEU	Avg BERTScore	Avg CheXbert	Avg RadGraph
Metric-oracle model	0.566 [95% CI 0.566 0.566]	0.729 [95% CI 0.729 0.729]	0.956 [95% CI 0.956 0.956]	0.677 [95% CI 0.677 0.678]
Random	0.048 [95% CI 0.048 0.049]	0.214 [95% CI 0.214 0.214]	0.280 [95% CI 0.280 0.280]	0.049 [95% CI 0.049 0.049]
M ² Trans	0.087 [95% CI 0.087 0.087]	0.227 [95% CI 0.227 0.227]	0.268 [95% CI 0.268 0.268]	0.110 [95% CI 0.110 0.111]
R2Gen	0.059 [95% CI 0.059 0.059]	0.186 [95% CI 0.186 0.186]	0.204 [95% CI 0.203 0.204]	0.057 [95% CI 0.057 0.057]
CXR-RePaiR	0.055 [95% CI 0.055 0.055]	0.191 [95% CI 0.191 0.191]	0.379 [95% CI 0.379 0.379]	0.091 [95% CI 0.090 0.091]
WCL	0.064 [95% CI 0.064 0.064]	0.188 [95% CI 0.188 0.189]	0.218 [95% CI 0.218 0.218]	0.068 [95% CI 0.068 0.068]
CvT2DistilGPT2	0.066 [95% CI 0.066 0.066]	0.192 [95% CI 0.192 0.193]	0.264 [95% CI 0.264 0.264]	0.073 [95% CI 0.073 0.073]

663

664 **Supplementary Table 5:** Predicted total number of errors of prior models, as the average, lower-bound, and upper-
 665 bound of the 95% confidence interval.

	Predicted Number of Errors
Random	3.266 [95% CI 3.265 3.266]
M ² Trans	3.088 [95% CI 3.087 3.088]
R2Gen	3.233 [95% CI 3.232 3.233]
CXR-RePaiR	3.181 [95% CI 3.181 3.181]
WCL	3.205 [95% CI 3.204 3.205]
CvT2DistilGPT2	3.191 [95% CI 3.191 3.192]

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