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Smarter Healthcare: Leveraging GPT-5, Cosmos, and Predictive Models for Better Outcomes

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Table 1: Performance on QA benchmarks (%). The blue numbers and arrows indicate changes compared to GPT-4o-2024-11-20.

Dataset	GPT-5	GPT-5-mini	GPT-5-nano	GPT-4o-2024-11-20
MedQA				
US (4-option)	95.84 (↑4.80%)	93.48	91.44	91.04
MedXpertQA Text				
Reasoning	56.96 (↑26.33%)	45.94	36.38	30.63
Understanding	54.84 (↑25.30%)	43.80	33.96	29.54
MMLU				
Anatomy	92.59 (↑1.48%)	92.59	88.15	91.11
Clinical Knowledge	95.09 (↑2.64%)	91.32	89.81	92.45
College Biology	99.31 (↑2.09%)	99.31	97.92	97.22
College Medicine	91.91 (↑1.74%)	88.44	85.55	90.17
Medical Genetics	100.00 (↑4.00%)	99.00	98.00	96.00
Professional Medicine	97.79 (↑1.10%)	97.43	96.69	96.69

3.2 Performance of GPT-5 on USMLE Self Assessment

As shown in Table 2, GPT-5 outperformed all baselines on all three steps, with the largest margin on Step 2 (+4.17%). Step 2 focuses on clinical decision-making and management, aligning with GPT-5's improved CoT reasoning. The average score across steps reached 95.22% (+2.88% vs GPT-4o), exceeding typical human passing thresholds by a wide margin, demonstrating the model's readiness for high-stakes clinical reasoning tasks.

Table 2: USMLE Sample Exam Performance (%). The blue numbers and arrows indicate changes compared to GPT-4o-2024-11-20.

	GPT-5	GPT-5-mini	GPT-5-nano	GPT-4o-2024-11-20
Step 1	93.28 (↑0.84%)	93.28	93.28	92.44
Step 2	97.50 (↑4.17%)	95.83	90.00	93.33
Step 3	94.89 (↑3.65%)	94.89	92.70	91.24
Average	95.22 (↑2.88%)	94.67	91.99	92.34

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Table. Model Performance on Original and None of the Other Answers (NOTA)-Modified Questions**Table. Model Performance on Original and None of the Other Answers (NOTA)-Modified Questions***

Model	Accuracy, % (No./total No.)		Accuracy drop, % (No./total No.) [95 % CI]
	Original	NOTA-modified	
1	92.65 (63/68)	83.82 (57/68)	8.82 (6/68) [2.70-18.92]
2	95.59 (65/68)	79.41 (54/68)	16.18 (11/68) [10.81-29.73]
3	88.24 (60/68)	61.76 (42/68)	26.47 (18/68) [17.57-39.19]
4	92.65 (63/68)	58.82 (40/68)	33.82 (23/68) [24.32-47.30]
5	85.29 (58/68)	48.53 (33/68)	36.76 (25/68) [28.38-51.35]
6	80.88 (55/68)	42.65 (29/68)	38.24 (26/68) [27.03-51.35]

* This table compares performance on validated questions. Original accuracy is performance on questions in the original set, while NOTA-modified accuracy is performance on questions when the correct answer was removed and replaced by the other answers" (NOTA). Models show an increasing accuracy drop. CIs were calculated using the McNemar test for paired nominal data.

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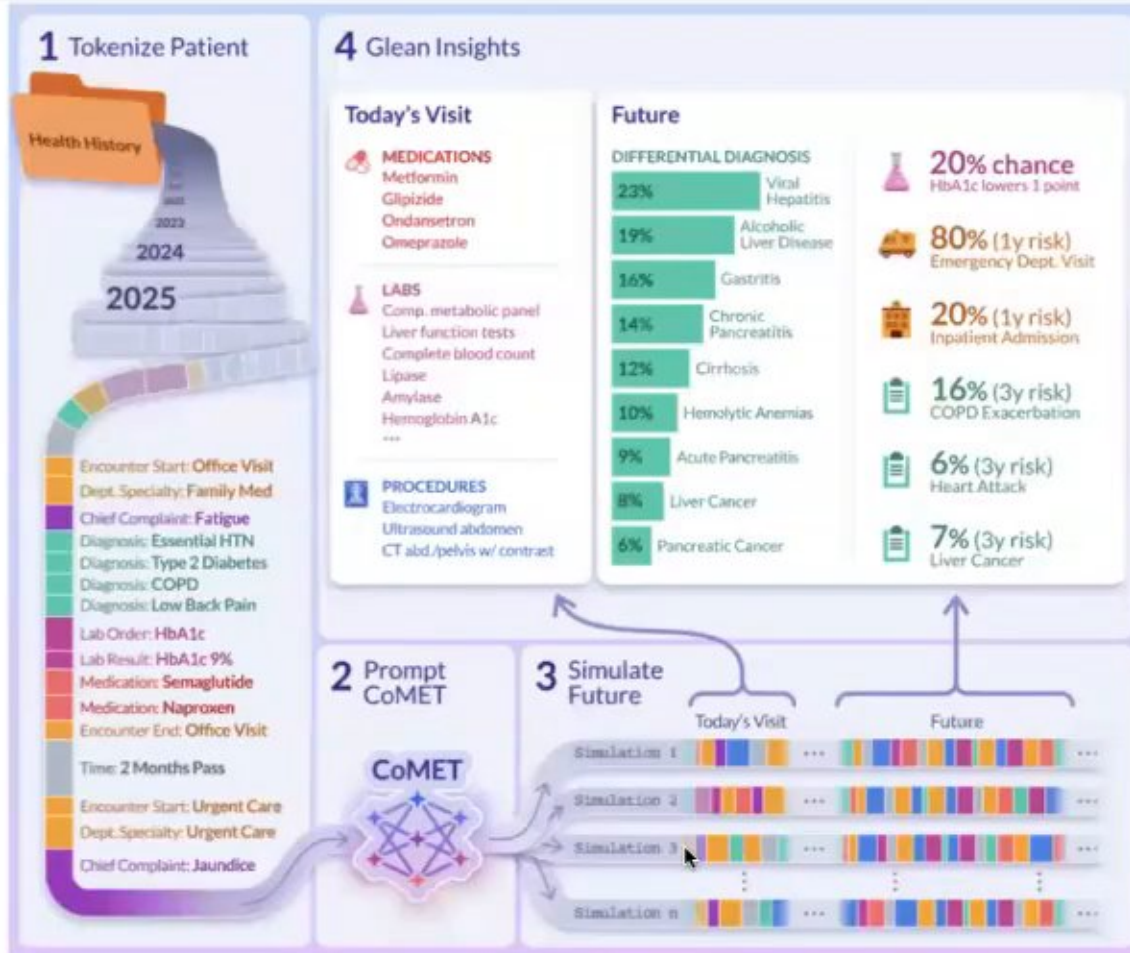


Figure 1: Overview of CoMET pretraining and inference. A patient journey is formulated as a sequence of medical events, and CoMET learns by predicting the next medical event. At inference time, CoMET is prompted with a patient's medical event history and simulates potential future trajectories by autoregressively generating the next events. Predictions for any target in CoMET's vocabulary are obtained from these simulated trajectories, enabling broad, out-of-the-box use on downstream tasks without task-specific fine-tuning or few-shot prompts.



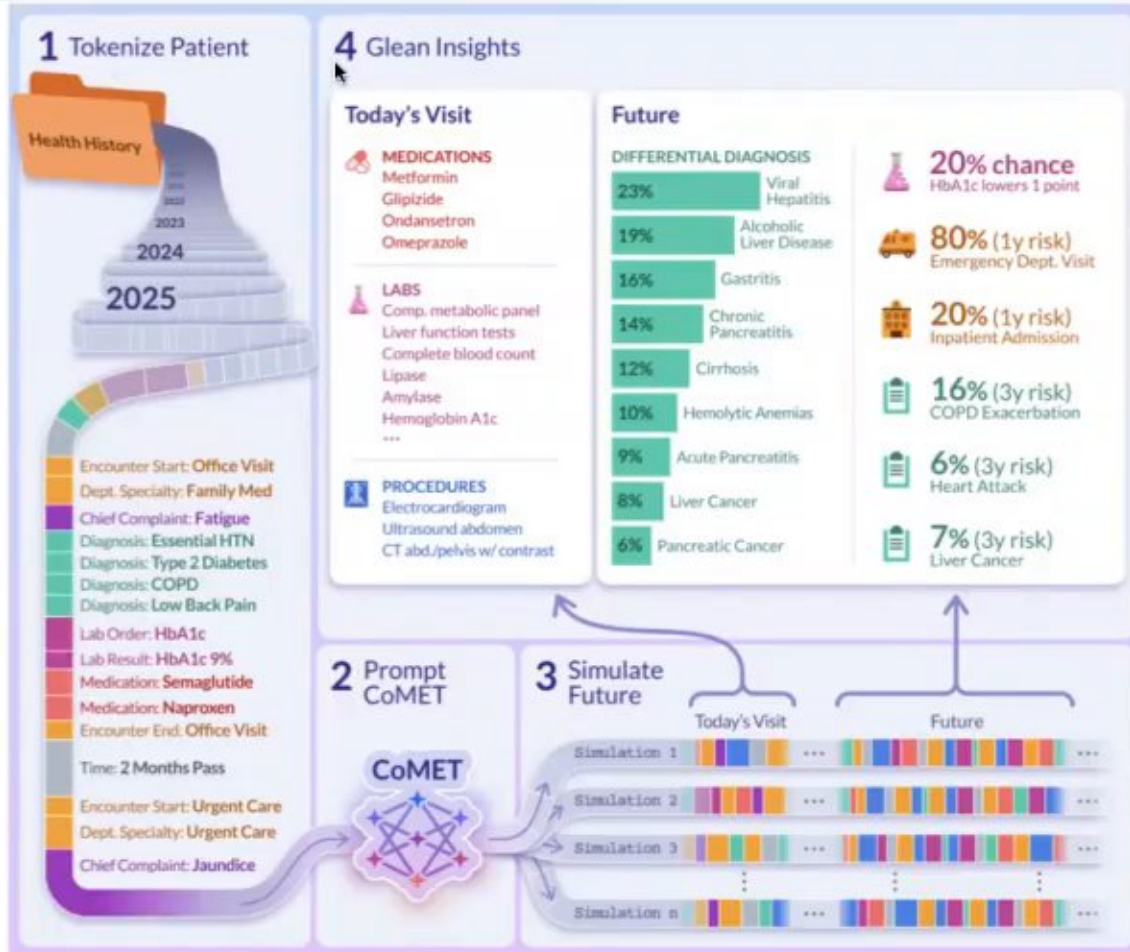


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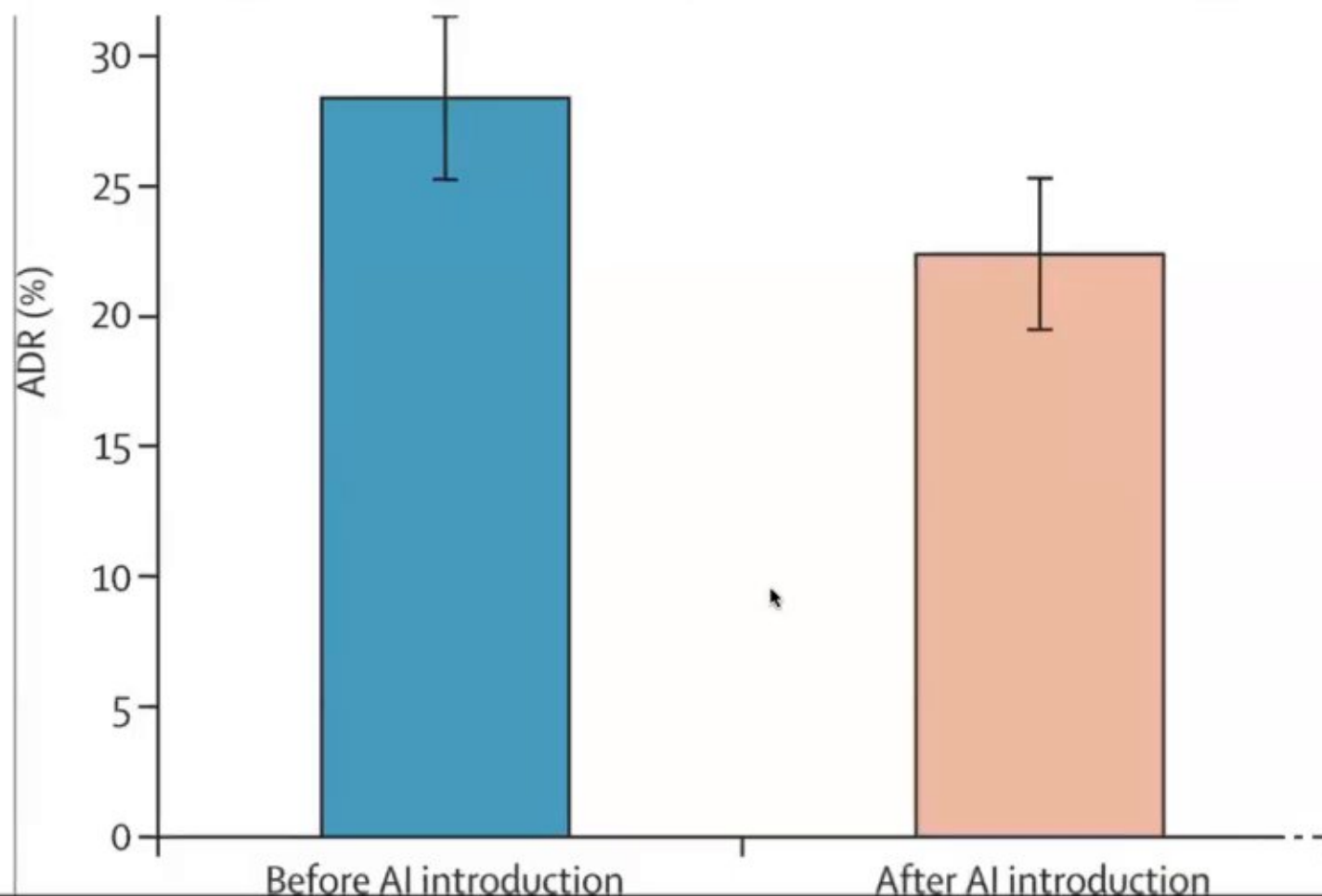
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Endoscopist deskilling risk after exposure to artificial intelligence in colonoscopy: a multicentre, observational study



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