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Adapted large language models can outperform medical experts in clinical text summarization

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Author contributions

D.V.V. collected data, developed code, ran experiments, designed reader studies, analyzed results, created figures and wrote the manuscript. All authors reviewed the manuscript and provided meaningful revisions and feedback. C.V.U., L.B. and J.B.D. provided technical advice, in addition to conducting qualitative analysis (C.V.U.), building infrastructure for the Azure API (L.B.) and implementing the MEDCON metric (J.B.). A.A. assisted in model fine-tuning. C.B., A.P., M.P., E.P.R. and A.S. participated in the reader study as radiologists. N.R., P.H., W.C., N.A. and J.H. participated in the reader study as hospitalists. C.P.L., J.P. and A.S.C. provided student funding. S.G. advised on study design, for which J.H. and J.P. provided additional feedback. J.P. and A.S.C. guided the project, with A.S.C. serving as principal investigator and advising on technical details and overall direction. No funders or third parties were involved in study design, analysis or writing.

Competing interests

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Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Code availability

All code used for experiments in this study can be found in a GitHub repository (https://github.com/StanfordMIMI/clin-summ), which also contains links to open-source models hosted by HuggingFace[87].

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Abstract

Analyzing vast textual data and summarizing key information from electronic health records imposes a substantial burden on how clinicians allocate their time. Although large language models (LLMs) have shown promise in natural language processing (NLP) tasks, their effectiveness on a diverse range of clinical summarization tasks remains unproven. Here we applied adaptation methods to eight LLMs, spanning four distinct clinical summarization tasks: radiology reports, patient questions, progress notes and doctor–patient dialogue. Quantitative assessments with syntactic, semantic and conceptual NLP metrics reveal trade-offs between models and adaptation methods. A clinical reader study with 10 physicians evaluated summary completeness, correctness and conciseness; in most cases, summaries from our best-adapted LLMs were deemed either equivalent (45%) or superior (36%) compared with summaries from medical experts. The ensuing safety analysis highlights challenges faced by both LLMs and medical experts, as we connect errors to potential medical harm and categorize types of fabricated information. Our research provides evidence of LLMs outperforming medical experts in clinical text summarization across multiple tasks. This suggests that integrating LLMs into clinical workflows could alleviate documentation burden, allowing clinicians to focus more on patient care.

Documentation plays an indispensable role in healthcare practice. Currently, clinicians spend a substantial amount of time summarizing vast amounts of textual information—whether it be compiling diagnostic reports, writing progress notes or synthesizing a patient's treatment history across different specialists[1–3]. Even for experienced physicians with a high level of expertise, this intricate task naturally introduces the possibility for errors, which can be detrimental in healthcare where precision is paramount[4–6].

The widespread adoption of electronic health records has expanded clinical documentation workload, directly contributing to increasing stress and clinician burnout[7–9]. Recent data indicate that physicians can expend up to 2 hours on documentation for each hour of patient interaction[10]. Similarly, documentation responsibilities for nurses can consume up to 60% of their time and account for considerable work stress[11–13]. These tasks divert attention from direct patient care, leading to worse outcomes for patients and decreased job satisfaction for clinicians[2,14–16].

Large language models (LLMs) have gained remarkable traction, leading to widespread adoption of models such as ChatGPT[17], which excel at information retrieval, nuanced understanding and text generation[18,19]. Although LLM benchmarks for general natural language processing (NLP) tasks exist[20,21], they do not evaluate performance on relevant clinical tasks. Addressing this limitation presents an opportunity to accelerate the process of clinical text summarization, hence alleviating documentation burden and improving patient care.

Crucially, machine-generated summaries must be non-inferior to those of seasoned clinicians, especially when used to support sensitive clinical decision-making. Previous work has demonstrated potential across clinical NLP tasks[22,23], adapting to the medical domain by training a new model[24,25], fine-tuning an existing model[26,27] or supplying task-specific examples in the model prompt[27,28]. However, adapting LLMs to summarize a diverse set of clinical tasks has not been thoroughly explored nor has non-inferiority to medical experts been achieved.

With the overarching objective of bringing LLMs closer to clinical readiness, we demonstrate here the potential of these models for clinical text summarization. Our evaluation framework (Fig. 1) follows a three-step process: (1) use quantitative NLP metrics to identify the best model and adaptation method across those selected on four summarization tasks; (2) conduct a clinical reader study with 10 physicians comparing the best LLM summaries to medical expert summaries across the key attributes of completeness, correctness and conciseness; and (3) perform a safety analysis of examples, potential medical harm and fabricated information to understand challenges faced by both models and medical experts. This framework aims to guide future enhancements of LLMs and their integration into clinical workflows.

Results

Constructing prompt anatomy

We structured prompts (Fig. 2) by following best practices[29,30] and evaluating a handful of options for model expertise and task instructions. Figure 2 also illustrates the effect of model expertise on GPT-3.5. For example, we achieved better performance by nudging the model toward medical expertise compared to specializing in wizardry or having no specific expertise at all. This illustrates the value of relevant context in achieving better outcomes for the target task. We also explored the temperature hyperparameter, which adjusts the LLM's conditional probability distributions during sampling, hence affecting how often the model will output less likely tokens or individual units of text. Higher temperatures lead to more randomness and 'creativity', whereas lower temperatures produce more deterministic outputs. After searching over temperature values {0.1, 0.5, 0.9} using GPT-3.5, Fig. 2 demonstrates that the lowest value, 0.1, performed best. We, thus, set temperature to this value for all models. Intuitively, a lower value seems appropriate given our goal of factually summarizing text with a high aversion to factually incorrect text.

Identifying the best model/method

Following Fig. 1, we identified the best model/method across four summarization tasks comprising six datasets (Extended Data Table 1). This includes eight LLMs described in Extended Data Table 2: six open-source (FLAN-T5 (ref. 31), FLAN-UL2 (ref. 32), Alpaca[33], Med-Alpaca[34], Vicuna[35] and Llama-2 (ref. 36)) and two proprietary (GPT-3.5 (ref. 37) and GPT-4 (ref. 38)). For adapting each model to a particular summarization task, we considered two proven adaptation strategies: in-context learning (ICL[39]), which adapts by including examples within the model prompt, and quantized low-rank adaptation (QLoRA[40]), which adapts by fine-tuning a subset of model weights on examples.

Impact of domain-specific fine-tuning.

When considering which open-source models to evaluate, we first assessed the benefit of fine-tuning open-source models on medical text. For example, Med-Alpaca is a version of Alpaca that was further instruction-tuned with medical question and answer (Q&A) text, consequently improving performance for the task of medical question–answering. Figure 3a compares these models for our task of summarization, showing that most data points are below the dashed lines, denoting equivalence. Hence, despite Med-Alpaca's adaptation for the medical domain, it actually performed worse than Alpaca for our tasks of clinical text summarization, highlighting a distinction between domain adaptation and task adaptation. With this in mind, and considering that Alpaca is known to perform worse than our other open-source autoregressive models, Vicuna and Llama-2 (refs. 21,35), for simplicity we excluded Alpaca and Med-Alpaca from further analysis.

Comparison of adaptation strategies.

Next, we compared ICL versus QLoRA across the remaining open-source models using the Open-i radiology reports dataset in Fig. 3b and the patient health questions dataset in Extended Data Fig. 1. We chose these datasets because their shorter context lengths allow for training with lower computational cost. FLAN-T5 emerged as the best-performing model with QLoRA. QLoRA typically outperformed ICL with the better models (FLAN-T5 and Llama-2); given a sufficient number of in-context examples, however, most models surpassed even the best QLoRA fine-tuned model, FLAN-T5 (Extended Data Fig. 2). FLAN-T5 (2.7B) eclipsed its fellow sequence-to-sequence (seq2seq) model, FLAN-UL2 (20B), despite being an older model with almost 10× fewer parameters.

Effect of context length for ICL.

Figure 3c displays MEDCON[41] scores, which capture the quality of summaries with respect to medical concepts. These scores are plotted for all models against number of in-context examples, up to the maximum number of examples permitted by each model and dataset. This graph also includes the best-performing model (FLAN-T5) with QLoRA as a reference, depicted by a horizontal dashed line. Compared to prompting a model without examples (zero-shot prompting), adapting with even one example considerably improved performance in almost all cases, underscoring the importance of adaptation methods. Although ICL and QLoRA were competitive for open-source models, proprietary models GPT-3.5 and GPT-4 far outperformed other models and methods given sufficient in-context examples. For a similar graph across all metrics, see Extended Data Fig. 2.

Head-to-head model comparison.

Figure 3d compares models using win rates—that is, the head-to-head winning percentage of each model combination across the same set of samples. In other words, for what percentage of samples do model A's summaries have a higher score than model B's summaries? Although FLAN-T5 was more competitive for syntactic metrics, such as BLEU[42], this model is constrained to a shorter context length of 512 (Extended Data Table 2).

Best model/method.

We deemed the best model and method to be GPT-4 (32,000 context length) with a maximum allowable number of in-context examples, hereon identified as the best-performing model.

Analyzing reader study results

Given our clinical reader study overview (Fig. 4a), pooled results across 10 physicians (Fig. 4b) demonstrate that summaries from the best-adapted model (GPT-4 using ICL) were more complete and contained fewer errors compared to medical expert summaries, which were created either by medical doctors during clinical care or by a committee of medical doctors and experts (Methods).

The distributions of reader responses in Fig. 4c show that medical expert summaries were preferred in only a minority of cases (19%), whereas, in a majority, the best model was either non-inferior (45%) or preferred (36%). Extended Data Table 3 contains scores separated by individual readers and affirms the reliability of scores across readers by displaying positive intra-reader correlation values. Based on physician feedback, we undertook a qualitative analysis to illustrate strengths and weaknesses of summaries by the model and medical experts (Fig. 5 and Extended Data Figs. 3 and 4).

We observed that the best model summaries were more complete, on average, than medical expert summaries, achieving statistical significance across all three summarization tasks with $P < 0.001$ (Fig. 4b). Lengths of summaries were similar between the model and medical experts for all three datasets: 47 ± 24 versus 44 ± 22 tokens for radiology reports, 15 ± 5 versus 14 ± 4 tokens for patient questions and 29 ± 7 versus 27 ± 13 tokens for progress notes. Hence, the model's advantage in completeness is not simply a result of generating longer summaries. We provide intuition for completeness by investigating a specific example in progress notes summarization. In Extended Data Fig. 3, the model correctly identified conditions that were missed by the medical expert, such as hypotension and anemia. Although the model was more complete than the expert in generating its progress note summary, it also missed historical context (a history of hypertension).

Regarding correctness, the best model generated significantly fewer errors ($P < 0.001$) compared to medical expert summaries (Fig. 4b) overall and on two of three summarization tasks. As an example of the model's superior correctness performance on the radiology report summarization task, we observe that it avoided common medical expert errors related to lateral distinctions (right versus left; Fig. 5). For the problem list summarization task, Extended Data Fig. 3 reveals an intriguing case: during the blinded study, the physician reader erroneously assumed that a hallucination—in this case, the incorrect inclusion of urinary tract infection—was made by the model. In this case, the medical expert was responsible for the hallucination. This instance underscores the point that even medical experts, not just LLMs, can hallucinate. Despite this promising performance, the model was not perfect across all tasks. We see a clear example in Extended Data Fig. 3 where the model mistakenly generated (hallucinated) several absent conditions, such as eosinophilia.

Regarding conciseness, the best model performed significantly better than medical experts ($P < 0.001$) overall and on two tasks, whereas, for radiology reports, it performed similarly to medical experts. We note that the model's summaries are more concise while concurrently being more complete. Figure 5 provides an example in which the model's summary includes correct information that readers deemed not important.

We then conducted a supplemental reader study connecting summarization errors to medical harm, inspired by the Agency for Healthcare Research and Quality (AHRQ)'s harm scale[43]. The results of this harm study (Fig. 4d) indicate that the medical expert summaries would have both a higher likelihood (14%) and a higher extent (22%) of possible harm compared to the summaries from the best model (12% and 16%, respectively).

Fabricated information

Fabricated information, or factually incorrect text, poses a substantial obstacle to the clinical integration of LLMs given the critical need for accuracy in medical applications. Our reader study results for correctness (Fig. 4b) indicate that the best model produces fewer instances of fabricated information than medical experts. Further, the need for accuracy motivates a more nuanced understanding of correctness for clinical text summarization. As such, we define three types of fabricated information: (1) misinterpretations of ambiguity; (2) factual inaccuracies: modifying existing facts to be incorrect; and (3) hallucinations: inventing new information that cannot be inferred from the input text. We found that the model committed misinterpretations, inaccuracies and hallucinations on 6%, 2% and 5% of samples, respectively, compared to 9%, 4% and 12%, respectively, by medical experts. Given the model's lower error rate in each category, this suggests that incorporating LLMs could actually reduce fabricated information in clinical practice.

Connecting quantitative and clinical evaluations

Figure 6 captures the correlation between NLP metrics and physicians' preferences. These values are calculated as the Spearman correlation coefficient between NLP metric scores and the magnitudes of reader scores. For correctness, the metrics BERTScore[44] (measuring semantics) and MEDCON[41] (measuring medical concepts) correlated most strongly with reader preference; meanwhile, the BLEU[42] metric (measuring syntax) correlated most with completeness and least with conciseness. However, the low magnitude of correlation values (approximately 0.2) underscores the need to go beyond NLP metrics with a clinical reader study when assessing clinical readiness.

Separately, we note the inclusion of additional results analyzing model size, demonstrating the dialogue task and comparing to summarization baselines in Extended Data Figs. 5 and 6 and Extended Data Table 4, respectively.

Discussion

In this research, we evaluated methods for adapting LLMs to summarize clinical text, analyzing eight models across a diverse set of summarization tasks. Our quantitative results underscore the advantages of adapting models to specific tasks and domains. The ensuing clinical reader study demonstrates that LLM summaries are often preferred over medical expert summaries due to higher scores for completeness, correctness and conciseness. The subsequent safety analysis explores qualitative examples, potential medical harm and fabricated information to demonstrate the limitations of both LLMs and medical experts. Evidence from this study suggests a potential avenue for LLMs to reduce documentation burden for clinicians.

We first highlight the importance of 'prompt engineering', or modifying and tuning the input prompt to improve model performance. This is well reflected in our evaluation of conciseness. We specified the desired summary length in the instruction—for example, with 'one question of 15 words or less' for summarizing patient questions (Extended Data Table 1). Without this instruction, the model might generate lengthy outputs, occasionally even longer than the input text. When considering conciseness scores (Fig. 4b), radiology reports were the only task in which physicians did not prefer the best model's summaries to the medical experts. This could be attributed to the relatively vague length specification in the radiology reports instruction—that is, '…with minimal text'—whereas the other two task instructions quantify length.

Overall, our best-adapted model achieved non-inferior results to medical experts while performing a basic search across 1–2 options for each task instruction (Extended Data Table 1). Prompt phrasing and model temperature can have a considerable effect on LLM output, as demonstrated in the literature[45,46] and in Fig. 2. This suggests that results could be further improved with additional prompt engineering and model hyperparameters, which is subject to future studies. In addition, beyond the scope of this manuscript, there is further potential to improve accuracy through incorporating checks by human operators and checks by other LLMs or using a model ensemble[47,48].

Model performance generally improved with more context. Even one example provided considerable benefit compared to zero-shot prompting, underscoring the value of adaptation methods. Note that the number of allowable examples depends on the number of tokens per example and the model context length. This motivates future work to pursue more challenging tasks, such as summarizing longer documents or multiple documents of different types. Addressing these cases demands two key advancements: (1) extending model context length, potentially through multi-query aggregation or methods that increase context length[49,50], and (2) introducing open-source datasets that include broader tasks and lengthier documents.

In terms of trade-offs between lightweight adaptation methods, while QLoRA fine-tuning performed similarly for some cases, ICL was the best overall, especially when including proprietary models GPT-3.5 and GPT-4. The proprietary nature of these models raises an interesting consideration for healthcare, where data and model governance are important, especially if summarization tools are cleared for clinical use by the Food and Drug Administration. This could motivate the use of fine-tuning methods on open-source models. Governance aside, ICL provides many benefits: (1) model weights are fixed, hence enabling queries of pre-existing LLMs, and (2) adaptation is feasible with even a few examples, whereas fine-tuning methods, such as QLoRA, typically require hundreds or thousands of examples.

We consider trade-offs of different model types: autoregressive and seq2seq. Seq2seq models (FLAN-T5 and FLAN-UL2) performed very well on syntactical metrics, such as BLEU, but worse on others (Fig. 3d), suggesting that these models excel more at matching word choice than matching semantic or conceptual meaning. Note that seq2seq models are often constrained to much shorter context length than autoregressive models, such as GPT-4, because seq2seq models require the memory-intensive step of encoding the input sequence into a fixed-size context vector. Among open-source models, seq2seq models performed better than autoregressive models (Llama-2 and Vicuna) on radiology reports but worse on patient questions and progress notes (Fig. 3c). Given that these latter datasets have higher lexical variance (Extended Data Table 1) and more heterogeneous formatting compared to radiology reports, we hypothesize that autoregressive models may perform better with increasing data heterogeneity and complexity.

The evidence from our reader study suggests that adapting LLMs can outperform medical experts in terms of completeness, correctness and conciseness. When qualitatively analyzing summaries, we notice a few general trends. As implied by the completeness scores, the best-adapted model (GPT-4 using ICL) excelled at identifying and understanding the most relevant information from the source text. However, both the model and the medical experts faced challenges interpreting ambiguity, such as user queries in patient health questions. Consider example 1 in Extended Data Fig. 4, in which the input question mentioned ‘diabetes and neuropathy’.

The model mirrored this phrasing verbatim, whereas the medical expert interpreted it as ‘diabetic neuropathy’. This highlights the model’s tendency toward a literal approach without interpretation, which may be either advantageous or limiting. In example 2 of Extended Data Fig. 4, the model simply reformulated the input question about tests and their locations, whereas the medical expert inferred a broader query about tests and treatments. In both cases, the model’s summaries leaned toward literalness, a trait that readers sometimes favored and sometimes did not. In future work, a systematic exploration of model temperature could further illuminate this trade-off.

Regarding general trends for our clinical NLP metrics, the syntactic metric BLEU provided the highest correlation with physician preference for completeness. Given that BLEU measures sequence overlap, this result seems reasonable, as more text provides more ‘surface area’ for overlap; more text also reduces the brevity penalty that BLEU applies on generated sequences, which are shorter than the reference[42]. In addition, the metrics BERTScore and MEDCON correlated most strongly with physician preference for correctness. This implies that the semantics (BERTScore) and concepts (MEDCON) measured by these metrics correspond to correctness more effectively than syntactic metrics BLEU and ROUGE-L[51].

Many previous clinical NLP studies rely primarily on quantitative metrics for evaluation[41,52–54]. Given the critical nature of nuanced medical tasks, such as summarization, that typically have no objective solutions, including human experts in the evaluation process beyond quantitative metrics is crucial to demonstrate clinical readiness. To address this, there have been recent releases of expert evaluations for adjacent clinical

NLP tasks[3,55]. Other studies employ human experts to evaluate synthesized abstracts, demonstrating that NLP metrics are not sufficient to measure summary quality[56]. Aside from the low correlation values in Fig. 6, our reader study results in Fig. 4 also highlight another limitation of NLP metrics, especially as model-generated summaries become increasingly viable. These metrics rely on a reference (in our case, the medical expert), which we have demonstrated may contain errors. Hence, we suggest that human evaluation is essential when assessing the clinical feasibility of new methods. When human evaluation is not feasible, Fig. 6 suggests that syntactic metrics are better at measuring completeness, whereas semantic and conceptual metrics are better at measuring correctness.

The present study has several limitations that must be addressed in future research. First, we did not consider the inherently context-specific nature of summarization. For example, a gastroenterologist, a radiologist and an oncologist may have different preferences for summaries of a cancer patient with liver metastasis. Or perhaps an abdominal radiologist will want a different summary than a neuroradiologist. Furthermore, individual clinicians may prefer different styles or amounts of information. Although we did not explore such a granular level of adaptation, this may not require much further development: because the best model and method uses a handful of examples via ICL, one could plausibly adapt using examples curated for a particular specialty or clinician. Another limitation is that radiology report summaries from medical experts occasionally recommend further studies or refer to prior studies—for example, '… not significantly changed from prior' in Fig. 5. These instances are out of scope for the LLM, as it does not have access to prior studies nor the purview to make recommendations. Hence, for our clinical reader study, physicians were told to disregard these phrases. However, future work can explore providing more context via prior reports and allow the LLM to make a treatment suggestion. An additional consideration for our study and other LLM studies, especially with proprietary models, is that it is not possible to verify whether a particular open-source dataset was included in model training. Although three of our datasets (MIMIC-CXR, MIMIC-III and ProbSum) require PhysioNet[57] access to ensure safe data usage by third parties, this is no guarantee against data leakage. This complication highlights the need for validating results on internal data when possible. We further note the potential for LLMs to be biased[58,59]. Although our datasets do not contain demographic information, we advocate for future work to consider whether summary qualities have any dependence upon group membership.

The findings from our study demonstrate that adapting LLMs can outperform medical experts for clinical text summarization across the diverse range of documents that we evaluated. This suggests that incorporating LLM-generated candidate summaries could reduce documentation load, potentially leading to decreased clinician strain and improved patient care. Testing this hypothesis requires future prospective studies in clinical environments.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information;

details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41591-024-02855-5.

Methods

LLMs

We investigated a diverse collection of transformer-based LLMs for clinical summarization tasks. This included two broad approaches to language generation: seq2seq models and autoregressive models. Seq2seq models use an encoder–decoder architecture to map the input text to a generated output, often requiring paired datasets for training. These models have shown strong performance in machine translation[60] and summarization[61]. In contrast, the autoregressive models typically use only a decoder. They generate tokens sequentially —where each new token is conditioned on previous tokens—thus efficiently capturing context and long-range dependencies. Autoregressive models are typically trained with unpaired data, and they are particularly useful for various NLP tasks, such as text generation, question–answering and dialogue interactions[17,35].

We included prominent seq2seq models owing to their strong summarization performance[61] and autoregressive models owing to their state-of-the-art performance across general NLP tasks[21]. As shown in Extended Data Table 2, our choice of models varied widely with respect to number of parameters (2.7 billion to 175 billion) and context length (512 to 32,000)—that is, the maximum number of input tokens a model can process. We organized our models into three categories:

Open-source seq2seq models.—The original T5 ‘text-to-text transfer transformer’ model[62] demonstrated excellent performance in transfer learning using the seq2seq architecture. A derivative model, FLAN-T5 (refs. 31,63), improved performance via instruction prompt tuning. This T5 model family has proven effective for various clinical NLP tasks[27,64]. The FLAN-UL2 model[32,31] was introduced recently, which features an increased context length (fourfold that of FLAN-T5) and a modified pre-training procedure called unified language learning (UL2).

Open-source autoregressive models.—The Llama family of LLMs[36] has enabled the proliferation of open-source instruction-tuned models that deliver similar performance to GPT-3 (ref. 17) on many benchmarks despite their smaller sizes. Descendants of this original model have taken additional fine-tuning approaches, such as fine-tuning via instruction-following (Alpaca[33]), medical Q&A data (Med-Alpaca[34]), user-shared conversations (Vicuna[35]) and reinforcement learning from human feedback (Llama-2 (ref. 36)). Llama-2 allows for twofold longer context lengths (4,096) relative to the aforementioned open-source autoregressive models.

Our focus was primarily on the 7B-parameter tier of these models despite some models, such as Llama-2, having larger versions. The benefit of larger models is explored in Extended Data Fig. 5, which found this improvement marginal for Llama-2 (13B) compared to Llama-2 (7B). Although other open-source models might have slightly outperformed our selections, this likely would not have substantially changed our analysis, especially because the clinical reader study employed a state-of-the-art proprietary model[21].

Proprietary autoregressive models.—We include GPT-3.5 (ref. 37) and GPT-4 (ref. 38), the latter of which has been regarded as state of the art on general NLP tasks[21] and has demonstrated strong performance on biomedical NLP tasks, such as medical examinations[65–67]. Both models offer significantly higher context length (16,384 and 32,768) than open-source models. We note that, since sharing our work, GPT-4's context length has been increased to 128,000.

Adaptation methods

We considered two proven techniques for adapting pre-trained, general-purpose LLMs to domain-specific tasks:

ICL.—ICL is a lightweight adaptation method that requires no altering of model weights; instead, one includes a handful of in-context examples directly within the model prompt[62]. This simple approach provides the model with context, enhancing LLM performance for a particular task or domain[27,28]. We implemented this by choosing, for each sample in our test set, the m nearest neighbors training samples in the embedding space of the PubMedBERT model[68]. Note that choosing 'relevant' in-context examples has been shown to outperform choosing examples at random[69]. For a given model and dataset, we used $m = 2^x$ examples, where $x \in \{0, 1, 2, 3, \ldots, M\}$ for M such that no more than 1% of the $s = 250$ samples were excluded due to prompts exceeding the model's context length. Hence, each model's context length limited the allowable number of in-context examples.

To demonstrate the benefit of adaptation methods, we included the baseline zero-shot prompting—that is $m = 0$ in-context samples.

QLoRA.—Low-rank adaptation (LoRA)[70] has emerged as an effective, lightweight approach for fine-tuning LLMs by altering a small subset of model weights, often less than 0.1% (ref. 27). LoRA inserts trainable matrices into the attention layers; then, using a training set of samples, this method performs gradient descent on the inserted matrices while keeping the original model weights frozen. Compared to training model weights from scratch, LoRA is much more efficient with respect to both computational requirements and the volume of training data required. Recently, QLoRA[40] was introduced as a more memory-efficient variant of LoRA, employing 4-bit quantization to enable the fine-tuning of larger LLMs given the same hardware constraints. This quantization negligibly impacts performance[40]; as such, we used QLoRA for all model training. Note that QLoRA could not be used to fine-tune proprietary models on our consumer hardware, as their model weights are not publicly available. Fine-tuning of GPT-3.5 via API was made available after our internal model cutoff date of 31 July 2023[71].

Data

To robustly evaluate LLM performance on clinical text summarization, we chose four distinct summarization tasks, comprising six open-source datasets. As depicted in Extended

Data Table 1, each dataset contained a varying number of samples, token lengths and lexical variance. Lexical variance is calculated as the ratio of unique words to total words across the entire dataset; hence, a higher ratio indicates less repetition and more lexical diversity. We describe each task and dataset below. For examples of each task, see Fig. 5 and Extended Data Figs. 3, 4 and 6.

Radiology reports.—Radiology report summarization takes as input the findings section of a radiology study containing detailed examination analysis and results. The goal is to summarize these findings into an impression section that concisely captures the most salient, actionable information from the study. We considered three datasets for this task, where both reports and findings were created by attending physicians as part of routine clinical care. Open-i[72] contains de-identified narrative chest x-ray reports from the Indiana Network for Patient Care 10 database. From the initial set of 4,000 studies, Demner-Fushman et al.[72] selected a final set of 3,400 reports based on the quality of imaging views and diagnostic content. MIMIC-CXR[73] contains chest x-ray studies accompanied by free-text radiology reports acquired at the Beth Israel Deaconess Medical Center between 2011 and 2016. For this study, we used a dataset of 128,000 reports[69] pre-processed by the RadSum23 shared task at BioNLP 2023 (refs. 74,75). MIMIC-III[76] contains 67,000 radiology reports spanning seven anatomies (head, abdomen, chest, spine, neck, sinus and pelvis) and two modalities: magnetic resonance imaging (MRI) and computed tomography (CT). This dataset originated from patient stays in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012. For this study, we used a pre-processed version via RadSum23 (refs. 74,75). Compared to x-rays, MRIs and CT scans capture more information at a higher resolution. This usually leads to longer reports (Extended Data Table 1), rendering MIMIC-III a more challenging summarization dataset than Open-i or MIMIC-CXR.

Patient questions.—Question summarization consists of generating a condensed question expressing the minimum information required to find correct answers to the original question[77]. For this task, we employed the MeQSum dataset[77]. MeQSum contains (1) patient health questions of varying verbosity and coherence selected from messages sent to the US National Library of Medicine and (2) corresponding condensed questions created by three medical experts such that the summary allows retrieving complete, correct answers to the original question without the potential for further condensation. These condensed questions were then validated by a medical doctor and verified to have high inter-annotator agreement. Due to the wide variety of these questions, MeQSum exhibited the highest lexical variance of our datasets (Extended Data Table 1).

Progress notes.—The goal of this task was to generate a ‘problem list’, or a condensed list of diagnoses and medical problems using the provider’s progress notes during hospitalization. For this task, we employed the ProbSum dataset[78]. This dataset, generated by attending internal medicine physicians during the course of routine clinical practice, was extracted from the MIMIC-III database of de-identified hospital intensive care unit (ICU) admissions. ProbSum contains (1) progress notes averaging more than 1,000 tokens and substantial presence of unlabeled numerical data—for example, dates and test results—and (2) corresponding problem lists created by attending medical experts in the ICU. We accessed these data via the BioNLP Problem List Summarization shared task[75,79,80] and PhysioNet[81].

Dialogue.—The goal of this task was to summarize a doctor–patient conversation into an 'assessment and plan' paragraph. For this task, we employed the ACI-Bench dataset[41,82–84], which contains (1) 207 doctor–patient conversations and (2) corresponding patient visit notes, which were first generated by a seq2seq model and subsequently corrected and validated by expert medical scribes and physicians. Because ACI-Bench's visit notes include a heterogeneous collection of section headers, we chose 126 samples containing an 'assessment and plan' section for our analysis. Per Extended Data Table 1, this task entailed the largest token count across our six datasets for both the input (dialogue) and the target (assessment).

As we are not the first to employ these datasets, Extended Data Table 4 contains quantitative metric scores from other works[25,27,41,52–54] that developed methods specific to each individual summarization task.

Experimental setup

For each dataset, we constructed test sets by randomly drawing the same s samples, where $s = 250$ for all datasets except dialogue ($s = 100$), which included only 126 samples in total. After selecting these s samples, we chose another s as a validation set for datasets, which incorporated fine-tuning. We then used the remaining samples as a training set for ICL examples or QLoRA fine-tuning.

We leveraged PyTorch for our all our experiments, which included the parameter-efficient fine-tuning[84] and the generative pre-trained transformers quantization[85] libraries for implementing QLoRA. We fine-tuned models with QLoRA for five epochs using the Adam optimizer with weight decay fix[86]. An initial learning rate of 1×10^{-3} was decayed linearly to 1×10^{-4} after a 100-step warm-up; we determined this configuration after experimenting with different learning rates and schedulers. To achieve an effective batch size of 24 on each experiment, we adjusted both individual batch size and number of gradient accumulation steps to fit on a single consumer GPU, a NVIDIA Quadro RTX 8000. All open-source models are available on HuggingFace[87].

Quantitative metrics

We used well-known summarization metrics to assess the quality of generated summaries. BLEU[42], the simplest metric, calculates the degree of overlap between the reference and generated texts by considering 1-gram to 4-gram sequences. ROUGE-L[51] evaluates similarity based on the longest common subsequence; it considers both precision and recall, hence being more comprehensive than BLEU. In addition to these syntactic metrics, we employed BERTScore, which leverages contextual BERT embeddings to evaluate the semantic similarity of the generated and reference texts[44]. Lastly, we included MEDCON[41] to gauge the consistency of medical concepts. This employs QuickUMLS[88], a tool that extracts biomedical concepts via string-matching algorithms[89]. MEDCON was restricted to relvant UMLS semantic groups (Anatomy, Chemicals & Drugs, Device, Disorders, Genes

& Molecular Sequences, Phenomena and Physiology). All four metrics ranged from [0, 100] with higher scores indicating higher similarity between the generated and reference summaries.

Reader study

After identifying the best model and method via NLP quantitative metrics, we performed a clinical reader study across three summarization tasks: radiology reports, patient questions and progress notes. The dialogue task was excluded owing to the unwieldiness of a reader parsing many lengthy transcribed conversations and paragraphs; see Extended Data Fig. 6 for an example and Extended Data Table 1 for the token count.

Our readers included two sets of physicians: (1) five board-certified radiologists to evaluate summaries of radiology reports and (2) five board-certified hospitalists (internal medicine physicians) to evaluate summaries of patient questions and progress notes. For each task, each physician viewed the same 100 randomly selected inputs and their A/B comparisons (medical expert versus the best model summaries), which were presented in a blinded and randomized order. An ideal summary would contain all clinically important information (‘completeness’) without any errors (‘correctness’) or superfluous information (‘conciseness’). Hence, we posed the following three questions for readers to evaluate using a five-point Likert scale.

- Completeness: ‘Which summary more completely captures important information?’ This compares the summaries’ recall—that is, the amount of clinically important detail retained from the input text.
- Correctness: ‘Which summary includes less false information?’ This compares the summaries’ precision—that is, instances of fabricated information.
- Conciseness: ‘Which summary contains less non-important information?’ This compares which summary is more condensed, as the value of a summary decreases with superfluous information.

To obfuscate any formatting differences between the model and medical expert summaries, we applied simple post-processing to standardize capitalization, punctuation, newline characters, etc. Figure 4e demonstrates the user interface for this study, which we created and deployed via Qualtrics.

Statistical analysis

Given these non-parametric, categorical data, we assessed the statistical significance of responses using a Wilcoxon signed-rank test with type 1 error rate = 0.05, adjusted for multiple comparisons using Bonferroni correction. We estimated intra-reader correlation based on a mean-rating, fixed-agreement, two-may mixed-effects model[90] using the Pingouin package[91]. Additionally, readers were provided comment space to make observations for qualitative analysis.

Connecting errors to medical harm

We then conducted a supplemental reader study connecting summarization errors to medical harm, inspired by the AHRQ harm scale[43]. We selected radiology reports ($n_r = 27$) and progress notes ($n_n = 44$) samples that contained disparities in completeness and/or correctness between the best model and medical expert summaries. Here, disparities occur if at least one physician significantly preferred, or at least two physicians slightly preferred, one summary to the other. These summary pairs were then randomized and blinded. For each sample, we asked the following multiple-choice questions: 'Summary A is more complete and/or correct than Summary B. Now, suppose Summary B (worse) is used in the standard clinical workflow. Compared to using Summary A (better), what would be the…' (1) '… extent of possible harm?' options: {none, mild or moderate harm, severe harm or death} and (2) '… likelihood of possible harm?' options: {low, medium, high}. The percentages displayed in Fig. 4d were computed with respect to all samples, such that the subset of samples with similar A/B summaries (in completeness and correctness) were assumed to contribute no harm.

Connecting quantitative and clinical evaluations

We next outlined our calculation of correlation values between NLP metrics and clinical reader scores in Fig. 6. Note that, in this work, these tools measured different quantities: NLP metrics measured the similarity between two summaries, whereas reader scores measured which summary is better. Consider an example where two summaries are exactly the same: NLP metrics would yield the highest possible score (100), whereas clinical readers would provide a score of 0 to denote equivalence. As the magnitude of a reader score increases, the two summaries are increasingly dissimilar, yielding a lower quantitative metric score. Hence, the correlation values are calculated as the Spearman correlation coefficients between NLP metric scores and the magnitudes of the reader scores. Because these features are inversely correlated, for clarity we display the negative correlation coefficient values.

Statistics and reproducibility

When determining sample size, we used our best judgment based on the size of datasets and clinician time. Note that these models are new, and they were applied to a new set of tasks. Thus, there was no prior effect size available to guide our sample size estimates. For the quantitative experiments, our sample size of 250 was chosen to maximize the number of samples given constraints of dataset size and cost of computing resources. We deem this sufficient as it enabled reproducible results when running the same experiments with a different set of samples. Furthermore, our use of six datasets enhances the robustness of our experiments. Note that we reduced the temperature parameter of the LLMs to be near zero, hence reducing randomness in the generated output summaries. For the clinical reader study, our sample size of 100 comparisons per reader per task was chosen to maximize the number of comparisons that could be made in a reasonable amount of time, which we estimated as 10 h. We deem this sufficient as it enabled statistically significant results for many combinations of tasks and attributes. No data were excluded from the analyses.

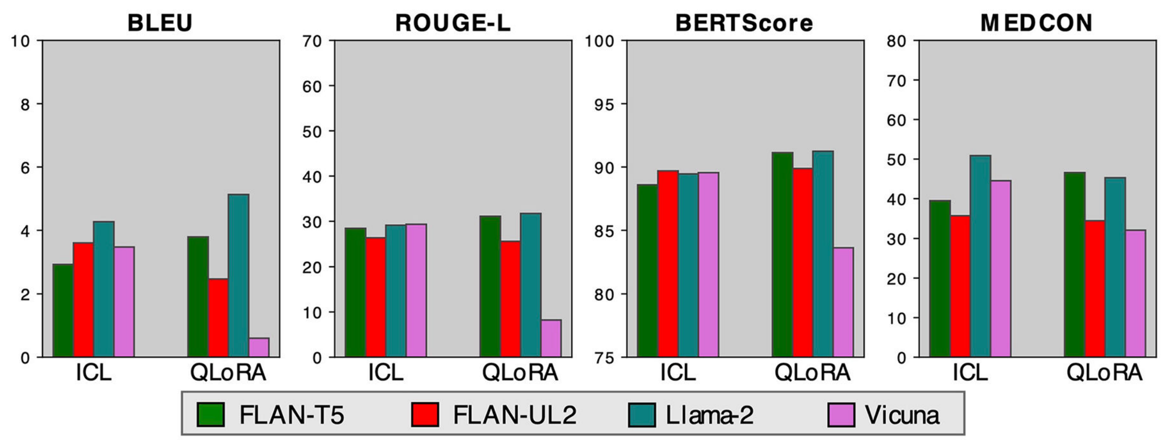
Data, models and code are all publicly available (https://github.com/StanfordMIMI/clin-summ). Internally, we verified reproducibility by achieving similar results across all six datasets. Because the LLM temperature parameter is near zero, outputs have very little randomness and are, thus, reproducible. Additionally, we chose the smallest dataset—which consequently required the lowest cost of computational resources—and re-ran a set of experiments that rendered very similar quantitative metric scores. This provided confidence moving forward with datasets that required higher computational resources.

Regarding randomization, for the quantitative experiments, we randomly selected 250 test samples and then randomly divided remaining samples into training and validation sets. For the clinical reader study, we randomly selected 100 samples for comparison; these samples and the A/B comparisons within each sample are displayed in random order. Regarding blinding, for the clinical reader study, we presented, in a blinded manner, the A/B comparison of summaries from the model and human experts. To obfuscate any formatting differences between A and B, we applied simple post-processing to standardize capitalization, punctuation, newline characters, etc.

Ethics approval

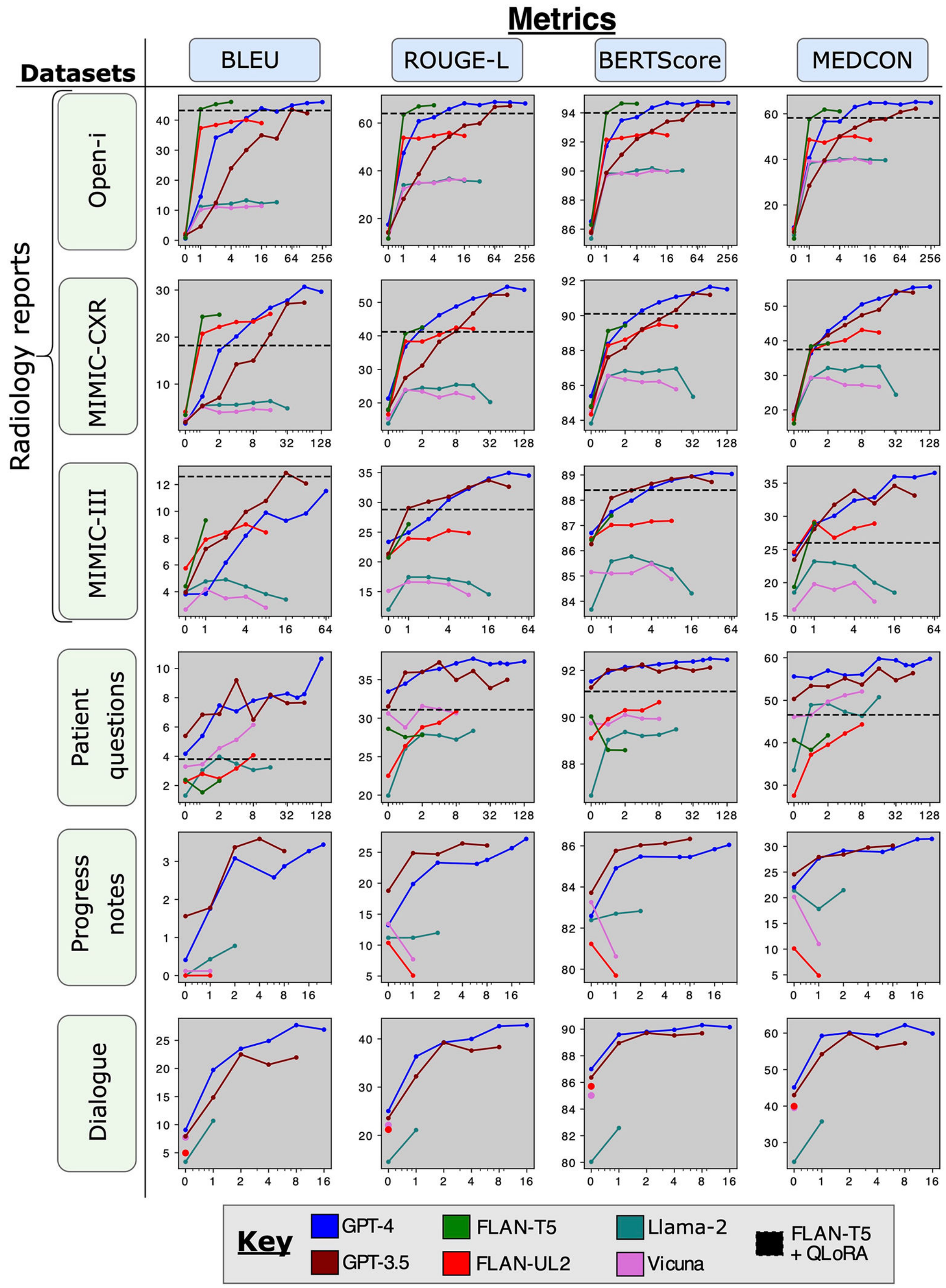
The clinical reader study component of this research involved the participation of physicians. This study adhered to the principles outlined in the Declaration of Helsinki. Informed consent was obtained from each physician before their participation. This study used only retrospective, de-identified data that fell outside the scope of institutional review board oversight.

Extended Data



Extended Data Fig. 1 |. ICL vs. QLoRA.

Summarization performance comparing one in-context example (ICL) vs. QLoRA across all open-source models on patient health questions.



Extended Data Fig. 2 |. Quantitative results across all metrics.

Metric scores vs. number of in-context examples across models and datasets. We also include the best model fine-tuned with QLoRA (FLAN-T5) as a horizontal dashed line.

Progress notes

Example 1: The model performed *better* because the medical expert missed (**green**) and mistakenly included (**red**) some conditions.

Input:
<ASSESSMENT>
Ms. [**Known lastname 12031**] is a [**Age over 90 **] yo female with HTN, CAD s/p CABG, osteoporosis, COPD, here with painless lower GI bleeding and active extravasation from branch of middle colic artery on CTA now s/p angiographic coiling of middle colic artery branch.

<SUBJECTIVE>
UOP low, gave 500cc NS bolus doing very well clinically track serial hcts still having bloody bowel movements as expected if hct stable likely plan for scope 2am hct dropped to 29 from 35 [**Doctor First Name 91**] - give 2 units and recheck 1 hr after 2nd unit, 3-4 hours Lactose Intolerance (Oral) (Lactase) Unknown; Codeine Nausea/Vomiting Bactrim Ds (Oral) (Sulfamethoxazole/Trimethoprim) Unknown; Changes to and f Review of systems is unchanged from admission except as noted below

Review of systems:
<OBJECTIVE>
Last dose of Antibiotics: Ciprofloxacin - [**2196-3-31**] 12:29 AM
Infusions: Other ICU medications: Pantoprazole (Protonix) - [**2196-3-30**] 08:20 PM
Other medications: Flowsheet Data as of [**2196-3-31**] 06:40 AM
Vital signs Hemodynamic monitoring Fluid balance 24 hours Since [**98**] AM
Tmax: 36.3 C (97.3 Tcurrent: 36.3 C (97.3
HR: 79 (79 - 92) bpm
BP: 115/45(62) {93/32(48) - 126/85(96)} mmHg
RR: 19 (18 - 29) insp/min
SpO2: 95%
Heart rhythm: SR (Sinus Rhythm)
Height: 62 Inch
Total In: 3,554 mL 2,328 mL
PO: TF: IVF: 179 mL 1,698 mL
Blood products: 375 mL 630 mL
Total out: 230 mL 191 mL
Urine: 230 mL 191 mL
NG: Stool: Drains:
Balance: 3,324 mL 2,137 mL
Respiratory support O2 Delivery Device: None
SpO2: 95%
ABG: ///27/

General: Alert, oriented, no acute distress
HEENT: Sclera anicteric, dry MM, oropharynx clear, dentures on upper teeth
Neck: supple, JVP not elevated, no LAD
Lungs: Clear to auscultation bilaterally, no wheezes, rales, rhonchi
CV: Regular rate and rhythm, normal S1 + S2, II/VI SEM LUSB, well-healed thoracotomy scar
Abdomen: soft, non-tender, very mildly distended, hyperactive bowel sounds, no rebound tenderness or guarding, no organomegaly appreciated
Ext: upper extremities WWP, 2+ pulses; LE cool with weak but palpable distal pulses
107 K/uL 12.6 g/dL 139 mg/dL 0.5 mg/dL 27 mEq/L 4.4 mEq/L 13 mg/dL 107 mEq/L 139 mEq/L 29.7 % 10.7 K/uL image002.jpg] [**2196-3-30**] 03:10 PM [**2196-3-30**] 09:25 PM [**2196-3-31**] 01:54 AM

WBC 10.7
Hct 30 35.9 29.7
Plt 107
Cr 0.5
Glucose 139

Other labs: PT / PTT / INR:13.5/28.2/1.2, ALT / AST:14/23, Alk Phos / T Bili:43/2.0, Lactic Acid:1.1 mmol/L, Albumin:3.0 g/dL, LDH:223 IU/L, Ca++:7.8 mg/dL, Mg++:1.7 mg/dL, PO4:3.9 mg/dL

Summary (medical expert):
GI bleed; CAD; UTI ; HTN; Osteoporosis

Summary (best model):
Gastrointestinal bleed; Hypotension; Anemia; CAD; COPD; Osteoporosis

Color key:

Blue: correct; exists in input + expert + model
Purple: correct; exists in input + expert only
Green: correct; exists in input + model only
Orange: incoherent or filler
Red: incorrect

Reader scores:

Attribute	Average	Example 1
Completeness	2.6	8
Correctness	0.4	6
Conciseness	0.6	2

Progress notes

Example 2: The model performed *worse* because it missed (**purple**) and hallucinated (**red**) several conditions.

Input:
<ASSESSMENT>
9yo woman with HCV cirrhosis s/p TIPS [**2153**] (MELD 15), with ESBL E. Coli of R hip, transferred to the MICU in the setting of progressive hypoxia now P.O.D. #3 for R ex-plant

<SUBJECTIVE>
Intraop hip cx: Coag neg Staph: Per ID, continue [**Last Name (un) **] and Vanc. Follow vanco levels (holding now [**1-7**] elevated trough)
- Weaned vent settings. On [**4-10**] all night. ABG to be obtained.
- TF held in case extubation
- Changed Insulin gtt to glargine with HISS
- Decreased steroids to 25 IV q12
- Transfused 3 bags platelets to keep >50
- Increased free water flushes for Hypernatremia
- Alkalosis stable, given Lasix 80mg IV x 1 in afternoon, 40IV this AM
- Shellfish Rash; Flexeril (Oral) (Cyclobenzaprine Hcl)
- Hepatic toxicit Tricyclic Compounds Unknown; f
- Review of systems is unchanged from admission except as noted below
- Review of systems: None

<OBJECTIVE>
Last dose of Antibiotics:
- Vancomycin - [**2158-9-21**] 08:14 PM
- Meropenem - [**2158-9-23**] 04:00 AM

Infusions:
- Other ICU medications:
  - Midazolam (Versed) - [**2158-9-22**] 05:05 AM
  - Furosemide (Lasix) - [**2158-9-22**] 12:36 PM
  - Fentanyl - [**2158-9-23**] 02:00 AM

Other medications:
- Flowsheet Data as of [**2158-9-23**] 04:31 AM
- Vital signs
- Hemodynamic monitoring
- Fluid balance 24 hours Since 12 AM

Tmax: 37.2 C (99 Tcurrent: 36.7 C (98.1
- HR: 86 (71 - 105) bpm
- BP: 149/70(99) {120/56(78) - 174/86(122)} mmHg
- RR: 16 (13 - 26) insp/min
- SpO2: 98%
- Heart rhythm: SR (Sinus Rhythm)
- Height: 62 Inch
- CVP: 4 (2 - 15)mmHg
- Total In: 2,394 mL 497 mL
- PO: TF: 965 mL 177 mL
- IVF: 505 mL 100 mL
- Blood products: 354 mL
- Total out: 2,650 mL 145 mL
- Urine: 2,300 mL 145 mL
- NG: Stool: 100 mL
- Drains: 250 mL
- Balance: -256 mL 352 mL

Respiratory support
- O2 Delivery Device: Endotracheal tube
- Ventilator mode: CPAP/PSV
- Vt (Spontaneous): 504 (425 - 539) mL
- PS : 5 cmH2O
- RR (Spontaneous): 16
- PEEP: 5 cmH2O
- FiO2: 40%
- RSBI: 38
- PIP: 11 cmH2O
- SpO2: 98%
- ABG: 7.50/53/95.[**Numeric Identifier 218**]/40/15
- Ve: 8.1 L/min
- PaO2 / FiO2: 238

General:
- Intubated, Sedated, opens eyes, awakens to voice, following commands
- HEENT: PEERL, Sclera icteric, MMM
- Neck: Supple. JVP 7-8cm
- Resp: Improving exam with coarse BS bilaterally and decreased scattered exp wheezes bilaterally
- Card: S1S2 2/6 systolic ejection murmur
- Abd: Soft, non-tender, distended, hypoactive BS
- Extr: [**1-8**]+ Lower and Upper extremity edema; Multiple ecchymoses on UEs. R hip VAC in place. RLE hematoma stable
- 38 K/uL 9.4 g/dL 216 mg/dL 0.5 mg/dL 40 mEq/L 3.5 mEq/L 34 mg/dL 104 mEq/L 146 mEq/L 26.2 % 7.3 K/uL
- WBC 8.8 7.6 7.3
- Hct 24.4 26.5 26.4 25.5 25.0 26.2
- Plt 66 60 45 66 40 38
- Cr 0.6 0.5 0.5 0.5
- TCO2 41 43 43
- Glucose 104 122 200 216

Other labs:
- PT / PTT / INR:23.3/36.9/2.3,
- CK / CKMB / Troponin-T:128//,
- ALT / AST:31/49,
- Alk Phos / T Bili:113/4.2,
- Amylase / Lipase:25/21,
- Differential-Neuts:91.0 %, Lymph:5.6 %, Mono:3.3 %, Eos:0.0 %,
- Fibrinogen:107 mg/dL,
- Lactic Acid:1.6 mmol/L,
- Albumin:3.4 g/dL,
- LDH:357 IU/L,
- Ca++:9.4 mg/dL,
- Mg++:2.1 mg/dL,
- PO4:2.6 mg/dL

Summary (medical expert):
S P Ex Plant; Acute Hypoxemic Respiratory Failure; pulmonary edema; Hep C cirrhosis; Diabetes

Summary (best model):
Hypoxia; Acute on chronic systolic and diastolic HF; Hypertension; Thrombocytopenia; Anemia; DM Type I; Eosinophilia

Color key:

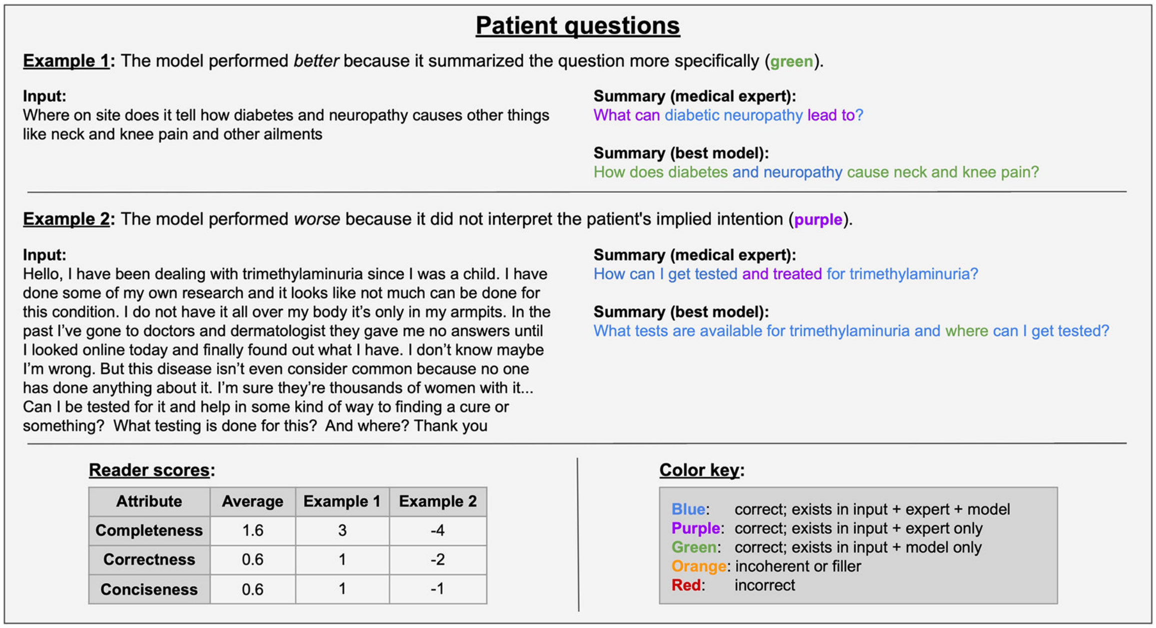
Blue: correct; exists in input + expert + model
Purple: correct; exists in input + expert only
Green: correct; exists in input + model only
Orange: incoherent or filler
Red: incorrect

Reader scores:

Attribute	Average	Example 2
Completeness	2.6	-5
Correctness	0.4	-7
Conciseness	0.6	-3

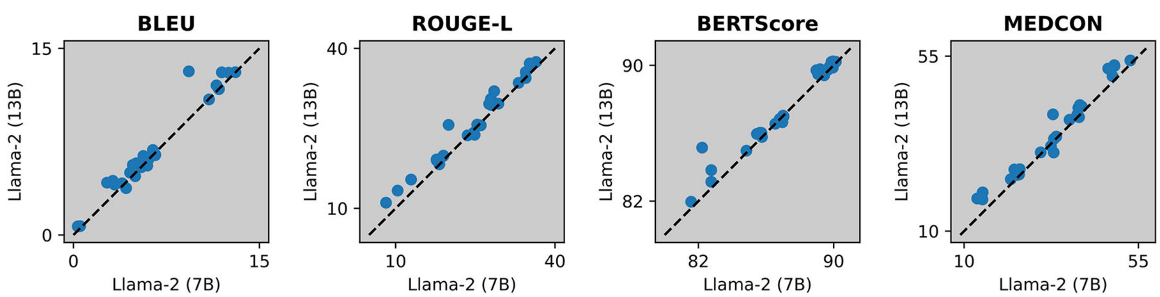
Extended Data Fig. 3 |. Annotation: progress notes.

Qualitative analysis of two progress notes summarization examples from the reader study. The table (lower right) contains reader scores for these examples and the task average across all samples.



Extended Data Fig. 4 |. Annotation: patient questions.

Qualitative analysis of two patient health question examples from the reader study. The table (lower left) contains reader scores for these examples and the task average across all samples.



Extended Data Fig. 5 |. Effect of model size.

Comparing Llama-2 (7B) vs. Llama-2 (13B). The dashed line denotes equivalence, and each data point corresponds to the average score of s = 250 samples for a given experimental configuration, that is {dataset x m in-context examples}.

Dialogue

Input:

[DOCTOR] hi , [PATIENT] , how are you ? [PATIENT] hi . good to see you . [DOCTOR] it's good to see you as well . so i know that the nurse told you about dax . i'd like to tell dax a little bit about you . [PATIENT] sure . [DOCTOR] okay ? so , [PATIENT] is a 62-year-old male with a past medical history significant for a kidney transplant , hypothyroidism , and arthritis , who presents today with complaints of joint pain . [PATIENT] , what's going on with your joint ? what happened ? [PATIENT] uh , so , over the the weekend , we've been moving boxes up and down our basements stairs , and by the end of the day my knees were just killing me . [DOCTOR] okay . is , is one knee worse than the other ? [PATIENT] equally painful . [DOCTOR] okay . [PATIENT] both of them . [DOCTOR] and did you , did you injure one of them ? [PATIENT] um , uh , i've had some knee problems in the past but i think it was just the repetition and the weight of the boxes . [DOCTOR] okay . all right . and , and what have you taken for the pain ? [PATIENT] a little tylenol . i iced them for a bit . nothing really seemed to help , though . [DOCTOR] okay . all right . um , and does it prevent you from doing , like , your activities of daily living , like walking and exercising and things like that ? [PATIENT] uh , saturday night it actually kept me up for a bit . they were pretty sore . [DOCTOR] mm-hmm . okay . and any other symptoms like fever or chills ? [PATIENT] no . [DOCTOR] joint pain ... i mean , like muscle aches ? [PATIENT] no . [DOCTOR] nausea , vomiting , diarrhea ? [PATIENT] no . [DOCTOR] anything like that ? [PATIENT] no . [DOCTOR] okay . all right . now , i know that you've had the kidney transplant a few years ago for some polycystic kidneys . [PATIENT] mm-hmm . [DOCTOR] um , how are you doing with that ? i know that you told dr. gutierrez- [PATIENT] mm . [DOCTOR] . a couple of weeks ago . [PATIENT] yes . [DOCTOR] everything's okay ? [PATIENT] so far , so good . [DOCTOR] all right . and you're taking your immunosuppressive medications ? [PATIENT] yes , i am . [DOCTOR] okay . all right . um , and did they have anything to say ? i have n't gotten any reports from them , so ... [PATIENT] no , n- nothing out of the ordinary , from what they reported . [DOCTOR] okay . all right . um , and in terms of your hyperthyroidism , how are you doing with the synthroid ? are you doing okay ? [PATIENT] uh , yes , i am . [DOCTOR] you're taking it regularly ? [PATIENT] on the clock , yes . [DOCTOR] yes . okay . and any fatigue ? weight gain ? anything like that that you've noticed ? [PATIENT] no , nothing out of the ordinary . [DOCTOR] okay . and just in general , you know , i know that we've kind of battled with your arthritis . [PATIENT] mm-hmm . [DOCTOR] you know , it's hard because you ca n't take certain medications 'cause of your kidney transplant . [PATIENT] sure . [DOCTOR] so other than your knees , any other joint pain or anything like that ? [PATIENT] every once in a while , my elbow , but nothing , nothing out of the ordinary . [DOCTOR] okay . all right . now i know the nurse did a review of systems sheet when you checked in . any other symptoms i might have missed ? [PATIENT] no . [DOCTOR] no headaches ? [PATIENT] no headaches . [DOCTOR] anything like that w- ... okay . all right . well , i wan na go ahead and do a quick physical exam , all right ? hey , dragon , show me the vital signs . so here in the office , your vital signs look good . you do n't have a fever , which is good . [PATIENT] mm-hmm . [DOCTOR] your heart rate and your , uh , blood pressure look fine . i'm just gon na check some things out , and i'll let you know what i find , okay ? [PATIENT] perfect . [DOCTOR] all right . does that hurt ? [PATIENT] a little bit . that's tender . [DOCTOR] okay , so on physical examination , on your heart exam , i do appreciate a little two out of six systolic ejection murmur- [PATIENT] mm-hmm . [DOCTOR] . which we've heard in the past . okay , so that seems stable . on your knee exam , there is some edema and some erythema of your right knee , but your left knee looks fine , okay ? um , you do have some pain to palpation of the right knee and some decreased range of motion , um , on exam , okay ? so what does that mean ? so we'll go ahead and we'll see if we can take a look at some of these things . i know that they did an x-ray before you came in , okay ? [PATIENT] mm-hmm . [DOCTOR] so let's take a look at that . [PATIENT] sure . [DOCTOR] hey , dragon , show me the right knee x-ray . so here's the r- here's your right knee x-ray . this basically shows that there's good bony alignment . there's no acute fracture , which is not surprising , based on the history . [PATIENT] mm-hmm . [DOCTOR] okay ? hey , dragon , show me the labs . and here , looking at your lab results , you know , your white blood cell count is not elevated , which is good . you know , we get concerned about that in somebody who's immunocompromised . [PATIENT] mm-hmm . [DOCTOR] and it looks like your kidney function is also very good . so i'm , i'm very happy about that . [PATIENT] yeah . [DOCTOR] okay ? so i just wan na go over a little bit about my assessment and my plan for you . [PATIENT] mm-hmm . [DOCTOR] so for your knee pain , i think that this is an acute exacerbation of your arthritis , okay ? so i wan na go ahead and if ... and prescribe some ultram 50 milligrams every six hours as needed . [PATIENT] okay . [DOCTOR] okay ? i also wan na go ahead and just order an autoimmune panel , okay ? hey , dragon , order an autoimmune panel . and you know , i , i want , i want you to just take it easy for right now , and if your symptoms continue , we'll talk about further imaging and possibly referral to physical therapy , okay ? [PATIENT] you got it . [DOCTOR] for your second problem , your hypothyroidism , i wan na go ahead and continue you on this ... on the synthroid , and i wan na go ahead and order some thyroid labs , okay ? [PATIENT] sure . [DOCTOR] hey , dragon , order a thyroid panel . and then for your last problem , the arthritis , you know , we just kinda talked about that . you know , it's gon na be a struggle for you because again , you ca n't take some of those anti-inflammatory medications because of your kidney transplant , so ... [PATIENT] mm-hmm . [DOCTOR] you know , let's see how we do over the next couple weeks , and again , we'll refer you to physical therapy if we need to , okay ? [PATIENT] you got it . [DOCTOR] you have any questions ? [PATIENT] not at this point . [DOCTOR] okay . hey , dragon , finalize the note.

Summary (medical expert):

ASSESSMENT AND PLAN

[PATIENT] is a 62-year-old male with a past medical history significant for a kidney transplant, hypothyroidism, and arthritis. He presents today with complaints of joint pain.

Arthritis.
- Medical Reasoning: The patient reports increased joint pain in his bilateral knees over the past weekend. Given that his right knee x-ray was unremarkable, I believe this is an acute exacerbation of his arthritis.
- Additional Testing: We will order an autoimmune panel for further evaluation.
- Medical Treatment: Initiate Ultram 50 mg every 6 hours as needed.
- Patient Education and Counseling: I advised the patient to rest his knees. If his symptoms persist, we can consider further imaging and possibly a referral to physical therapy.

Hypothyroidism.
- Medical Reasoning: The patient is doing well on Synthroid and is asymptomatic at this time.
- Additional Testing: We will order a thyroid panel.
- Medical Treatment: Continue Synthroid.

Status post renal transplant.
- Medical Reasoning: He is doing well and has been compliant with his immunosuppressive medications. On recent labs, his white blood cell count was within a normal limits and his kidney function is stable.
- Medical Treatment: Continue current regimen.

Summary (best model):

ASSESSMENT AND PLAN

[PATIENT] is a 62-year-old male with a past medical history significant for a kidney transplant, hypothyroidism, and arthritis. He presents today with complaints of joint pain.

Acute exacerbation of arthritis.
- Medical Reasoning: His right knee is swollen and erythematous, and he has pain with palpation and decreased range of motion. His recent history of physical exertion and the findings on his physical exam are consistent with an acute exacerbation of his arthritis.
- Additional Testing: I will order an autoimmune panel to rule out any autoimmune causes of his arthritis.
- Medical Treatment: I will prescribe Ultram 50 mg every six hours as needed for pain.

Hypothyroidism.
- Medical Reasoning: He has been stable on Synthroid.
- Additional Testing: I will order a thyroid panel to ensure his thyroid levels are within normal limits.
- Medical Treatment: Continue Synthroid at current dosage.

Kidney transplant.
- Medical Reasoning: His kidney function is good, and he has no signs of infection.
- Medical Treatment: Continue current immunosuppressive medications.
- Patient Education and Counseling: I advised him to take it easy and avoid physical exertion that could exacerbate his arthritis. If his symptoms continue, we will consider further imaging and possibly referral to physical therapy.

Extended Data Fig. 6 |. Example: dialogue.

Example of the doctor-patient dialogue summarization task, including ‘assessment and plan’ sections generated by both a medical expert and the best model.

Extended Data Table 1 |

Datasets, task instructions

Model	Context	Parameters	Proprietary?	Seq2seq	Autoreg.
FLAN-T5	512	2.7B	-	✓	-
FLAN-UL2	2,048	20B	-	✓	-
Alpaca	2,048	7B	-	-	✓
Med-Alpaca	2,048	7B	-	-	✓
Vicuna	2,048	7B	-	-	✓
Llama-2	4,096	7B, 13B	-	-	✓
GPT-3.5	16,384	175B	✓	-	✓
GPT-4	32,768 *	unknown	✓	-	✓

* The context length of GPT-4 has since been increased to 128,000.

We quantitatively evaluated eight models, including state-of-the-art seq2seq and autoregressive models. Unless specified, models are open source (versus proprietary).

Extended Data Table 2 |

Models

Dataset descriptions

Dataset	Task	Number of samples	Avg. number of tokens: Input	Avg. number of tokens: Target	Lexical variance
Open-i	Radiology reports	3.4K	52 ± 22	14 ± 12	0.11
MIMIC-CXR	Radiology reports	128K	75 ± 31	22 ± 17	0.08
MIMIC-III	Radiology reports	67K	160 ± 83	61 ± 45	0.09
MeQSum	Patient questions	1.2K	83 ± 67	14 ± 6	0.21
ProbSum	Progress notes	755	1,013 ± 299	23 ± 16	0.15
ACI-Bench	Dialogue	126	1,512 ± 467	211 ± 98	0.04

Task Instructions

Task	Instruction
Radiology reports	“Summarize the radiology report findings into an impression with minimal text.”
Patient questions	“Summarize the patient health query into one question of 15 words or less.”
Progress notes	“Based on the progress note, generate a list of 3–7 problems (a few words each) ranked in order of importance.”
Dialogue	“Summarize the patient/doctor dialogue into an assessment and plan.”

Top, description of six open-source datasets with a wide range of token Length and Lexical variance, or the ratio of unique words to total words. Bottom, instructions for each of the four summarization tasks.

Extended Data Table 3 |

Individual reader scores

Task	Reader	Completeness	Correctness	Conciseness
Radiology reports	1	3.5 ± 5.6	1.7 ± 3.6	1.2 ± 4.8
	2	3.6 ± 6.6	2.5 ± 4.7	−0.3 ± 5.4
	3	0.8 ± 2.9	0.6 ± 3.2	−1.7 ± 3.0
	4	4.7 ± 4.7	2.9 ± 3.9	1.2 ± 3.8
	5	1.4 ± 4.0	0.6 ± 2.2	−0.6 ± 3.4
	Pooled	2.8 ± 5.1 *	1.7 ± 3.7 *	0.0 ± 4.3
	ICC	0.45	0.58	0.48
Patient questions	1	1.7 ± 7.2	0.6 ± 3.4	0.3 ± 3.4
	2	1.0 ± 5.6	−0.1 ± 3.6	0.1 ± 3.6
	3	2.3 ± 7.2	2.0 ± 5.3	2.2 ± 5.9
	4	1.9 ± 6.7	0.0 ± 0.0	0.0 ± 0.0
	5	0.9 ± 5.7	0.4 ± 3.6	0.4 ± 3.6
	Pooled	1.6 ± 6.5 *	0.6 ± 3.7 *	0.6 ± 3.9 *
	ICC	0.67	0.31	0.21
Progress notes	1	3.4 ± 7.5	0.5 ± 2.5	0.1 ± 4.5

Task	Reader	Completeness	Correctness	Conciseness
	2	2.3 ± 6.5	0.6 ± 4.4	0.4±4.2
	3	2.7 ± 6.3	1.0 ± 4.4	0.9 ± 3.7
	4	2.5 ± 7.2	0.5 ± 6.8	1.7 ± 6.9
	5	2.0 ± 6.8	−0.8 ± 4.5	−0.1 ± 1.2
	Pooled	2.6 ± 6.9 *	0.4 ± 4.8	0.6 ± 4.5 *
	ICC	0.77	0.74	0.42
Overall	Pooled	2.3 ± 5.8 *	0.8 ± 3.7 *	0.4 ± 4.0 *
	ICC	0.63	0.56	0.38

Reader study results evaluating completeness, correctness and conciseness (columns) across individual readers and pooled across readers. Scores are on the range [−10, 10], where positive scores denote that the best model is preferred to the medical expert. Asterisks (*) on pooled rows denote statistical significance by a one-sided Wilcoxon signed-rank test, $P < 0.001$. Intra-class correlation (ICC) values across readers are on a range of [−1, 1] where −1, 0 and +1 correspond to negative, no and positive correlations, respectively.

Extended Data Table 4 |

Summarization baselines

Dataset	Baseline	BLEU	ROUGE-L	BERTScore	MEDCON
Open-i	Ours	46.0	**68.2**	94.7	64.9
	ImpressionGPT [52]	-	65.4	-	-
MIMIC-CXR	Ours	**29.6**	**53.8**	**91.5**	55.6
	RadAdapt [27]	18.9	44.5	90.0	-
	ImpressionGPT [52]	-	47.9	-	-
MIMIC-III	Ours	11.5	34.5	89.0	36.5
	RadAdapt [27]	**16.2**	**38.7**	**90.2**	-
	Med-PaLM M [25]	15.2	32.0	-	-
Patient questions	Ours	10.7	37.3	92.5	59.8
	ECL° [53]	-	**50.5**	-	-
Progress notes	Ours	3.4	27.2	86.1	31.5
	CUED [54]	-	**30.1**	-	-
Dialogue	Ours	26.9	42.9	90.2	**59.9**
	ACI-Bench° [41]	-	**45.6**	-	57.8

Comparison of our general approach (GPT-4 using ICL) against baselines specific to each individual dataset. We note that the focal point of our study is not to achieve state-of-the-art quantitative results, especially given the discordance between NLP metrics and reader study scores. A dash (-) indicates that the metric was not reported; a ° indicates that the dataset was pre-processed differently.

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Data availability

This study used six datasets that are all publicly accessible at the provided references. Three of those datasets require PhysioNet[81] access due to their terms of use: MIMIC-CXR[73] (radiology reports), MIMIC- III[76] (radiology reports) and ProbSum[79] (progress notes). For the other three datasets not requiring PhysioNet access—Open-i[72] (radiology reports), MeQSum[77] (patient questions) and ACI-Bench[41] (dialogue)—researchers can access original versions via the provided references, in addition to our data via the following GitHub repository: https://github.com/StanfordMIMI/clin-summ. Note that any further distribution of datasets is subject to the terms of use and data-sharing agreements stipulated by the original creators.

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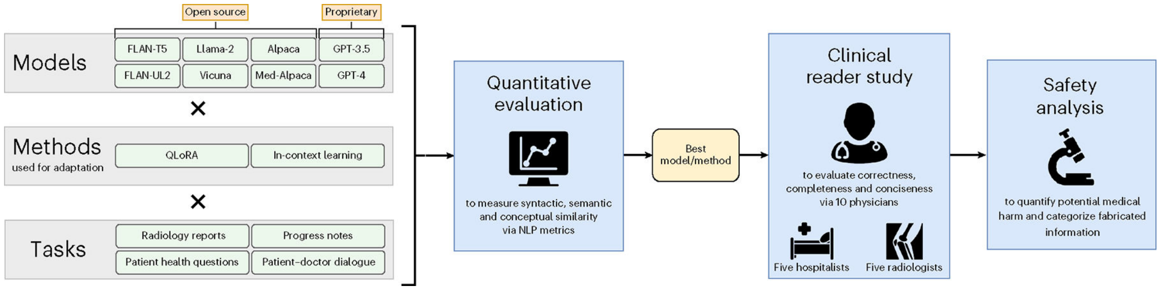

Fig. 1 |. Framework overview.

First, we quantitatively evaluated each valid combination (×) of LLM and adaptation method across four distinct summarization tasks comprising six datasets. We then conducted a clinical reader study in which 10 physicians compared summaries of the best model/method against those of a medical expert. Lastly, we performed a safety analysis to categorize different types of fabricated information and to identify potential medical harm that may result from choosing either the model or the medical expert summary.

Expertise	You are an expert medical professional.
Instruction (task-specific)	Summarize the [radiology report findings] into an [impression with minimal text].
Examples $i = 1, \ldots, m$ #: delimiters for ICL only, else $m = 0$	Use the examples to guide word choice. ... input i: [example input] summary i: [example summary] ## ...
Input	... input $m+1$: [input text] summary $m+1$: [summarized text]

Parameter	Value	BLEU	ROUGE-L	BERTScore	MEDCON
Temperature	0.1	4.9	28.1	89.6	28.2
	0.5	4.9	27.1	89.7	27.5
	0.9	4.3	25.4	89.3	25.3
Expertise	None	10.4	34.3	90.2	30.7
	Medicine[1]	11.1	35.5	90.5	35.5
	Wizardry[2]	4.3	27.8	89.7	28.5

1: "You are an expert medical professional." 2: "You are a mystical wizard in Middle Earth."

Fig. 2 |. Model prompts and temperature.

Left, prompt anatomy. Each summarization task uses a slightly different instruction. Right, model performance across different temperature values and expertise.

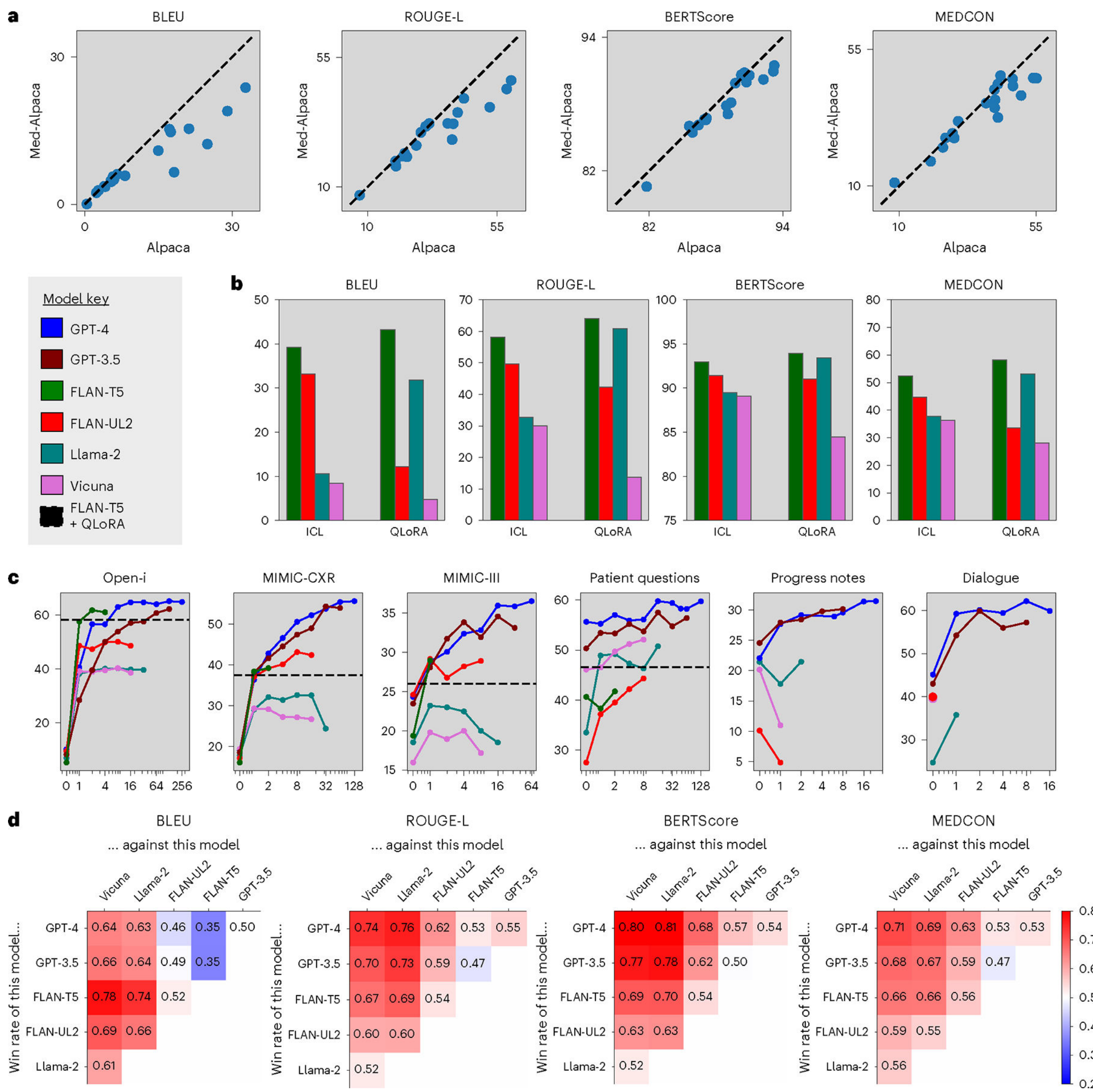

Fig. 3 |. Identifying the best model/method.

a, Impact of domain-specific fine-tuning. Alpaca versus Med-Alpaca. Each data point corresponds to one experimental configuration, and the dashed lines denote equal performance. **b**, Comparison of adaptation strategies. One in-context example (ICL) versus QLoRA across all open-source models on the Open-i radiology report dataset. **c**, Effect of context length for ICL. MEDCON scores versus number of in-context examples across models and datasets. We also included the best QLoRA fine-tuned model (FLAN-T5) as a horizontal dashed line for valid datasets. **d**, Head-to-head model comparison. Win percentages of each head-to-head model combination, where red/blue intensities highlight the degree to which models on the vertical axis outperform models on the horizontal axis.

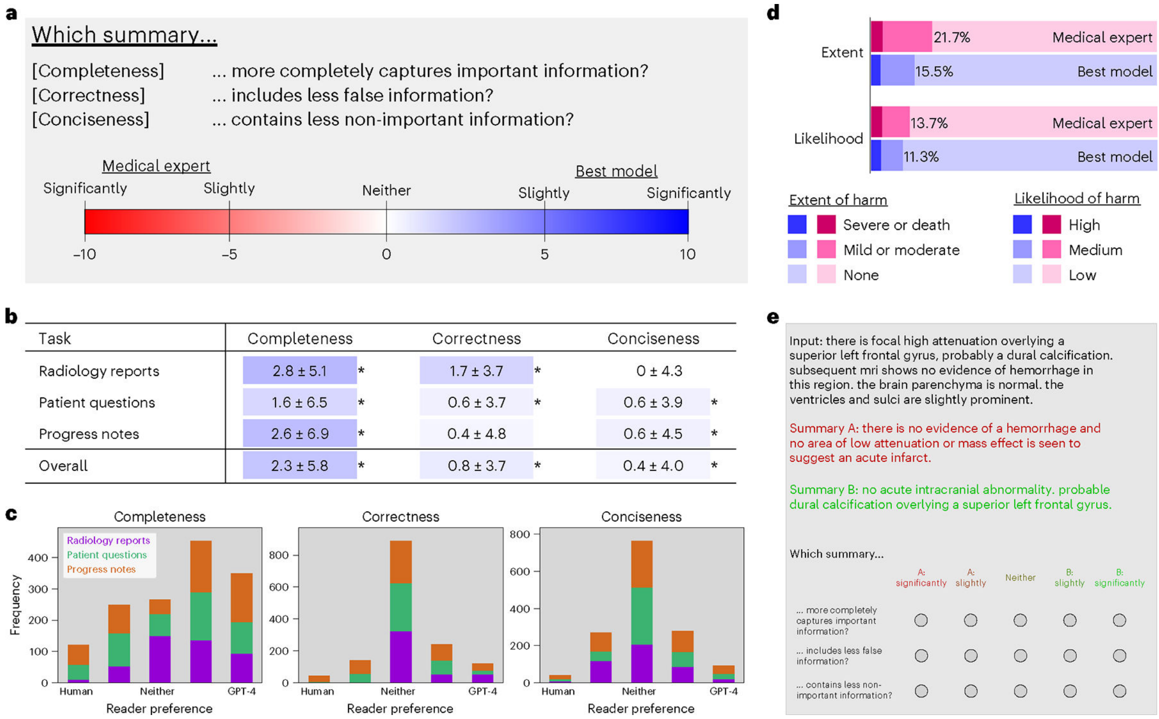

Fig. 4 |. Clinical reader study.

a, Study design comparing summaries from the best model versus that of medical experts on three attributes: completeness, correctness and conciseness. **b**, Results. Highlight colors correspond to a value's location on the color spectrum. Asterisks (*) denote statistical significance by a one-sided Wilcoxon signed-rank test, $P < 0.001$. **c**, Distribution of reader scores for each summarization task across attributes. Horizontal axes denote reader preference as measured by a five-point Likert scale. Vertical axes denote frequency count, with 1,500 total cases for each plot. **d**, Extent and likelihood of possible harm caused by choosing summaries from the medical expert (pink) or best model (purple) over the other. **e**, Reader study user interface.

Radiology reports

Example 1: The model performed *better* because the medical expert made a laterality mistake (red).

Input:
The patient is s/p left frontal craniotomy. A small amount of intracranial gas is seen posterior to the surgical intervention, which could represent postoperative changes. Extensive edema is seen in the left frontal lobe at the site of presumed surgery. Additionally multiple foci of hemorrhage are seen in the region of the left frontal lobe. Midline shift to the right is seen in the frontal region. The ventricles, cisterns, and sulci are unremarkable, without effacement. Comparison with prior studies from outside institution would be helpful in further evaluation of these findings.

Summary (medical expert):
1. Left frontal craniotomy. 2. Frontal midline shift to the right. 3. Extensive left frontal lobe edema. 4. Multiple foci of hemorrhage in the right frontal lobe.

Summary (best model):
Postoperative changes following left frontal craniotomy with intracranial gas, extensive edema, and multiple foci of hemorrhage in the left frontal lobe. Midline shift to the right is noted.

Example 2: The model performed *worse* because it was less concise, i.e. included non-important information (green).

Input:
Right frontoparietal craniotomy again identified, with decreasing pneumocephalus and small amount of subdural fluid. There is persistent mild leftward shift of approximately 2–3 mm, not significantly changed from prior study. Size and configuration of the ventricles is unchanged from prior study. There is no new hemorrhage. Multiple facial fractures, better evaluated on prior dedicated maxillofacial CT. Increasing opacification is seen in the ethmoid and sphenoid sinuses. Large right subgaleal hematoma again identified.

Summary (medical expert):
Postoperative changes in the right frontoparietal region identified, with decreasing pneumocephalus. No new hemorrhage. Persistent mild leftward shift, not significantly changed from prior.

Summary (best model):
Stable post-craniotomy changes with decreasing pneumocephalus and persistent mild leftward shift. No new hemorrhage. Increasing opacification of ethmoid and sphenoid sinuses. Large right subgaleal hematoma unchanged.

Reader scores:

Attribute	Average	Example 1	Example 2
Completeness	2.8	5	–1
Correctness	1.7	8	0
Conciseness	0	0	–4

Color key:

- Blue: Correct; exists in input + expert + model
- Purple: Correct; exists in input + expert only
- Green: Correct; exists in input + model only
- Orange: Incoherent or filler
- Red: Incorrect

Fig. 5 |. Annotation: radiology reports.

Qualitative analysis of two radiologist report examples from the reader study. The table (lower left) contains reader scores for these two examples and the task average across all samples.

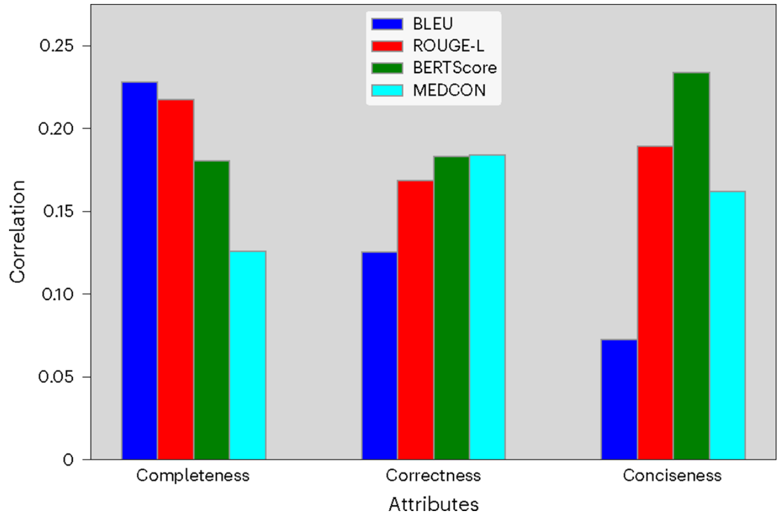

Fig. 6 |. Connecting NLP metrics and reader scores.

Spearman correlation coefficients between quantitative metrics and reader preference assessing completeness, correctness and conciseness.