Process-Supervised Reward Models for Verifying Clinical Note Generation: A Scalable Approach Guided by Domain Expertise

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Abstract

Process-supervised reward models (PRMs) excel at providing step-by-step verification for large language model (LLM) outputs in domains like mathematics and coding. However, their application to fields lacking ground-truth answers, such as clinical note generation, poses significant challenges. We introduce a novel framework for training PRMs to deliver step-level reward signals for LLM-generated clinical notes. By precisely defining meaningful "**steps**," injecting realistic "**errors**" informed by domain expertise, and leveraging LLMs to generate process supervision data at scale, we overcome previous limitations. **Our PRM, built on LLaMA-3.1 8B, consistently outperforms proprietary reasoning and non-reasoning models**, achieving state-of-the-art (SOTA) performance on two key evaluations: (1) distinguishing gold-standard from error-containing samples with 98.8% accuracy, and (2) selecting physician-preferred clinical notes with 56.2% accuracy. We investigate critical components for effective PRM training, including optimal loss functions and data selection strategies, and present a comprehensive physician reader study identifying predictors of downstream Best-of-N performance. Our study sheds light on unlocking the potential of PRMs for diverse generative tasks across domains.[1]

1 Introduction

LLMs show promise in generating clinical notes (Van Veen et al., 2024), but their outputs may contain errors and misalign with physician preferences (Omiye et al., 2024; Jin et al., 2024). Currently, no automated, scalable method exists to evaluate the quality of LLM-generated clinical notes, leaving manual evaluation the gold standard. Consequently, costly clinician reader studies are required to validate LLM-based products, such as ambient AI scribes (Liu et al., 2024). This challenge is amplified by the rapid adoption of ambient scribing technology in the real world (Tierney et al., 2025), with projections indicating that 30% of the healthcare market will use LLM-generated clinical notes by 2025 (Beavins, 2024).

A potential solution to this challenge is to verify LLM outputs using a reward model (RM). RMs are integral to reinforcement learning for LLM post-training (Ouyang et al., 2022; Stiennon et al., 2020). When employed as verifiers, RMs are categorized into two types: outcome-supervised reward models (ORMs) (Cobbe et al., 2021) and, more recently, process-supervised reward models (PRMs) (Lightman et al., 2023). ORMs evaluate an entire generation and assign a single reward score at the end, whereas PRMs provide reward scores at each step of the generation, offering several notable advantages. PRMs enable fine-grained verification of LLM outputs, improving explainability by pinpointing errors at their exact location. This step-wise reward signaling also facilitates inference-time scaling, such as Monte Carlo Tree Search (MCTS), and supports step-by-step reinforcement learning (Wang et al., 2023b; Snell et al., 2024).

However, despite significant success in mathematical and coding tasks (Lightman et al., 2023; Wang et al., 2023b; Ma et al., 2023), the application of PRMs to other domain remains underexplored (Beeching et al.). This gap arises from several key challenges: (1) **Verification of correctness**: Unlike mathematical or coding problems, which have objective ground-truth answers, verifying correctness in open-ended generative tasks is inherently more complex. (2) **Process-supervised data collection**: Training PRMs requires datasets with annotations for each step of the answer, which makes it difficult to scale when relying on human annotators.

To address these challenges, we introduce a novel framework for training PRMs to verify open-

[1]Our code is available at https://github.com/hanyin88/prm-clinic.

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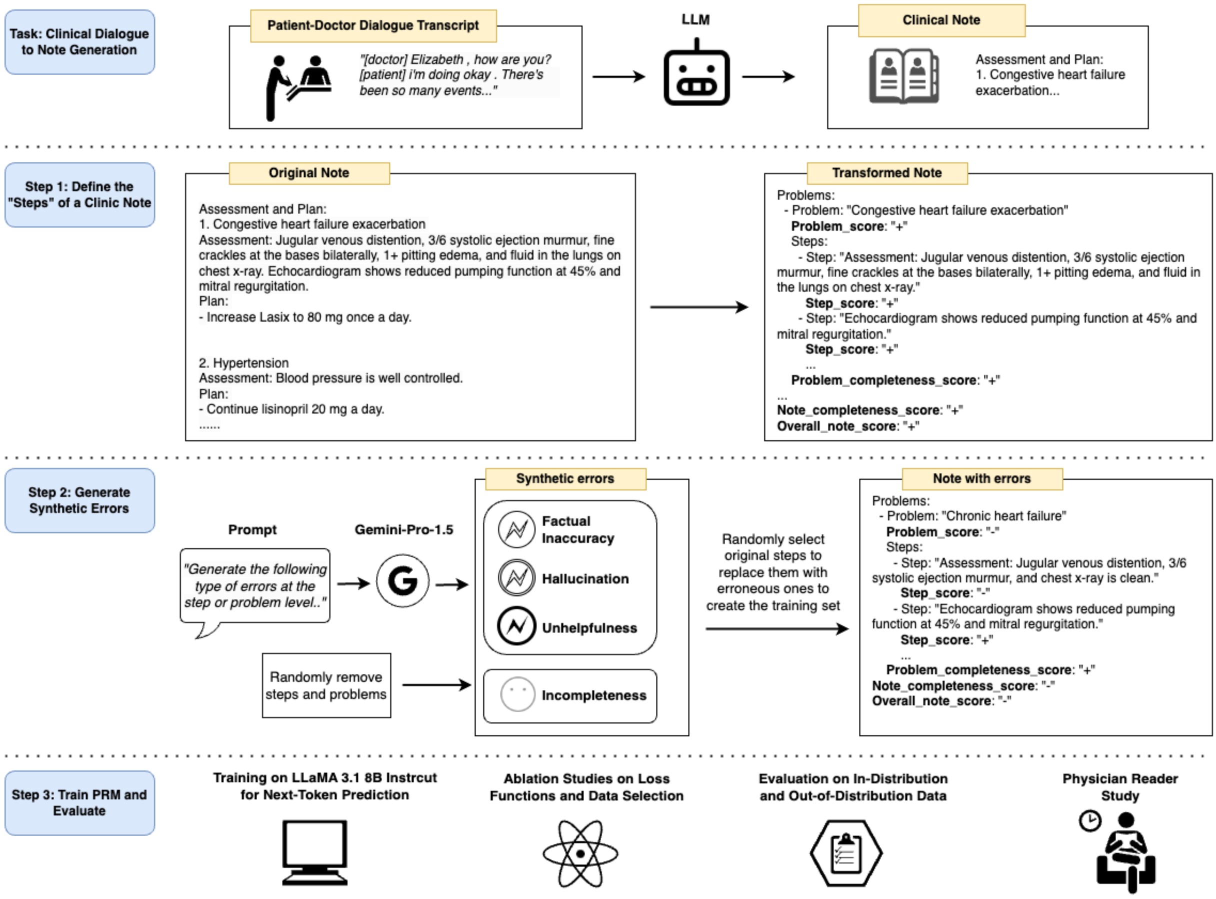

Figure 1: Overview of study design. We train a PRM to step-by-step verify clinical notes generated by LLMs from patient-doctor dialogues. **Step 1**: Clinical notes are transformed into a hierarchical structure of steps, designed based on domain expertise to capture the key considerations in clinical documentation. **Step 2**: Gemini Pro 1.5 is utilized to generate synthetic errors from predefined categories. These errors are systematically swapped with the original steps to create negative samples. **Step 3**: The PRM is trained using LLaMA-3.1 8B instruct, followed by ablation studies and a physician reader study.

ended text generation in the clinical domain (Figure 1). We specifically target the rapidly growing use case of **ambient scribing**, where LLMs generate clinical notes from patient-doctor dialogues (Barr et al., 2024). Drawing on domain expertise, we carefully design clinically meaningful "steps" and inject realistic "errors" to reflect authentic documentation practices. To scale supervision, we employ an LLM to generate process-labeled data by systematically introducing errors into high-quality reference notes. Our main contributions are as follows:

1. Our PRM, built on LLaMA-3.1 8B, significantly outperforms both proprietary reasoning and non-reasoning models for clinical note verification. It achieves 98.8% accuracy in detecting erroneous samples and 56.2% accuracy in selecting physician-preferred notes, setting a new SOTA in this critical domain.

2. We broaden the scope of PRMs beyond domains with clear ground-truth answers, introducing a generalizable framework that integrates LLMs with domain knowledge to generate process-supervised data at scale.

3. To support future research, we release our full dataset, including process supervision annotations and physician preference labels.

2 Background and Related Work

Verify LLM Outputs Step-by-Step Recent research highlights a growing interest in process supervision of LLMs to improve their reasoning capabilities. In contrast to earlier work on ORMs (Cobbe et al., 2021; Yu et al., 2024), PRMs assess the correctness of LLM outputs step-by-step (Lightman et al., 2023; Uesato et al., 2022). One of the core applications of PRMs is Best-of-N sampling, where N complete solutions are generated, and the most suitable one is selected based on the PRM's reward signal. This method has proven exceptionally effective in mathematical reasoning and code generation tasks, frequently surpassing ORMs (Wang et al., 2023b; Ma et al., 2023). Furthermore, PRMs can facilitate step-level reinforcement learning and guide inference-time scaling through techniques such as MCTS (Wang et al., 2023b; Ma et al., 2023; Snell et al., 2024). They are considered crucial to the success of advanced reasoning models (Jiang et al., 2024; Qin et al., 2024; Wang et al., 2024b).

Process-Supervised Data Acquiring human-labeled annotations for each step of PRM training data poses a prohibitive scaling cost, a challenge central to our work. To address this limitation, several studies have proposed methods to automatically generate process supervision data, using techniques such as Monte Carlo estimation (Wang et al., 2023b; Luo et al., 2024; Wang et al., 2024c). However, these approaches are primarily confined to the mathematical domain, where they are effective due to the unambiguous and easily verifiable nature of mathematical solutions. Our exploration of PRM is also related to prior work on evaluating step-by-step reasoning chains (Hao et al., 2024), though our focus is on open-ended text generation tasks, which present unique challenges.

Generate Clinical Note From Dialogue Ambient scribe systems that transcribe patient-provider conversations into clinical notes are among the most impactful applications of LLMs in healthcare, offering substantial reductions in documentation burden (Barr et al., 2024; Tierney et al., 2025). This task was explored at the 2023 ACL ClinicalNLP and CLEFImage workshops, where the best results were achieved using proprietary models (Abacha et al., 2023; Yim et al., 2023a). Recent studies also show promise in fine-tuning open-source LLMs to generate expert-level clinical notes (Wang et al., 2024a, 2023a; Li et al., 2024), though challenges such as inaccuracies and hallucinations remain.

3 Our Approach: Building PRMs to Verify Clinical Note Generation

In this section, we first introduce the task, followed by an explanation of the core method for constructing the process supervision dataset. We then discuss the training, usage, and evaluation methods for PRMs. An overview of our study is illustrated in Figure 1.

3.1 Problem Formation

Given a patient-doctor dialogue, an LLM can generate clinical notes comparable to those written by physicians. We aim to train PRMs to effectively verify LLM-generated notes step-by-step, enabling them to evaluate multiple candidates and select the most accurate and physician-preferred note. Guided by recent work (see details in Appendix D.3), we target the most challenging "Assessment and Plan" (A&P) section of the note.

Top-Scoring Sample: PRM Score Greater than 0.5 for Each Step

1. Neck strain
Assessment: Patient presented with neck pain after a car accident...
Plan:
-Will start Motrin 600mg Q6H and Flexeril 10mg Q12H as needed.
- Recommend rest and ice pack application to the affected area.
- Order MRI to rule out any structural injury.
...
Follow-up instructions:
- Return to clinic in 1 week for follow-up.

A Sample with Erroneous Steps and Their PRM Scores

Problem_1: Neck strain
Step_3: Will start patient on NSAID (ibuprofen) ... ice pack, heat wrap, and neck brace.
Step_Score: 0.0067
Error: Hallucination about treatments
Problem_Completeness_Score: 0.1066
Error: Omission of MRI in the plan

Problem_2: Mild postconcussive syndrome
Problem_Score: 0.0097
Error: Inaccurate description of the problem
Step_1: Patient ... reported hearing losses, visual disturbances, and memory loss.
Step_Score: 0.0022
Error: Hallucination about symptoms
Step_3: Referral to neurologist for further evaluation and treatment.
Step_Score: 0.0293
Error: Hallucination about referring to neurologist

Problem_3: Follow-up instructions
Step_1: Return to clinic in 1 month, unless symptoms improve sooner.
Step_Score: 0.0067
Error: Factual inaccuracy about follow-up timing

Figure 2: Two notes to the same dialogue, graded by the PRM. In the top-scoring sample, the note is accurate and concise, with the PRM score (probability of a "+" score for a given step) exceeding 0.5 for each step. In the negative sample, various errors occur across steps, and PRM effectively assigns low scores to those erroneous steps. Items ending in **_Score** represent the PRM score assigned to each step.

3.2 Training Data Construction

Base Dataset We utilized the Dialogue-G dataset and modified ACI-BENCH (Wang et al., 2024a; Yim et al., 2023b). These datasets comprise synthetic transcripts of patient-doctor dialogues and corresponding notes generated by Gemini Pro 1.0, strictly adhering to the "Best Practice" format recommended by a panel of internal medicine physicians. The original notes from these datasets are considered the *gold-reference*.

Define Steps Unlike mathematical problems, where each solution step is typically a single sentence, the concept of a "step" in an open-ended text generation task is less clear. The A&P sections of clinical notes are semi-structured, consisting of multiple problems, each encompassing several clinical reasoning narratives related to their assessment and plan (Figure 1 and 2). While various design options exist, we adopted a heuristic approach informed by physician expertise (see Section D.4 for details), as outlined below.

1. The description of each problem is treated as a step, reflecting the importance of the problem list, which is critical for various medical coding and insurance purposes.

2. Within each problem, every sentence constitutes an individual step.

3. After all sentences within each problem, we include a **problem-level completeness** step. Similarly, after addressing all problems, we add a **note-level completeness** step. This design aims to prevent the reward model from favoring shorter but incomplete answers.

4. At the end of the note, we introduce an **end-of-note** step, with its score label representing the overall quality of the note.

Introduce Errors Through discussions with clinical experts who reviewed LLM-generated notes, we identified three common types of errors:

- **Factual Inaccuracy**: Errors involving incorrect information that are referenced in the conversation but not supported by its content.

- **Hallucination**: Introduction of entirely unrelated subject entities that were not mentioned in the conversation.

- **Unhelpfulness**: Expressions that are vague, incomplete, confusing, or lacking critical details.

We tasked Gemini Pro 1.5 (Team et al., 2024) with generating a pool of unique errors for each error type in each case. This was achieved through careful prompt engineering and manual inspection of the errors by our physician co-authors. Subsequently, we randomly swapped original steps in the gold-reference notes with entries from the error pools, ensuring that each error was used only once. At this stage, we introduced a fourth error type, **Incompleteness**, by randomly removing specific steps or entire problems from the samples.

Introduce Semantic Diversity Lastly, we tasked Gemini Pro 1.5 with generating a pool of paraphrased sentences to enhance the semantic diversity of the notes. These paraphrases were designed to convey the same information as the original sentences without introducing any new content. We randomly replaced the remaining correct steps in the samples with these paraphrases.

	Counts
Total No. of cases by data source	
ACI-BENCH	67
Dialogue-G	1205
Total No. of samples	9680
Mean No. of samples per case	7.61
Mean No. of errors per sample	
Factual Inaccuracy	1.16
Hallucination	1.18
Unhelpfulness	1.19
Incompleteness	1.27
Mean No. of paraphrases per sample	2.38

Table 1: Summary statistics of PRM-Clinic. The reported numbers are calculated solely from negative samples. Samples from the same case share the same dialogues. During training, gold-reference samples are randomly mixed with negative samples.

Step Scores Each step is assigned a **score label** of "+" or "−". The "+" label represents a correct step, and the "−" label indicates an incorrect or incomplete step. For gold-reference samples, every step receives a "+" label. For samples containing errors, the erroneous step is assigned a score label of "−". For samples with incompleteness, we also assign the corresponding problem-level or note-level completeness score label to "−". Lastly, for any samples containing errors, we assign a score label of "−" to the end-of-note step.

PRM-Clinic Dataset We named our final dataset PRM-Clinic and present its statistics in Table 1. Cases derived from Dialogue-G account for 95.1% of the total instances. For ACI-BENCH, we utilized its training subset (Yim et al., 2023b), but with clinical notes generated using Gemini Pro 1.0 (Wang et al., 2024a).

3.3 Training of PRMs

Training Objective The model is trained using a standard pretraining process to optimize the cross-entropy loss:

$$L = -\sum_{i \in I} \log p_\theta(t_i \mid t_{<i}),$$

Tasks	Reference Type	Data Source	Case Counts	Data Distribution	Notes
A-Prefer	Physician-preference	ACI-BENCH test2 and test3 subsets	80	OOD	Includes physician preference data used in the first round of RLHF in (Wang et al., 2024a). Each case contains three notes generated by an early phase of LLaMA-Clinic.
A-Verify	Gold-reference	ACI-BENCH test2 and test3 subsets	80	OOD	Gold-reference notes generated by an later phase of LLaMA-Clinic. Negative samples are introduced in the same manner as PRM-Clinic.
Dialogue-G	Gold-reference	Dialogue-G testing subset	80	ID	Data constructed in the same manner as PRM-Clinic.
A-Validate	Gold-reference	ACI-BENCH validation subset	20	ID	Data constructed in the same manner as PRM-Clinic.

Table 2: Details of the evaluation tasks. For A-Prefer, A-Verify, and A-Validate, we utilized the original dialogues from the ACI-BENCH dataset. For ID tasks, the notes are generated by Gemini Pro, while for OOD tasks, the notes are generated by LLaMA-Clinic. ID: In-distribution. OOD: Out-of-distribution.

where $\{t_1, t_2, \ldots, t_N\}$ denotes the sequence of tokens in the dataset. The model predicts the probability of the next token given the previous tokens, represented as $p_\theta(t_i \mid t_{<i})$, with θ being the model parameters and $t_{<i} = \{t_1, t_2, \ldots, t_{i-1}\}$. The summation is taken over a set of token positions I.

Training Details The training corpus consists of dialogue concatenated with clinical notes, where each step in the notes is separated by a step token followed by a score label token. We used LLaMA-3.1 8B Instruct (Dubey et al., 2024) as the base model, utilizing its reserved special tokens for all step and score label tokens. Further implementation details can be found in Section B.

3.4 Usage of PRMs

Use PRMs at Inference Time At inference time, we perform a single PRM forward pass over the entire clinical note to obtain PRM's predicted score label for each step. The clinical note itself is generated by a separate LLM. We define the **PRM score** as the probability that a given step is correct, which is the softmax probability of the special "+" token at that step position.

Use Model as PRM or ORM To compare multiple notes, it is necessary to compute a single note-level score. A key implementation decision is whether to use the reward model as an **ORM**, which applies when the PRM score at the final end-of-note step serves as the note-level score. In contrast, for PRM, the note-level score is computed as the product of all step-level PRM scores. We experimented with various scoring strategies and found that the product of step-level scores yielded the best results (Appendix C.2).

3.5 Evaluation of PRMs

Evaluation Metrics We evaluated the reward model's ability to select the superior note within the Best-of-N framework using two key metrics: (1) **Accuracy of selecting the gold-reference note**, which measures the model's ability to identify the gold-reference note among error-containing samples (i.e., negative samples), and (2) **Accuracy of selecting the physician-preferred note**, which assesses its capability to identify the physician-preferred note from a set of candidate notes.

Notably, the task can be categorized as either in-distribution (ID) or out-of-distribution (OOD). Since our training dataset was developed using the Gemini Pro model family, tasks involving clinical notes generated by other models are considered OOD. For OOD tasks, we used outputs from LLaMA-Clinic. LLaMA-Clinic is a LLaMA-2 13B model that underwent comprehensive domain adaptation for clinical dialogue-to-note generation (Wang et al., 2024a). The details of the evaluation dataset are shown in Table 2.

Baseline We compare our PRM against several strong baselines, including LLM-as-a-judge setups using Gemini Pro 1.0 (Team et al., 2023), Gemini Pro 1.5 (Team et al., 2024), OpenAI's GPT-4o (Hurst et al., 2024), o1 (Jaech et al., 2024), and o3-mini (OpenAI, 2025). Additionally, we evaluate a

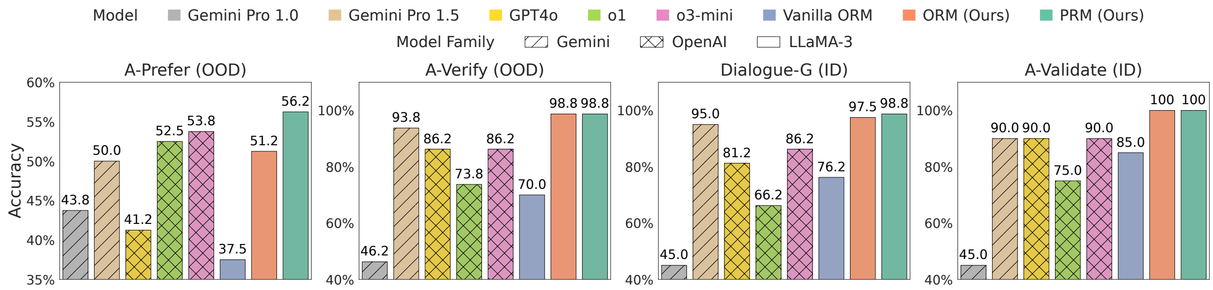

Figure 3: Main results. Our PRM outperforms all baseline models, including the vanilla ORM, Gemini Pro 1.5, and SOTA reasoning models, across all evaluated tasks. For A-Prefer, the task involves selecting the physician-preferred note from three candidate notes. For all other tasks, the objective is to identify the correct gold-reference sample from negative samples. For ID tasks, the notes are generated by Gemini Pro, while for OOD tasks, the notes are generated by LLaMA-Clinic. The results of the best-performing PRM are presented alongside the ORM results from the same checkpoint. ID: In-distribution. OOD: Out-of-distribution.

vanilla ORM implementation, where the training corpus lacks step-level annotations and includes only a single score for the entire clinical note. For our ablation studies, we directly compare the performance of PRMs and ORMs derived from the same model checkpoint.

Physician Reader Study To identify predictors of downstream Best-of-N performance, we conducted a comprehensive reader study involving nine physicians. For each case, LLaMA-Clinic (Wang et al., 2024a) generated 2,000 notes from the same patient-provider dialogue. We then used various PRM checkpoints to select the top-scoring note for physician evaluation. Each experiment was conducted in a randomized and blinded manner, involving at least three physicians. Additional details are provided in Section 4.3.

4 Experimental Results

4.1 Main Results

Comparison with Baselines We present the main results in Figure 3. **Our PRM consistently outperforms all baselines across all tasks**, including the vanilla ORM, Gemini Pro 1.5, and SOTA reasoning models. Our analysis focuses on PRM performance in OOD settings (A-Verify and A-Prefer), given its near-perfect accuracy in the two ID verification tasks (Dialogue-G and A-Validate). Despite the inherent challenges of OOD tasks, PRM exhibits strong generalization, achieving 98.8% accuracy on the A-Verify task (compared to 93.8% for Gemini Pro 1.5). Among all tasks, A-Prefer proves to be the most challenging, reflecting the complexity of physician preferences. Here, PRM achieves 56.2% accuracy in selecting physician-preferred notes (compared to 50.0% for Gemini Pro 1.5). We discuss the explanation for the strong OOD performance in Section C.3. Importantly, while we utilized Gemini Pro 1.5 to generate synthetic data for PRM training, our results demonstrate that **PRMs significantly outperform Gemini Pro 1.5 itself**. This suggests that the proprietary model used for data generation doesn't impose an inherent upper bound on PRM performance within our methodology.

PRM vs. ORM Our model can function as either an ORM or a PRM, differing in the aggregation strategy from step-wise to note-level scoring, as detailed in Section 3.4. In verification tasks, PRMs perform comparably to our ORMs when using the same model checkpoint, aligning with prior findings (Beeching et al.; Snell et al., 2024). However, in preference-based evaluations (A-Prefer), PRM surpasses our ORM, achieving 56.2% accuracy compared to 51.2%.

Comparison with Vanilla ORM Interestingly, our ORM implementation significantly outperforms the vanilla ORM, which predicts only the overall correctness of a generation without learning to estimate step-level reward signals. This suggests that even when functioning as an ORM and relying solely on the end-of-note score, **learning to predict step-level correctness during training is essential for achieving strong performance.**

Performance of Proprietary Models As expected, the most advanced reasoning models are better suited for the challenging A-Prefer task, with o3-mini delivering the strongest baseline performance. Notably, newer-generation models within each family show clear performance improvements

Model	Out-of-Distribution				In-Distribution			
	A-Prefer		A-Verify		Dialogue-G		A-Validate	
	PRM	ORM	PRM	ORM	PRM	ORM	PRM	ORM
Baseline (Vanilla Approach)								
All Data, Full-Token Loss	46.2	38.8	95.0	97.5	98.8	100.0	100.0	100.0
Ablation: Loss Functions								
Score-Token-Only Loss	37.5	27.5	77.5	11.2	81.2	13.8	80.0	10.0
Special-Token Loss	48.8	42.5	90.0	92.5	96.2	95.0	100.0	100.0
Notes-Only Loss	**55.0**	**48.8**	**91.2**	**96.2**	96.2	98.8	100.0	100.0
Ablation: Data Selection								
High Quality Only	**50.0**	**46.2**	97.5	97.5	98.8	98.8	100.0	100.0
High Quality Only + Paraphrases	47.5	36.2	95.0	93.8	97.5	96.2	100.0	95.0
High + Medium Quality	45.0	42.5	86.2	97.5	95.0	98.8	100.0	100.0
High + Medium Quality + Paraphrases	43.8	40.0	**98.8**	**100.0**	97.5	98.8	100.0	100.0
All Data + paraphrases	43.8	40.0	97.5	98.8	97.5	98.8	100.0	100.0
Notes-Only Loss with Data Selection								
High Quality Only	35.0	32.5	87.5	96.2	95.0	98.8	100.0	100.0
High Quality Only + Paraphrases	45.0	38.8	93.8	97.5	97.5	98.8	100.0	100.0
High + Medium Quality	48.8	41.2	93.8	98.8	96.2	96.2	100.0	95.0
High + Medium Quality + Paraphrases	46.2	42.5	96.2	**100.0**	97.5	98.8	95.0	100.0
All Data + Paraphrases	**56.2**	**51.2**	**98.8**	98.8	98.8	97.5	100.0	100.0

Table 3: Ablation studies on loss functions and data selection. We evaluated different strategies for cross-entropy loss computation and training data selection. The best performing model used notes-only loss and the full dataset with paraphrases. PRM and ORM results are reported from the checkpoint with the highest PRM A-Prefer performance. Numbers represent percentages of accuracy. **Bold** values indicate the highest PRM and ORM accuracy in each ablation study for OOD tasks. In ID tasks, multiple models achieved perfect accuracy.

(e.g., Gemini Pro 1.5 outperforms Gemini Pro 1.0, and o3-mini surpasses o1).

4.2 Ablation Studies

In the ablation studies, we examined loss functions and data selection strategies to identify key factors for PRM training. The results are presented in Table 3.

Vanilla Implementation In the vanilla implementation, the full PRM-Clinic dataset was used without the addition of paraphrases. The training objective is the standard cross-entropy loss applied to all tokens in the corpora, encompassing those from dialogues and notes. While the vanilla PRM model exhibits strong performance on the ID dataset, its performance is weaker on the OOD dataset.

Experiments with Loss Functions We further investigated the impact of various loss functions, all derived from the same cross-entropy loss framework but differing in the selection of tokens included in the loss computation. The formal definitions of these loss functions are detailed in Appendix A. Restricting the loss computation to only the score label tokens resulted in a marked degradation of performance. Including losses over all special tokens (i.e., step tokens and score label tokens) produced performance similar to the vanilla approach but with slightly worse outcomes in verification tasks.

Notably, masking out losses from dialogue tokens while restricting the loss computation to the notes led to a positive impact on performance, particularly in the A-Prefer task. These findings suggest that it is important for the PRM to learn to generate notes (based on the dialogue) while simultaneously learning to predict reward labels in a step-by-step manner. This observation may be influenced by the fact that our PRM did not undergo task-specific supervised finetuning prior to reward model training. Masking dialogue losses likely helps prevent overfitting, as dialogues often include lengthy, repetitive content across samples from the same case.

Experiments with Data Selection While keeping the vanilla loss function, we first evaluated the impact of adding paraphrases to enhance semantic diversity. The results indicate that incorporating paraphrases is beneficial, leading to a general performance improvement in the A-Verify task compared to the baseline, although a slight decrease in A-Prefer accuracy was observed.

During manual inspection of the PRM-Clinic dataset, we identified lower-quality samples in the Dialogue-G subset, characterized by overly brief or unrealistic conversations. To address this, we experimented with selecting only cases with high or medium-quality dialogues, reflecting real-world conversations as judged by Gemini Pro. After filtering out low-quality data, the dataset contains 10,094 samples when retaining high and medium quality, and 5,854 samples when retaining only high quality, compared to the original dataset of 10,952 samples. Despite reducing the total number of training cases by up to 46%, this selection process resulted in modest performance gains.

Best Results Lastly, we experimented with different data selections while applying cross-entropy loss solely to the notes. Interestingly, the best results came from using the full dataset, which included all quality levels and added paraphrases. For the high-quality data group, masking out the dialogue loss caused a significant drop in performance. This suggests that when the training sample size is small, PRM may depend on learning from dialogue data to enhance step-level reward signal prediction. We used the best-performing PRM for the results shown in Figure 3 and the physician reader study.

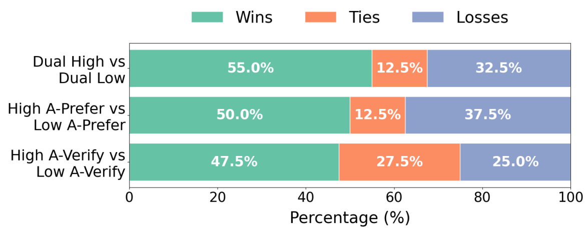

Figure 4: Physician Reader Study Results. We selected PRM checkpoints with varying A-Prefer and A-Verify performances for group comparisons. When analyzing the effect of a single metric, we identified two checkpoints with similar scores on the other metric. The Best-of-2000 note from each model was selected for physician review. Each group comparison involved at least three physicians, and the win rate was calculated based on the majority vote.

4.3 Physician Reader Study

In various ablation experiments, we frequently observed a divergence between the trends of A-Prefer (which selects physicians' preferred samples) and A-Verify (which selects gold-reference samples from those containing errors). To determine which metric better reflects the model's ability to select the highest-quality notes using Best-of-N in downstream tasks, we conducted a physician reader study. PRM checkpoints were selected based on varying combinations of A-Verify and A-Prefer performance (details provided in Appendix Table 1). The top-ranking notes from their Best-of-2000 selections were then submitted for physician review. As shown in Figure 4, the model with high performance on both metrics notably outperformed the one with low performance on both. Additionally, PRMs with high performance on either A-Prefer or A-Verify demonstrated superior note selection compared to those without, provided the other metric was of comparable value. This finding suggests that both metrics are predictive of Best-of-N performance. Notably, A-Prefer appears to have a greater impact than A-Verify, which is intuitively logical given that A-Prefer directly measures alignment with physician preferences.

5 Conclusions and Future Work

In this work, we introduce a methodology for developing PRMs for open-ended text generation in the clinical domain. Our PRM achieved SOTA performance in verifying clinical notes step-by-step and selecting physician-preferred notes via Best-of-N. Our work is among the first to demonstrate the effectiveness of PRMs for open-ended generative tasks beyond mathematics and coding. Notably, our framework is generalizable; it integrates LLMs and domain knowledge to produce process-supervised data at scale, and can be easily applied to other generative tasks across various domains.

While our PRM achieves the highest performance in predicting physician preferences, it is important to note that no current method achieves strong results. This suggests that additional factors influencing alignment with physicians remain unexplored, representing valuable opportunities for future research. Lastly, the application of PRMs for inference-time compute and scaling (e.g., MCTS) or step-by-step reinforcement learning is an exciting direction for future exploration.

6 Acknowledgments

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7 Ethical Considerations

Our work leveraged an LLM to generate synthetic data for training PRMs to verify clinical notes. In considering real-world deployment, several considerations are critical for minimizing harm in this clinical context. The scope of errors in synthetic data should be expanded beyond the four categories examined here to enable more comprehensive evaluation of clinical notes across diverse contexts. In addition, large-scale validation of PRM outputs is essential to identify unintended consequences such as overlooked errors or reward hacking. Finally, safeguards must be implemented to prevent synthetic data from introducing or amplifying biases, for instance when certain error types are disproportionately associated with specific disease populations, which could inadvertently reinforce inequities in documentation or care delivery.

8 Limitations

Our study is constrained by the limited number of physician reviewers and the relatively small dataset involved in the evaluation process. In addition, our approach to the task of clinical note generation builds upon prior work (Wang et al., 2024a), particularly their "Best Practice" note format, which was developed based on recommendations from a panel of internal medicine providers. When applying our framework to a different specialty, it may be necessary to recalibrate both the "Best Practice" note format and the corresponding definition of steps for the PRM. Lastly, our work used the proprietary Gemini model to generate synthetic data for PRM training, though the methodology could also be applied to other open-source frameworks (see Appendix D.2 for further discussion).

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A Formal Definitions of Loss Functions for Ablation Studies

A.1 Vanilla Loss

The vanilla implementation computes the cross-entropy loss over all tokens in the dataset, including dialogue and note tokens:

$$L_{\text{vanilla}} = -\sum_{i \in I_{\text{all}}} \log p_\theta(t_i \mid t_{<i}),$$

where I_{all} represents the positions of all tokens in the sequence.

A.2 Loss over Score Label Tokens Only

Focusing on score label tokens only, the loss is computed as:

$$L_{\text{score}} = -\sum_{i \in I_{\text{score}}} \log p_\theta(t_i \mid t_{<i}),$$

where I_{score} denotes the positions of score label tokens.

A.3 Loss over All Special Tokens

When including all special tokens, including both step tokens and score label tokens, the loss is defined as:

$$L_{\text{special}} = -\sum_{i \in I_{\text{special}}} \log p_\theta(t_i \mid t_{<i}),$$

with I_{special} being the set of positions corresponding to special tokens.

A.4 Loss over Notes Only

Restricting the loss to note tokens by masking out dialogue tokens results in:

$$L_{\text{notes}} = -\sum_{i \in I_{\text{notes}}} \log p_\theta(t_i \mid t_{<i}),$$

where I_{notes} represents the positions of note tokens, which also includes all special tokens.

B Details on Implementation

B.1 Training of PRM

All models were trained using either four 80GB NVIDIA A100 or H100 GPUs, employing DeepSpeed ZeRO Stage 3 optimization (Rasley et al., 2020) and the AdamW optimizer (Loshchilov and Hutter, 2017). We adopted Huggingface's Transformers library and utilized its Trainer module (Wolf et al., 2019). A limited search was conducted over learning rates [3e-4, 1.5e-4, 3e-5], with 3e-5 selected as the optimal value. The training process utilized consistent hyperparameters across all models, including a global batch size of 16, BF16 precision training, a warm-up phase of 50 steps, and a linear learning rate scheduler. All experiments were trained using one epoch of data.

B.2 Training of Vanilla ORM

For the training of vanilla ORM, we replace the true step score labels in the training corpora with the same placeholder token used during inference, except for the score label at the final end-of-note step. This effectively removes all step-level reward signals, retaining only a single score label for the entire generation during training. Otherwise, we keep the training corpora and pipeline the same as in the rest of the experiments.

B.3 Use PRMs at Inference Time

At inference time, we first use a regular expression to transform the LLM-generated clinical notes into the JSON format defined by our steps. We replace score label tokens with a placeholder token when concatenating the note with the dialogue to form the input context. We then perform a standard forward pass with the input context and obtain the softmax probability of the special "+" token at each step position, which represents the **PRM score** for that step.

When calculating the note-level score, we handle ORM and PRMs differently. For ORM, we simply use the PRM score at the final end-of-note step as the note-level score. For PRMs, to ensure mathematical stability, we avoid directly computing the product of step-level PRM scores. Instead, we take the logarithm of each score and sum the log values across all steps.

B.4 Evaluation Metrics

We calculate accuracy for all metrics at the case level, where each case includes one gold-reference or physician-preferred sample and multiple negative samples. In verification tasks (A-Verify, A-Validation, and Dialogue-G), accuracy is determined by whether the top-scoring sample from the Best-of-N selection, based on PRM or ORM, matches the gold-reference sample. Similarly, in the A-Prefer task, accuracy is determined by whether the top-scoring sample from the Best-of-N selection, based on PRM or ORM, matches the physician-preferred sample.

B.5 Physician Reader Study

The physician reader study was performed using dialogues from ACI-BENCH test1 subset (n = 40). We provided model details for each comparison group in Appendix Table 1. Checkpoints were selected from ablation studies to enable a controlled comparison of the effects of A-Prefer versus A-Verify.

When selecting top-scoring samples for physician review, we first attempt to select those in which the probability of each step's "+" score label exceeds that of its "−" score label. This approach mimics the strategy used in (Lightman et al., 2023). If no such samples exist, we select the top-scoring sample from all candidates.

Model (Checkpoint)	A-Prefer	A-Verify
Dual High vs Dual Low		
All Data + Paraphrases (500)	56.2	98.8
Score-Token-Only Loss (685)	33.8	86.2
High A-Prefer vs Low A-Prefer		
Notes-Only Loss (685)	55.0	91.2
Special-Token Loss (685)	43.8	91.2
High A-Verify vs Low A-Verify		
High Quality Only + Paraphrases (366)	45.0	96.2
High + Medium Quality (631)	45.0	86.2

Appendix Table 1: Details of models used in the physician reader study. Numbers represent percentages of accuracy from PRM.

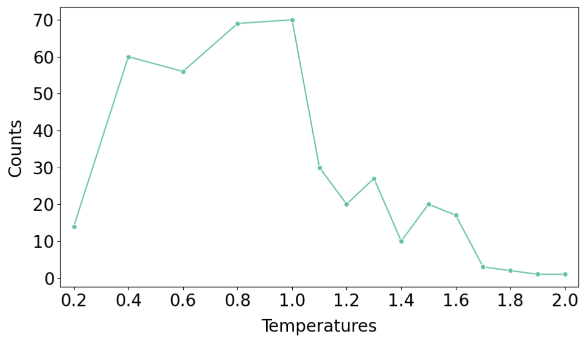
Of interest, the "Best Practice" note template was recommended by a panel of internal medicine physicians (Wang et al., 2024a). We explored collecting preferences from physicians in other specialties, such as obstetrics/gynecology and emergency medicine. As anticipated, there was a high rate of disagreement compared to the preferences of internal medicine physicians, particularly regarding fine-grained aspects such as the perceived target audience (e.g., peer physicians vs. patients) and the desired note length (e.g., concise vs. comprehensive). These findings underscore the complexity of physician preferences and highlight the importance of aligning priorities, criteria, and definitions of "ideal" documentation for real-world deployment. In this work, we report results exclusively from practicing internal medicine physicians.

C Additional Results

C.1 Distribution of Top-Scoring Samples

Previous studies in the clinical domain have commonly employed lower temperature settings for generative tasks (Van Veen et al., 2024; Wang et al., 2024a). In our study, we analyzed the distribution of top-scoring samples derived from PRMs. Specifically, when using LLaMA-Clinic to generate 2,000 samples per case for the physician reader study, we explored various temperature settings. For temperatures in the range of [0.2, 0.4, 0.6, 0.8, and 1.0], we generated 200 samples each. For temperatures ranging from 1.1 to 2.0, samples were generated at 0.1 intervals, with 100 samples per interval.

The distribution of the top-10 scoring samples across all 40 cases is illustrated in Appendix Figure 1. Consistent with prior research, the most frequent temperature range for high-scoring samples was found to be between 0.4 and 1.0.



Appendix Figure 1: Distribution of top-10 scoring samples by PRM across temperature settings. This figure shows the counts of top-scoring samples per temperature setting for the physician reader study, with 2,000 samples generated using LLaMA-Clinic at various temperatures for each case. The highest frequency of top-scoring samples occurred in the temperature range of 0.4 to 1.0.

C.2 Scoring Strategies

We present the A-Prefer results using various scoring strategies for note-level PRM scores, as shown in the Appendix Table 2. These results are derived from the best-performing PRM. The highest performance was achieved by computing the note-level score as the product of all step-level PRM scores.

C.3 Quantitative Assessment of In-Distribution and Out-of-Distribution Clinical Notes

To investigate the factors contributing to the robust performance of PRMs in out-of-distribution tasks (A-Prefer and A-Verify), we computed the ROUGE scores of clinical notes generated by physicians, LLaMA-Clinic, and Gemini Pro, based on prior work (Wang et al., 2024a) (Appendix Table

Product	Last	Min	Mean	Median	Max	Geo Mean	Sum	Threshold
56.2%	51.2%	45.0%	55.0%	46.2%	42.5%	50.0%	37.5%	38.8%

Appendix Table 2: Accuracy of various scoring strategies for A-Prefer. Each column represents a different method for deriving note-level scores from step-level PRM scores. The **Product** method multiplies all step-level PRM scores, utilizing the sum of their logarithms during calculations for mathematical stability. The **Last** method uses the step-level score at the end-of-note token, which is the approach used to obtain scores for ORM. **Min** takes the minimum score, **Mean** computes the average, **Median** uses the median, **Max** selects the maximum, **Geo Mean** calculates the geometric mean, **Sum** adds all scores, and **Threshold** counts the number of step-level PRM scores that exceed 0.5. Accuracy is determined by whether the top-scoring sample from each method matches the physician-preferred sample. Results are based on the best-performing PRM.

3). The high ROUGE scores across various cross-comparison groups suggest strong semantic similarities among all three sources. This result is unsurprising, given that different models should conform to the same best-practice standards and produce similarly high-quality notes for the same case.

Model Comparison	ROUGE-1	ROUGE-L	ROUGE-Lsum
LLaMA-Clinic vs Physician	0.46	0.34	0.43
Gemini vs Physician	0.49	0.37	0.46
LLaMA-Clinic vs Gemini	0.52	0.40	0.49

Appendix Table 3: Comparison of ROUGE scores among clinical Notes by physicians, LLaMA-Clinic, and Gemini Pro 1.0. Cases are from the physician reader study in (Wang et al., 2024a) and include only the "Assessment and Plan" section. Overall, high ROUGE scores were observed for each group comparison.

D Additional Discussion

D.1 Application of PRMs in Real-World Deployment

Currently, no automated, scalable method exists to evaluate the quality of LLM-generated clinical notes at a fine-grained level. As a result, healthcare institutions rely on costly and time-consuming manual clinician evaluation as the gold standard. Taking the field of ambient AI scribes as an example, a healthcare institution may need to evaluate offerings from multiple industry vendors concurrently. Each evaluation group typically consists of tens to hundreds of clinicians who manually grade LLM-generated clinical notes and provide feedback based on a comprehensive rubric, primarily focusing on detecting errors, inaccuracies, or hallucinations. Furthermore, whenever vendors update their products—for instance, by incorporating a newer version of a foundation model—such evaluations must be repeated.

By applying effectively trained and validated PRMs, the evaluation of LLM-generated notes can be automated at scale, significantly reducing reliance on manual assessment. PRMs enable fine-grained, step-by-step verification of LLM outputs, precisely identifying errors at their exact locations. As demonstrated in our study, PRMs can also select notes that best align with physician preferences. Therefore, PRM-assessed performance can serve as a benchmark for evaluation, akin to the LLM-as-a-judge approach. Furthermore, our study shows that PRMs outperform the vanilla LLM-as-a-judge method. PRMs can also be employed for product monitoring after deployment in healthcare institutions, aiding in the detection of quality issues related to model shift and drift. Importantly, PRMs should first be validated on real-world data and undergo iteration and improvement—for example, through the introduction of additional error types.

Lastly, AI companies can use PRMs to enhance their products. This can be achieved through a simple Best-of-N filtering approach at inference time—similar to our experiments—ensuring that only the highest-quality note is output. Further model improvements are also promising with inference-time scaling techniques such as Monte Carlo Tree Search or step-wise reinforcement learning.

D.2 Training PRMs with an Open-Source Framework

The core of our methodology lies in designing "errors" and structuring "steps" to align with real-world clinical documentation needs. While we opted to use the proprietary Gemini model to generate synthetic errors due to its strong performance and ease of API access, our methodology is model-agnostic. These synthetic errors could just as effectively be generated using other powerful open-source models, such as LLaMA-3.1 405B (Dubey et al., 2024) or Deepseek-R1 (Guo et al., 2025) (given adequate GPU resources), provided that the critical decisions regarding error types are made beforehand. Furthermore, our model training is based on the open-source LLaMA model. Lastly, while we used Gemini Pro to generate synthetic cases for PRM development, PRMs outperform both Gemini Pro 1.0 and 1.5, indicating that the proprietary model does not impose an upper bound on PRM performance within our methodology.

D.3 Assessment and Plan of Clinical Note

Building on recent research on ambient clinical charting and the real-world feedback (Wang et al., 2024a), we concentrate solely on the "Assessment and Plan" (A&P) section of the clinical note in our work for the following reasons: (1) The A&P section is arguably the most critical and time-intensive part of a clinical note, as it encapsulates key clinical reasoning and medical decision-making. (2) After domain-specific adaptation, the "Subjective" section produced by LLMs is generally of high quality and nearly indistinguishable from human-written content, whereas notable gaps persist in the A&P section. (3) Other sections are considered less significant, as they are often imported directly from the electronic medical record (e.g., "Objective") or fit less naturally into the physician's workflow during ambient scribing (e.g., "Physical Exam").

D.4 Considerations in defining "steps" for clinical note

When defining the "steps" for clinical note, we took into account the diverse real-world requirements of clinical documentation from various stakeholders. For example, the problem list within a note plays a critical role in billing processes for insurance companies and also serves as a key reference for daily clinical communication, warranting special attention (Chowdhry et al., 2017). In addition, we drew on existing guidelines and best practices for clinical note writing, which explicitly emphasize the value of structured, problem-oriented documentation (Li et al., 2018; DeParle, 2000).

E Additional Related Work

After our preprint, DeepSeek-R1-Zero and DeepSeek-R1 were released (Guo et al., 2025). These models demonstrate remarkable reasoning capabilities through large-scale reinforcement learning with rule-based rewards. In their paper, the authors discussed their reasons for not using PRMs, citing concerns such as reward hacking and the complexity of scaling.

In this exciting new paradigm of large-scale RL, we believe that PRMs remain effective for the following reasons: (1) As a simple yet powerful approach, PRMs serve as an effective means for Best-of-N filtering, guiding test-time computation. (2) In general domains where a verifiable answer is difficult to define, PRMs provide a reliable single reward signal when functioning as ORMs. As demonstrated in our study, this approach outperforms the standard ORM implementation. Moreover, recent research highlights the potential of PRMs in guiding test-time scaling, offering both effectiveness and computational efficiency (Liu et al., 2025; Cheng et al., 2025).

F Prompts and Instructions

We present the prompts to Geimino Pro for clinical notes-to-JSON format transformation (Appendix Table 4), error generation (Appendix Table 5), paraphrase generation (Appendix Table 6), case quality annotation (Appendix Table 7). and preferred note selection (Appendix Table 8) here. We provided instructions to reviewers in Appendix Table 9.

G PRM Examples

We presented additional example notes along with their PRM scores in Appendix Table 10 and 11.

Category	Prompt
Note to Json	Task: Given a clinical note, extract specific information and structure it into a JSON format according to the rules and schema provided. Instructions: 1. Output Format: - The response should be in JSON format following the schema outlined below. 2. Sections to Ignore: - Do not include any content labeled or titled “Assessment and Plan”. 3. Content Extraction: - Extract the remaining content of the clinical note and organize it into different problems. - Problems can be identified using a numbered problem list within the note. - When there’s a section titled “Follow-up instructions:”, treat this as a separate problem. 4. For Each Problem: - Extract each step as a separate sentence. - Ignore bullet point symbols, such as -, •, or other similar characters, when extracting steps. - If the words “Assessment:” or “Plan:” appear in the clinical note, include those words at the beginning of the first sentence that follows their occurrence. 5. Adding Ratings: - For each step, add a field called “Step_score” with the value “+”. - For each problem, add a field called “Problem_score” and “Problem_completeness_score” with the value “+”. 6. Add Sequential Numbering: - For each problem, add a field called “Problem_no”. Number them sequentially starting from “1”, and use strings (e.g., “"1"”, “"2"”). - For each step, add a field called “Step_no”. Number them sequentially starting from “1”, and use strings. 7. Add Note Score: - Add a field called “Note_completeness_score” with the value “+” at the root level of the JSON. 8. JSON Schema: { “Problems”: [{ “Problem”: “Problem Description”, “Problem_no”: “1”, “Problem_score”: “+”, “Steps”: [{ “Step”: “First step of the problem.”, “Step_no”: “1”, “Step_score”: “+” }, { “Step”: “Second step of the problem.”, “Step_no”: “2”, “Step_score”: “+” }], “Problem_completeness_score”: “+”, }], “Note_completeness_score”: “+” } Here is an example: {Example Note} Desired output: {Example Json} Here is the clinical note for your task: {Note}

Appendix Table 4: Prompts to Gemini Pro 1.5 to transform clinical notes into JSON format.

Category	Prompt
Prompt Template	You are provided with a doctor-patient conversation and its corresponding clinical note in JSON format. Your task is to introduce 10 errors into the clinical note, following the instructions below. Instructions: {Error Type Instruction} - Number of Errors: Introduce 10 errors from the list above at the "Problem" or "Step" level. - These errors can be introduced at the "Step" field or "Problem" field. - Do not change other fields such as "Problem_no," "Problem_score," "Step_no," "Step_score" or "Problem_completeness_score." - Recording Changes: For each change, only include the following information: - "Error_type": The type of error introduced. - "Problem_no": The number of the affected problem. - "Step_no": The number of the affected step. If change is at the problem level, output null. - "Error_level": With a value of "Problem" or "Step." - "Detailed_error": A description of the error introduced. - "New_content": The new "Problem" or "Step" content after modification. - "Original_content": The original "Problem" or "Step" content before modification. - Output JSON format with an "Errors" item only, including all information below. Do not include the original JSON file. Here is the conversation: {dialogue} Here is the clinical note for your task: {problems}
Factual Inaccuracy	Error type is "Factual Inaccuracy": Introduce detailed factual errors related to the information or topics discussed in the conversation but not supported by it. Examples include changing "left" to "right," altering medication names, or modifying the follow-up timeframe from "1 month" to "6 months."
Hallucination	Error type is "Hallucination": Add completely unrelated subject entities that were not discussed in the conversation. This may include fabricated content related to symptoms, diagnostics, treatments, or other aspects. The new information should be major and entirely made up, different from minor factual inaccuracies.
Unhelpfulness	Error type is "Unhelpfulness": Rewrite sentences in a vague, incomplete, or confusing manner. Remove important details, use imprecise language, and avoid specific medical terminology or clear instructions so that the note becomes unhelpful and unclear.

Appendix Table 5: Prompts to Gemini Pro 1.5 for error generation. Each error type is generated using different prompts by incorporating its Error Type Instruction into the prompt template.

Category	Prompt
Paraphrase	You are provided with a doctor-patient conversation and its corresponding clinical note in JSON format. Your task is to introduce 20 paraphrases based on the original note, following the instructions below. Instructions: - You want to paraphrase original sentences to improve semantic diversity of the clinical note. Please make sure the new sentence faithfully represents the same information and knowledge of the original sentence, without adding any new information. Please keep the same academic style but easy to follow, as you would expect from a medical note. - Number of Errors: Introduce 20 different paraphrases at the "Step" level. Do not introduce paraphrases at the "Problem" level. - It is ok to introduce multiple paraphrases for the same step. Ideally, we want to introduce paraphrases at various steps. ... Here is the conversation: {dialogue} Here is the clinical note: {problems}

Appendix Table 6: Prompts to Gemini Pro 1.5 for paraphrase generation. Sections of the prompts related to JSON formatting, similar to those in Appendix Table 5, are omitted for brevity.

Category	Prompt
Annotate Quality	You are provided with a synthetic doctor-patient conversation and its corresponding clinical note in JSON format. Your task is to assess the quality of the conversation and the note. Instructions: - Context: The conversations and clinical notes are generated by a large language model. Your task is to assess the quality of these cases by focusing on whether the conversation and notes represent real-world scenarios accurately. - Conversation Assessment: Evaluate if the conversations are realistic and mimic true clinical interactions during outpatient visits. Be alert for unrealistic conversations, such as interactions involving a newborn speaking or inappropriate dialogue with the mother of a newborn. Identify low-quality conversations that lack sufficient detail or context. - Clinical Note Assessment: Assess the quality of the clinical note. Identify notes that may contain inaccuracies, hallucinations not supported by the conversation, or that are incoherent or below the standard expected of high-quality medical documentation. ... - Recording Changes: Include only the following information in your output. - Have two root items of "Conversation_quality" and "Note_quality". For each, include the following items: - "Rational": Provide an explanation for your quality assessment. - "Quality": Choose among "High," "Medium," or "Low." This indicates your quality assessment. - "Confidence": Choose between "High," "Medium," or "Low." This indicates your confidence in the quality assessment. - Output JSON format according to the specified structure. Do not include the original JSON data in your output. Here is the conversation: {dialogue} Here is the clinical note: {problems}

Appendix Table 7: Prompts to Gemini Pro 1.5 for quality annotation. Notably, while we tasked Gemini Pro 1.5 with generating ratings for both conversations and clinical notes, we only used its ratings for conversations in data filtering. This decision was based on manual inspection, which revealed that its ratings and reasoning for clinical notes were of lower quality and accuracy.

Category	Prompt
Preferred Note Selection	You are given a patient-doctor conversation and several clinical notes based on the conversation. The clinical notes only cover the "Assessment and Plan" section of the note. Your job is to select the best note and provide reasoning. Here's the dialogue: {dialogue} Here are the notes: Note 1: {note_1} Note 2: {note_2} Note 3: {note_3} Provide answers in JSON format with two fields: "Rationale" and "Preferred Note". Explain your reasoning in the "Rationale" field step-by-step. The "Preferred Note" should be the number of the note you select (1, 2, or 3). Make sure your output is in valid JSON format.

Appendix Table 8: Prompts to Gemini Pro 1.5 for preferred note selection.

Instructions
1. In each row, you will be given a synthetic outpatient patient-provider dialogue from Aci-bench, and two clinical notes based on the same dialogue. We will only evaluate the "Assessment and Plan" parts of a note. 2. We have performed randomization of the notes and simple processing to unify the format of notes. 3. The dialogues from Aci-bench include conversations with (a) calls to a virtual assistant, (b) unconstrained directions or discussions with a scribe, and (c) natural conversations between a doctor and patient. Most conversations occurred in the outpatient setting. 4. Since we are focusing solely on the "Assessment and Plan," you may assume that all other pertinent information from the dialogue has been documented elsewhere in the note, which is not shown here. Please evaluate the "Assessment and Plan" as you would in a real note. For example, relevant physical exam findings may be helpful in the "Assessment and Plan." 5. For each row, please start by reading the dialogue and then select your preferred notes. Make your selection based on the overall quality of the note. Essentially, choose the note you would prefer to use in a real patient encounter, imagining you are adopting AI-generated clinical notes for your daily clinical work. You may consider aspects including but not limited to: (a) Accuracy: Does the information in the clinical note accurately reflect the details from the dialogue? (b) Completeness: How well does the note cover the important information from the dialogue? (c) Helpfulness: Does this note include useful information that you would expect from a real "Assessment and Plan"? However, remember that, ultimately, the selection should reflect your personal preference as a physician. 6. It's perfectly acceptable to select a tie if you feel that two notes are equally good (or equally poor). 7. Please enter brief comments about each note to help us understand the rationale behind your selection. This is appreciated but not mandatory.

Appendix Table 9: Instructions to physicians for note preference selection.

Category	Example
Top-Scoring Sample	ASSESSMENT AND PLAN: 1. Allergic Asthma Assessment: The patient has a history of allergic asthma, recently diagnosed by his primary care physician. He experiences episodic shortness of breath, eye watering, and occasional diarrhea after heavy drinking. Physical exam shows faint expiratory wheezing bilaterally in all lung fields. Chest X-ray and pulmonary function tests were normal. Plan: - Continue Albuterol Inhaler as needed. - Prescribe Singulair 10mg once daily. - Start allergy testing (skin testing) and try to identify triggers. If unsuccessful, will need further testing in the blood and possibly immunotherapy. Follow-up instructions: - Schedule follow-up appointment in one week to review results of skin testing and plan for further treatment.
Negative Sample	**Problem_1:** Newly diagnosed allergic asthma **Step_1: Assessment:** Patient reports symptoms of shortness of breath, fatigue, and dry mouth after exposure to his cat. **Step_score:** 0.0026 **Error:** Inaccuracy regarding symptoms after exposure to cat. ... **Step_4:** Differential diagnosis includes COPD, heart failure, pneumonia, bronchitis, PFT abnormalities, vocal cord paralysis, GERD, gastroparesis, esophageal spasm, peptic ulcer disease, irritable bowel syndrome, celiac disease, lactose intolerance, Crohn's disease, ulcerative colitis, colon cancer, hemorrhoids, anal fissures, fistula, abscess, vasculitis, and sarcoidosis. **Step_score:** 0.0086 **Error:** Hallucination about differential diagnosis. **Problem_2:** Lip edema **Problem_score:** 0.0420 **Error:** Hallucination about lip edema. **Step_1: Assessment:** Patient has lip swelling and diarrhea following alcohol consumption. **Step_score:** 0.2017 **Error:** In the dialogue the patient answered no to lip edema. ... **Problem_3:** Nausea and vomiting after drinking **Problem_score:** 0.0473 **Error:** Hallucination about these symptoms. In the dialogue the patient answered no to nausea and vomiting.

Appendix Table 10: Example 1 of clinical notes with PRM Scores.

Category	Example
Top-Scoring Sample	1. ASSESSMENT AND PLAN: Hepatitis C Assessment: The patient's HCV Ab test was positive, and her liver panel showed an elevated AST (39), but her ALB, Tbili, and Total Bilirubin were all within normal limits. This suggests that she has chronic hepatitis C. Plan: - Confirm the diagnosis with additional blood work, including HCV RNA and HCV Genotype. - Determine the severity of liver disease with a special ultrasound. - Once the diagnosis and severity are confirmed, discuss treatment options with the patient. 2. Fatigue Assessment: The patient reports feeling tired at the end of the day after working. She denies any other symptoms. Plan: - Recommend the patient to prioritize rest and relaxation. - Encourage the patient to maintain a healthy sleep schedule. - Consider referral to a sleep specialist if fatigue persists despite lifestyle modifications. Follow-up instructions: - Return to clinic in 3 weeks for follow-up.
Negative Sample	**Problem_1:** Hepatitis C virus (HCV) infection ... **Step_7:** Plan: - Obtain follow-up blood tests including HCV RNA, HCV genotype, FIBROSIS OF THE LIVER, LFTS, TSH, UA, BMP. **Step_score:** 0.0081 **Error:** Inaccuracy about tests ordered. **Problem_Completeness_score:** 0.0159. **Error:** Failed to include liver ultrasound. **Problem_2:** Fatigue and mild anemia **Problem_score:** 0.0110 **Error:** Hallucination about anemia. ... **Step_4:** She denies any recent change in bowel movements, urination, fevers, chills, weight loss, joint pain, night sweats, shortness of breath. **Step_score:** 0.2225 **Error:** These symptoms are not discussed in the dialogue. ... **Step_6:** Plan: - Recommend restful activities, stress reduction techniques, counseling on healthy eating habits, exercise. **Step_score:** 0.0293 **Error:** These plans are not discussed in the dialogue.

Appendix Table 11: Example 2 of clinical notes with PRM Scores