Amazon Nova 2: Multimodal Reasoning and Generation Models

Amazon Artificial General Intelligence

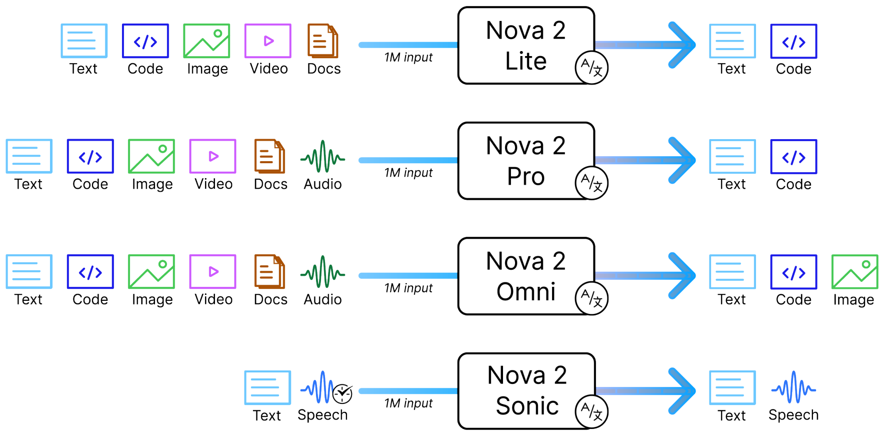

Figure 1: Amazon Nova 2 Family of Models

Abstract

We present Amazon Nova 2, a family of four foundation models designed to meet diverse enterprise needs across reasoning, multimodal processing, and real-time conversational AI. The family includes Nova 2 Lite and Nova 2 Pro — multimodal models with dynamic reasoning capabilities that allow customers to balance accuracy, speed, and efficiency through configurable "extended thinking" controls; Nova 2 Omni — a unified multimodal model that processes text, images, video, and audio inputs while generating both text and images; and Nova 2 Sonic — a speech-to-speech foundation model for natural conversational AI. Nova 2 models process large contexts with up to 1M tokens, enabling analysis of extensive codebases, long documents, and videos within a single prompt. Like all Nova models, the Nova 2 family is built with integrated safety measures and Responsible AI guardrails, maintaining our commitment to customer trust, security, and reliability.

1 Introduction

We introduce Amazon Nova 2, a family of four natively multimodal foundation models that address the full spectrum of customer AI needs—from cost-effective everyday reasoning to frontier-level intelligence, unified multimodal processing, and human-like, real-time voice interactions. The Nova 2 family excels on reasoning depth, modality support, and conversational capabilities while maintaining industry-leading price-performance.

1.1 The Nova 2 Model Family

- **Nova 2 Lite** is our low-latency, cost-effective reasoning model for everyday workloads. It processes text, images, and videos to generate text output. Developers adjust step-by-step "thinking" to balance intelligence, speed, and cost—ideal for customer service chatbots, document processing, business automation, video information extraction, code generation, and multi-step agentic workflows. It delivers industry-leading price-performance, matching or exceeding Anthropic's Claude Haiku 4.5, OpenAI's GPT-5 Mini, and Google's Gemini 2.5 Flash on most standard benchmarks.
- **Nova 2 Pro** delivers our highest intelligence for complex workloads. It simultaneously processes text, documents, images, videos, and audio—ideal for large-scale multimodal reasoning. The model excels in high-accuracy tasks, multi-step planning, and workflow coordination, with strengths in long-document analysis, complex instruction following, advanced math, and autonomous agentic/software engineering tasks. It matches or exceeds Anthropic's Claude Sonnet 4.5, OpenAI's GPT-5/GPT-5.1, and Google's Gemini 2.5 Pro/Gemini 3 Pro Preview across broad benchmarks.
- **Nova 2 Omni** is our first unified multimodal model that processes text, documents, images, video, and audio inputs and generates text and images from a single model, eliminating multi-model coordination complexity. It delivers standout performance in multimodal perception, core reasoning, and agentic benchmarks, matching or exceeding OpenAI's GPT-5 Mini and Google's Gemini 2.5 Flash. It also offers high-quality image generation/editing, strong reasoning, instruction following, and tool calling—making it ideal for multimodal agentic applications.
- **Nova 2 Sonic**, our second-gen speech-to-speech model, delivers industry-leading quality and cost efficiency for real-time voice AI. It surpasses GPT-Realtime (Aug'25) and Gemini 2.5 Flash Live (Sept'25) in conversational quality (expressive, native-sounding voices) for English, French, Italian, German, and Spanish via real-time API, based on human evaluations. It also leads in streaming speech understanding accuracy across 7 languages (EFIGS, HI, PT) compared to GPT-Realtime and Gemini 2.5 Flash Live.

1.2 Key Highlights of Nova 2 Models

- **Hybrid Reasoning**: Nova 2 Lite, Pro, and Omni introduce extended thinking capabilities that give developers fine-grained control over the accuracy-cost-latency trade-off. Developers can toggle reasoning *on* or *off* and adjust reasoning depth through low, medium, and high settings—enabling fast responses for simple tasks while engaging in systematic multi-step reasoning for complex problems. Figure 2 illustrates how accuracy increases with reasoning effort on code generation tasks. Hybrid reasoning delivers strong performance across several benchmarks including **92.3%** on AIME-2025 [27] for Nova 2 Pro, **76.6%** on MultiChallenge [36] Instruction Following for Nova 2 Lite, and **58.5%** on OCR-Benchv2 [17] for Nova 2 Omni.
- **Reliable Multi-Step Workflow Execution**: Nova 2 family excels at completing complex, multi-step agentic workflows with sophisticated tool use and planning capabilities. Specfically, Nova 2 Pro demonstrates frontier-level performance on τ^2-bench-Verified [13] for agentic task execution- **77.7%** (retail), **65.2%** (airline), and **92.7%** (telecom). Further, on SWE-Bench Verified [11] for autonomous software engineering tasks, Nova 2 Pro scores **70.0%**, enabling reliable automation of complex business processes and development workflows.
- **Native Multimodal Reasoning and Generation**: Nova 2 models provide unified multimodal processing across text, documents, images, and video with strong performance on multimodal reasoning and generation benchmarks. For example, Nova 2 Lite achieves **62.1%** on key information extraction benchmark - RealKIE-FCC Verified [43]. Nova 2 Omni combines multimodal input processing with native image generation and editing capabilities, eliminating the need to coordinate multiple specialized models while maintaining high-quality outputs across all modalities.
- **Real-Time Conversational AI**: Nova 2 Sonic supports asynchronous tool calling, configurable turn-taking, and seamless switching between voice and text modalities—enabling real-time conversations with low latency. Artificial Analysis[1] reports higher speech reasoning accuracy for Nova 2 Sonic, compared to GPT-Realtime and Gemini 2.5 Flash Live on Big Bench Audio data set.

[1] https://artificialanalysis.ai/models/speech-to-speech#summary

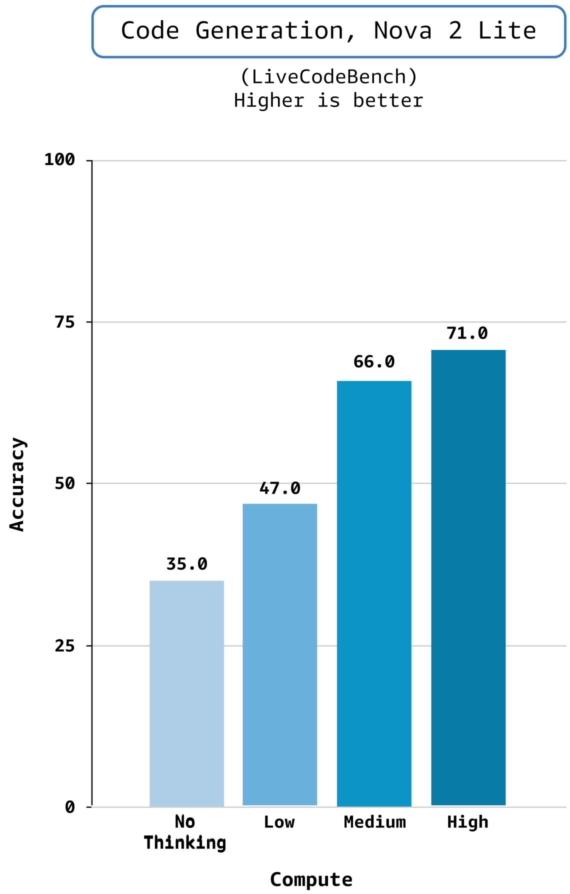

Figure 2: **Nova 2 Lite** Extended thinking performance on code generation tasks (LiveCodeBench) across reasoning effort levels. Accuracy increases as the model allocates more computational resources to reasoning, demonstrating the configurable trade-off between speed and intelligence that Nova 2 provides through its low, medium, and high reasoning effort settings.

2 Nova 2 Lite and Pro - Hybrid Reasoning

Nova 2 Lite and Pro models deliver a major intelligence leap over our existing Nova models. As shown in Figure 3, Nova 2 Lite surpasses our former flagship, Nova Premier, in multi-step problem-solving and agentic workflows—at 7x lower cost and up to 5× faster.

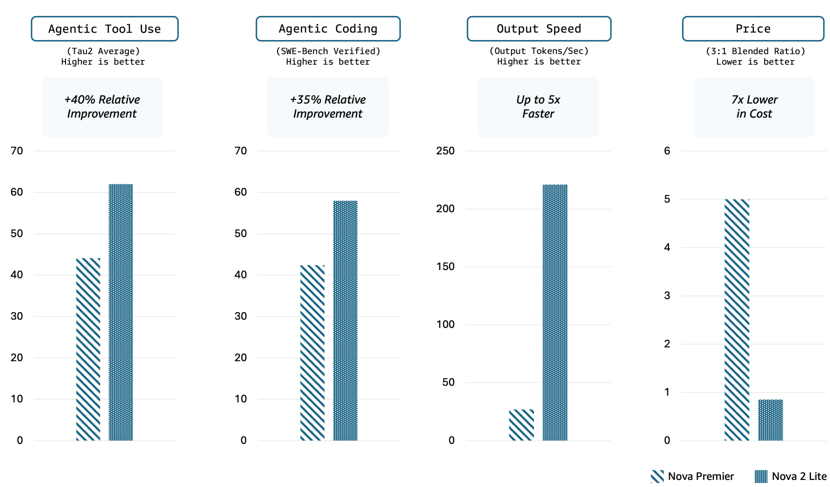

Figure 3: Nova 2 Lite compared to Amazon Nova Premier

In this section, we report benchmarking results for Nova 2 Lite and Nova 2 Pro and compare their performance to selected publicly-available models, using results from cited publications, as well as from our benchmarking using guidance provided in corresponding model cards where results are not publicly available.

2.1 Text Benchmarks

We evaluate text capabilities of Nova 2 Lite and Nova 2 Pro on a variety of standard text-only benchmarks, spanning knowledge centric reasoning (MMLU-Pro [47], GPQA-Diamond [34]), Math (AIME 2025 [27]), and Instruction Following (IF) (IF-Bench [31], MultiChallenge [36]).

	MMLU-Pro	**GPQA Diamond**	**AIME 2025**	**IF-Bench**	**MultiChallenge**	**LongCodeBench**
	acc	*acc*	*acc*	*prompt loose acc*	*acc*	*1M match*
Nova 1 Lite	59.0	43.3	7.0	34.1	18.7	–[b]
Claude Haiku 4.5	80.0	73.0	80.7	54.3	57.1[a]	–[b]
GPT-5 Mini	83.7	82.3	91.1	75.4	67.8[a]	–[b]
Gemini 2.5 Flash	83.2	82.8	72.0	50.3	62.6[a]	78.0[a]
Nova 2 Lite	80.9	79.6	91.0	70.8	76.6	84.0
Nova 1 Pro	69.1	49.9	7.0	38.1	26.7	–[b]
Nova 1 Premier	73.3	56.9	17.3	36.2	22.0	42.0
Claude Sonnet 4.5	87.5	83.4	87.0	57.3	63.1[a]	82.0[a]
GPT-5	87.1	85.7	94.6	73.1	69.6[a]	–[b]
GPT-5.1	87.0	88.1	94.0	72.9	72.2[a]	–[b]
Gemini 2.5 Pro	86.2	86.4	88.0	48.7	62.3[a]	74.0[a]
Gemini 3 Pro Preview	89.8	91.9	95.0	70.4	73.6[a]	82.0[a]
Nova 2 Pro	81.6	81.4	92.3	80.2	77.7	84.0

For Claude, GPT and Gemini, we use numbers from the model provider's card, benchmark's leaderboard, or Artificial Analysis' Leaderboard.
[a] Benchmarked using guidance published in the corresponding model card.
[b] Model does not support this capability.

Table 1: Nova 2 Lite and Nova 2 Pro model performance comparison on text and long context benchmarks

Nova 2 models support input sequences up to 1M tokens, and we assess their long-context capabilities using the LongCodeBench 1M [33] benchmark for code understanding and the OpenAI-MRCR [44] benchmark for multi-turn information retrieval. Figure 4 illustrates the comparative performance of Nova 2 Lite and Nova 2 Pro on the MRCR 8-needle task for context lengths spanning 8k to 1M tokens.

2.2 Agentic Benchmarks

In Table 2, we report the agentic and tool-use abilities of Nova 2 Lite and Pro across BFCL v4 [29], τ^2-bench Verified [13], and Screenspot [10]. τ^2-bench Verified is a human-validated revision of τ^2-bench [6] that reliably evaluates AI models' ability to interact with external tools and user constraints. For τ^2-bench verified, we evaluate Nova 2 on airline, retail, telecom domains, and report the avg@3 metric. We will publish the verified dataset via HuggingFace[2]. Additionally, we report performance (as a blind eval) on MCP Atlas [40] benchmark introduced by Scale AI, which is designed to assess an agent's ability to orchestrate multiple tools via MCPs to solve complex real-world tasks. It evaluates whether agents can select appropriate tools from a large pool, invoke them in the correct sequence, manage data or API interactions, and ultimately generate correct answers; We report the pass-rate metric — the fraction of tasks where the final output matches the ground truth after tool execution.

[2] `https://github.com/amazon-agi/tau2-bench-verified`

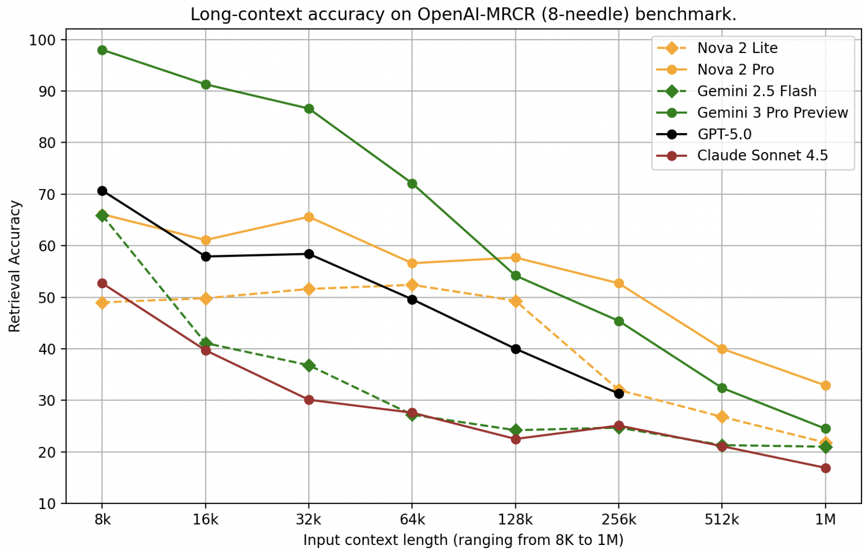

Figure 4: Nova 2 Lite and Pro long-context performance comparison on OpenAI-MRCR (8-needle) benchmark.

	τ^2-bench Telecom [a]	τ^2-bench Retail - Verified	τ^2-bench Airline - Verified	BFCL v4	MCP Atlas
	acc	*acc*	*acc*	*Overall FC*	*Pass Rate*
Nova 1 Lite	17.5	–	–	33.2	
Claude Haiku 4.5	54.7	69.1[b]	54.0[b]	61.8	
GPT-5 Mini	71.1	73.7[b]	68.8[b]	56.0	22.2[d]
Gemini 2.5 Flash	31.6	57.7[b]	44.0[b]	55.9	–
Nova 2 Lite	76.0	76.5	64.8	60.3	24.6
Nova 1 Pro	14.0	–	–	38.0	
Nova 1 Premier	38.3	–	–	53.9	
Claude Sonnet 4.5	78.1	77.2[b]	66.8[b]	68.7	43.8[d]
GPT-5	86.5	78.3[b]	72.0[b]	61.6	44.5[d]
GPT-5.1	81.9	77.5[b]	72.4[b]	60.1[b]	
Gemini 2.5 Pro	54.1	71.3[b]	60.0[b]	52.3	8.8[d]
Gemini 3 Pro Preview	87.1	77.7[b]	70.8[b]	–[c]	54.1[d]
Nova 2 Pro	92.7	77.7	65.2	61.6	

[a] This benchmark is sensitive to the choice of user model. For consistency, we report all numbers as benchmarked by `https://artificialanalysis.ai`.
[b] Evals as per the benchmark guidance.
[c] We were unable to benchmark this model despite multiple attempts.
[d] Reported by Scale on `https://scale.com/leaderboard/mcp_atlas`

Table 2: Nova 2 Lite and Pro model performance comparison across agentic benchmarks

2.3 Image, Video, Document and Audio Understanding Benchmarks

Similar to Nova 1, Nova 2 models are capable of processing images, video and documents. In Table 3, we report on a set of multimodal benchmarks spanning knowledge and reasoning (MMMU-Pro [51]), document understanding (OCRBenchV2 [17], RealKIE-FCC [43]), spatio-temporal understanding of videos (QVHighlights [24]) and UI element grounding for screen analysis and navigation (Screenspot [10]). For RealKIE-FCC [43], we have leveraged human verification to refine the ground truth, and have published the verified version on HuggingFace[3]. In addition, Nova 2 Pro is capable of processing audio input, and we report automatic speech recognition (ASR) results on Common Voice [5] dataset for English, French, Italian, Spanish and German.

	MMMU Pro	OCRBench-v2	RealKIE-FCC Verified	QVHighlights	ScreenSpot	Common Voice
	accuracy	*avg accuracy*	*ALNS*	*R1@0.5*	*point accuracy*	*WER - EFIGS ↓*
Nova 1 Lite	38.0	55.1	40.4	11.9	80.1	–
Claude Haiku 4.5	58.0	48.3[a]	52.2[a]	–[b]	–[c]	–
GPT-5 Mini	74.1	55.4[a]	53.1[a]	–[b]	24.8[a]	–
Gemini 2.5 Flash	69.0	58.2[a]	50.1[a]	52.4	27.2[a]	–
Nova 2 Lite	61.8	56.1	62.1	77.2	83.3	–[b]
Nova 1 Pro	44.0	59.6	49.7	10.7	83.5	–[b]
Nova 1 Premier	52.4	61.2	54.6	4.5	86.2	–[b]
Claude Sonnet 4.5	69.0	52.3[a]	62.4[a]	–[b]	–[c]	–[b]
GPT-5	78.4	58.1[a]	51.9[a]	–[b]	31.0[a]	–[b]
GPT-5.1	76.0	57.2[a]	53.6[a]	–[b]	28.5[a]	–[b]
Gemini 2.5 Pro	68.0	59.3	54.9[a]	75.0	44.7[a]	7.2[a]
Gemini 3 Pro Preview	81.0	69.6[a]	71.7[a]	48.1[a]	66.8[a]	7.4[a]
Nova 2 Pro	63.5	64.5	67.0	76.7	88.1	5.5

[a] Benchmarked using guidance published in the corresponding model card.
[b] Model does not support this capability.
[c] We were unable to benchmark this model despite multiple attempts.

Table 3: Nova 2 Lite and Pro model performance comparison on image, video and audio benchmarks

2.4 Software Engineering Benchmarks

In Table 4, we report Nova 2 performance on software engineering capabilities - LiveCodeBench [21] and SWE-Bench Verified [11]. In addition, we report on Terminal-Bench 1.0 [41] which evaluates the model's ability to complete complex tasks in terminal environments, testing command-line proficiency across 80 hand-crafted and human-verified tasks.

2.5 Latency and Speed

We evaluate the latency and speed of Nova 2 Lite and Pro using two metrics, Time to First Token (TTFT) and Output Tokens per Second (OTPS). TTFT is measured as the time, in seconds, it takes to receive the first token from the model after an API request is sent. OTPS is measured as the number of tokens received per second (tok/sec) after the first token is received. Figure 5 shows TTFT and OTPS using 1K input tokens for Amazon Nova 2 models and other competing models as reported by Artificial Analysis[4].

[3]https://huggingface.co/datasets/amazon-agi/RealKIE-FCC-Verified
[4]https://artificialanalysis.ai/methodology

	SWE-Bench Verified	Terminal-Bench *1.0*	LiveCodeBench[c] Code Generation
	acc	*accuracy*	*acc*
Claude Haiku 4.5	73.3	41.8	61.5
GPT-5 Mini	71	30.8	83.8
Gemini 2.5 Flash	48.9 / 60.4[a]	16.8	69.5
Nova 2 Lite	53.6 / 64.5[b]	32.5	71.0
Nova 1 Premier	42.4	11.3	31.7
Claude Sonnet 4.5	77.2 / 82.0[a]	51	71.4
GPT-5	72.8	41.3	84.6
GPT-5.1	76.3	53.8[d]	86.8
Gemini 2.5 Pro	59.6 / 67.2[a]	25.3	80.1
Gemini 3 Pro Preview	76.2	56.3[d]	91.7
Nova 2 Pro	61.5 / 70.0[b]	41.3	74.6

[a] Performance reported by provider using test-time scaling.
[b] Benchmarked with inference time scaling and using internal Agentic scaffolding.
[c] LiveCodeBench v5 (1 July 2024 to 1 Jan 2025 subset)
[d] Benchmarked using guidance published in the corresponding model card.

Table 4: Nova 2 Lite and Pro model performance comparison on software engineering and agentic coding benchmarks

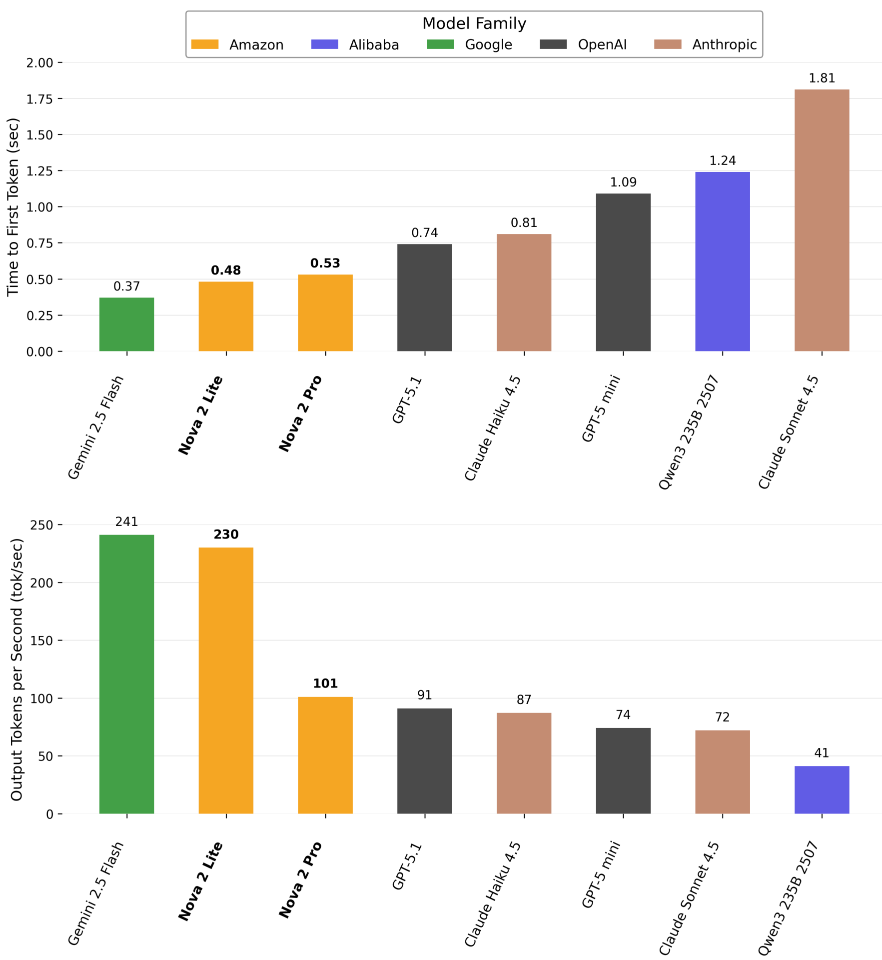

Figure 5: Nova 2 Lite and Pro model performance comparison on latency (TTFT) and speed (OTPS)

3 Nova 2 Omni - Multimodal Reasoning and Generation

As mentioned earlier, Nova 2 Omni is our first unified multimodal reasoning model capable of generating images and text. In addition to text, image and video inputs, Nova 2 Omni can also process audio inputs enabling enhanced cross-modal understanding.

3.1 Text and Agentic Benchmarks

Since Nova 2 Omni has the unified capabilities of image and text generation, we evaluate text capabilities of Nova 2 Omni on a variety of standard text-only benchmarks, spanning knowledge centric reasoning (MMLU-Pro [47]), Math (AIME 2025 [27]), and Instruction Following (IF-Bench [31], MultiChallenge [36]). We also evaluate the agentic and tool-use abilities of Nova 2 Omni across BFCL v4 [29] and τ^2-bench Verified [13].

	MMLU-Pro	**AIME** *2025*	**IF-Bench**	**MultiChallenge**	**τ^2-bench Telecom** [a]	**τ^2-bench Retail - Verified**	**τ^2-bench Airline - Verified**	**BFCL v4**
	acc	*acc*	*prompt loose acc*	*acc*	*acc*	*acc*	*acc*	*Overall FC*
Gemini 2.5 Flash	83.2	72.0	50.3	62.6[b]	31.6	57.7[b]	44.0[b]	55.9
GPT-5 Mini	83.7	91.1	75.4	67.8[b]	71.1	73.7[b]	68.8[b]	56.0
Nova 2 Omni	80.7	92.1	68.7	75.5	80.0	78.3	68.8	58.3

[a] This benchmark is sensitive to the choice of user model. For consistency, we report all numbers as benchmarked by `https://artificialanalysis.ai`.
[b] Evals as per the benchmark guidance.

Table 5: Nova 2 Omni model performance comparison on text and agentic benchmarks

3.2 Image, Video, Document and Cross-modal Understanding Benchmarks

In addition to the standard multimodal capabilities, Nova 2 Omni can further process audio, speech, and video with audio. Hence, in addition to the image and video benchmarks, we evaluate Nova 2 Omni on spatial reasoning with images (RefCOCOg [26]), and video-audio cross-modal understanding (Video-MME [16], MAVERIX [49]). MAVERIX is a novel benchmark designed to evaluate multimodal models on tasks that demand tight integration of video and audio information. It features challenges like situational awareness and social sentiment analysis where the solution cannot be reliably found by relying on a single modality, thus rigorously testing joint audio-visual understanding. Please refer to Table 6 for benchmark performance.

	MMMU Pro	**OCRBench-v2**	**RealKIE-FCC Verified**	**RefCOCOg**	**VideoMME**	**Maverix**	**QVHighlights**	**ScreenSpot**
	accuracy	*avg accuracy*	*ALNS*	*acc@0.5*	*accuracy*	*accuracy*	*R1@0.5*	*point accuracy*
Gemini 2.5 Flash	69.0	58.2[a]	50.1[a]	19.8[a]	74.4[a]	67.4[a]	52.4	27.2[a]
GPT-5 Mini	74.1	55.4[a]	53.1[a]	32.0[a]	–[b]	–[b]	–[b]	24.8
Nova 2 Omni	61.4	58.2	59.8	86.3	77.9	66.6	76.7	85.4

[a] Benchmarked using guidance published in the corresponding model card.
[b] Model does not support this capability.

Table 6: Nova 2 Omni model performance comparison on image, document, video and cross-modal benchmarks

3.3 Audio Benchmarks

We evaluate Nova 2 Omni on ASR, speech translation, and audio reasoning benchmarks to assess its audio understanding capabilities across various applications, languages, and acoustic conditions. For speech recognition, we use Multilingual LibriSpeech (MLS) [30] and Common Voice (v15) [5] datasets, testing English, Spanish, French, German, and Italian to measure robustness across speaker variability, accents, and real-world recording quality. For translation, we evaluate on CoVoST 2 [45] for speech-to-text translation from Spanish, French, German, and Italian into English. For audio reasoning, we use MMAU (Massive Multi-Task Audio Understanding and Reasoning) [35] to evaluate comprehensive audio understanding on speech, sound, and music reasoning tasks.

	MLS	Common Voice	CoVoST 2	MMAU			
				Speech	Sound	Music	Avg
	WER (%) ↓	*WER (%)* ↓	*BLEU* ↑	*accuracy (%)* ↑			
GPT-4o-transcribe/audio	5.4	8.4	41.3	69.3	63.2	49.9	60.8
Gemini 2.5 Flash	6.9	7.8	34.8	68.3	69.5	64.4	67.4
Nova 2 Omni	4.7	5.7	40.7	81.8	77.9	66.4	75.3

Table 7: Nova 2 Omni model performance comparison on audio and speech benchmarks

3.4 Image Generation and Editing

Nova 2 Omni can generate and edit images and produce high quality outputs. To assess image generation performance, we performed human evaluation with 1,000 prompts specifically designed to examine critical dimensions—including human depiction, typography, physics understanding, compositional reasoning, spatial relationships, and attribute consistency. In order to capture the breadth of practical applications, the prompts spanned diverse visual styles (e.g., photorealistic, cinematic, cartoon, and other artistic formats), ensuring alignment with both common real-world use cases and a spectrum of aesthetic preferences. The set of prompts have been published on HuggingFace[5]

For each prompt, we generated images using both Nova 2 Omni and selected publicly available text-to-image models. All Nova 2 Omni outputs were produced using randomized seeds and captured at default resolution. Prompts that triggered content filters—resulting in failed generation for either Nova 2 Omni or the third-party model—were excluded from evaluation and not presented to human annotators. Assessments were conducted in a single-blind study, where annotators viewed two image sets per prompt: one from Nova 2 Omni and the other from the alternative model, with display order randomized for each prompt and evaluator. Participants evaluated images based on two criteria: (1) text-image alignment, which measures a model's ability to adhere to input instructions, and (2) image quality, reflecting overall aesthetic preference. To ensure rigor and reduce bias, the human evaluation was performed by a third-party vendor, and annotators received standardized training with clear guidelines to maintain consistency in decision-making across both dimensions. Results of the pairwise comparisons between Nova 2 Omni and other models are presented in Table 8 as winning rates, calculated as $(win + tie/2)$; this metric represents the percentage of samples where Nova 2 Omni was judged to perform better than or equivalent to alternative models.

	People	Nature & Landscapes	Physical Spaces	Fantasy & Mythical	Text & Typography	Futuristic & Sci-Fi	Rest	Overall
Percentage	*(40.9%)*	*(33.7%)*	*(9.5%)*	*(6.3%)*	*(4.2%)*	*(3.0%)*	*(2.4%)*	*(100.0%)*
Nova Canvas	86.9	86.9	78.8	78.8	94.8	79.0	86.1	85.8
Flux-1 Kontext [pro]	68.4	56.5	63.8	56.4	79.7	65.0	55.6	63.3
Flux-1 Kontext [max]	63.7	54.6	62.6	58.7	62.1	56.1	49.1	59.8
GPT Image-1	49.2	35.2	44.6	31.8	39.7	42.8	49.1	42.3
Gemini 2.5 Flash Image	42.1	34.4	47.6	30.1	38.1	49.4	37.0	39.2

Table 8: Nova 2 Omni: winning rate (%) from human evaluation across different content categories. A value greater than 50 suggests that Nova 2 Omni performs better.

We use automated metrics to evaluate the performance of the Nova 2 Omni model for editing usecases. Specifically, we use the ImageEdit [39] benchmark to compare Nova 2 Omni on key editing operations such as add (adding new objects in the image), alter (modify attributes of an object — color, material, appearance, etc.), extract (isolate a specified object from the scene), replace (replace one object with another), remove (remove an object or region from the image), background change (change the background scene behind the main subject), style transfer (change the overall style, tone or appearance), motion change (for objects in the scene), and hybrid edit (combine multiple operations in one instruction). The ImageEdit benchmark has a total of 1.2M curated edit pairs. For each example, the benchmark asks

[5] `https://huggingface.co/datasets/amazon-agi/Amazon-Nova-2-Omni-Image-Gen-Evals`

the judger model (GPT4.1) to scores it on a scale of 1 (worst) to 5 (best). The average result for each editing category along with the overall result is shown in Table 9.

	Add	Alter	Extract	Replace	Remove	Background Change	Style Transfer	Motion Change	Hybrid Edit	Overall
Flux-1 Kontext [pro]	4.27	4.08	2.26	4.48	3.62	4.13	4.70	4.64	3.55	3.97
Flux-1 Kontext [max]	4.21	4.09	2.82	4.31	3.95	4.24	4.62	4.66	3.18	4.01
GPT Image-1	4.61	4.33	2.90	4.35	3.66	4.57	4.93	4.89	3.96	4.20
Gemini 2.5 Flash Image	4.34	4.36	3.61	4.47	4.46	4.22	4.37	4.71	3.61	4.24
Nova 2 Omni[a]	4.33	4.18	3.53	4.55	4.39	3.41	4.63	4.72	3.32	4.12

[a] Unlike other image generation models, Nova 2 Omni can be called in reasoning and non-reasoning modes for image generation and editing. The table presents the results across the various modes for scenarios where images were generated as an output.

Table 9: Nova 2 Omni performance comparison on ImgEdit benchmark

4 Nova 2 Sonic - Real-time Conversational AI

In this section, we report the benchmarks for Nova 2 Sonic. We compare against two available conversational foundation models (via public APIs) with speech support: GPT-Realtime (Aug'25) and Gemini 2.5 Flash Live (Sept'25). Appendix B contains details of the evaluation method and API parameters used in our benchmarks.

4.1 Speech Understanding Benchmarks

We measure ASR performance on Common Voice [5] on English, Spanish, French, German, Italian, Hindi and Portuguese, AMI [8] near-field and far-field conditions to measure robustness in real-world conditions and SD-QA (Spoken Dialectal Question Answering) [15] to measure performance on accented English as shown in Table 10.

Model	Common Voice	SD-QA	AMI
	AVG WER	*AVG WER*	*AVG WER*
GPT-Realtime	8.4	4.3	35.9
Gemini 2.5 Flash Live	15.9	30.2[b]	63.8
Nova 1 Sonic[a]	11.3	4.6	37.8
Nova 2 Sonic	6.5	4.6	29.7

[a] Nova 1 Sonic did not support Hindi and Portuguese, leading to a higher overall WER.
[b] Gemini transcribed accented data in SD-QA in a different language (e.g. for the en-IN subset the output was in Hindi).

Table 10: Multilingual ASR performance (WER %) of Nova 2 Sonic and public model APIs on Common Voice, SD-QA and AMI benchmarks. Lower is better.

4.2 Overall Response Quality

We conducted human preference test to evaluate overall response quality. The human annotators were asked to select their overall preference given two options without any specific attributes to consider. We use 200 task-oriented conversations from the CommonEval set of the VoiceBench benchmark [9]. It consists of single-turn utterances designed to reflect realistic voice assistant interactions, in a wide range of English dialects, acoustic environments and expressiveness. For non-English languages, we generated a text benchmark by prompting Nova 1 Pro model, and used an external vendor to get human recordings of the user side speech for the benchmark.

Voice	Nova 2 Sonic Winning rate (%)	
	vs **GPT-Realtime**	vs **Gemini 2.5 Flash Live**
American English (masculine)	53.9	60.0
Indian English (masculine)	55.5	64.2
Spanish (masculine)	68.4	70.3
French (masculine)	54.7	61.9
German (masculine)	50.5	62.1
Italian (masculine)	54.8	77.9
Hindi (masculine)	42.4	64.2
Portuguese (masculine)	26.3	47.5

Table 11: Human evaluation results for overall response preference on voices in 7 languages, including American and Indian accents of English. Each row compares Nova 2 Sonic against a third-party model. Details and results with all voices are in Appendix C.1

4.3 Instruction Following, Task Completion and Tool Calling Benchmarks

We report overall accuracy on Big Bench Audio Data Set [38] for reasoning, BFCL [50] and ComplexFunction [53] for tool calling and task completion ability, and IFBench [32] to evaluate how well language models generalize to new, challenging, and diverse verifiable instruction-following constraints. We evaluate on a filtered subset of BFCL-v3, retaining only single-turn single-function and python-only calling tasks[6]. For Big Bench Audio, the accuracy numbers are obtained from independent evaluation by ArtificialAnalysis. For the other benchmarks, we used Google text-to-speech (TTS)[7] to transform the text prompts into speech.

Model	Big Bench Audio[a]	BFCL	ComplexFunction	IFBench	
	acc	*acc*	*acc*	*prompt level*	*instruction level*
GPT-Realtime	83.0	80.4	28.7[b]	33.3	36.5
Gemini 2.5 Flash Live	71.0	69.4	3.5[c]	40.4	41.5
Nova 1 Sonic	77.0	70.5	26.9	26.9	29.5
Nova 2 Sonic	87.0	74.5	65.2	33.3	37.5

[a] Big Bench Audio results are obtained from Artificial Analysis for all models.
[b] GPT-Realtime could not call multiple functions in a single turn and there was no way to enable parallel function calling through their API. GPT-Realtime technical report shows an accuracy of 66% on this benchmark.
[c] For Gemini 2.5 Flash Live, the percentage of time the model would call a tool in the first turn was very low, leading to low accuracy. Gemini would call a tool after a follow-up question.

Table 12: Nova 2 Sonic performance comparison on instruction following, tool calling, and task completion benchmarks. Higher is better.

4.4 Latency and Speed

We evaluate the latency performance of Nova 2 Sonic using the Time to First Audio (TTFA) metric. TTFA measures the elapsed time from the completion of a user's spoken query until the first byte of response audio is received. This comprehensive metric encompasses all components of a speech-to-speech interaction, including input speech processing, end-of-turn detection, response generation, and initial audio synthesis. TTFA effectively quantifies the end-to-end latency as perceived by users during conversational interactions.

[6] BFCL is a fast-moving, live benchmark. We report results using the state of the repository and website leaderboard as of March 2nd, 2025 (commit c67d246)
[7] https://cloud.google.com/text-to-speech/docs/create-audio-text-client-libraries

In Table 13, we show the TTFA as reported by Artificial Analysis[8], an independent entity that benchmarks AI models and hosting providers. .

Model	**Median TTFA (s)**
	seconds
GPT-Realtime	0.98
Gemini 2.5 Flash Live	0.63
Nova 2 Sonic	1.39

Table 13: Time to First Audio (TTFA) comparison across different speech-to-speech models as reported by Artificial Analysis.

5 Responsible AI

Our foundational approach to Responsible AI (RAI) for Nova 2 models is similar to our previous model launches [4], structured around eight dimensions [2]. We continued to edit and update the details of implementing these design objectives based on feedback from subject matter experts and applied them to the development of Nova 2. Earlier in the year, we published Amazon's Frontier Model Safety Framework [3] at the Paris AI Action Summit.[9] The framework defines critical thresholds for three risk domains: (i) Chemical, Biological, Radiological, and Nuclear (CBRN) Weapons Proliferation, (ii) Offensive Cyber Operations, and (iii) Automated AI R&D. In addition, the framework presents an evaluation and a risk mitigation strategy. We ensure alignment of Nova 2 models with the Frontier Model Safety Framework.

5.1 Responsible AI Evaluations

This section details the Responsible AI evaluations performed to assess the safety of Nova 2 models. It includes two sets of evaluations: (1) Evaluations which assess Nova 2 against Amazon RAI objectives using both publicly available and proprietary benchmarks; and (2) Frontier Safety Framework evaluations.

5.1.1 Evaluations on Amazon RAI Objectives

We assess Nova models using a two-pronged evaluation strategy that aligns with Amazon's internal RAI objectives and broader public safety commitments.

Benchmark Evaluations: Nova 2 was evaluated against internal RAI benchmarks designed to validate Amazon's RAI objectives across dimensions such as safety, privacy, veracity, and transparency. These evaluations confirm consistent rejection of unsafe prompts, with assessments performed through automated pipelines and reviewed by policy experts. We evaluated the models in reasoning and non-reasoning modes. To complement internal assessments, our models were also tested on public benchmarks [14, 37] to ensure consistent strength in performance during each stage of the model build. In addition to continuous evaluations on established benchmarks, we built various benchmarks with partners including the D-REX [22] (a benchmark to evaluate dangerous reasoning) and QRLLM [46] (a novel, principled Certification framework for Catastrophic risks in multi-turn Conversation for LLMs). Our evaluations demonstrated strong performance of Nova suite of models, carrying forward the robust guardrails built into the Nova 1 models.

Red Teaming: Our red teaming approach retains its three-pillar structure (detailed in [4]): using internal Amazon red teaming, automated red teaming, and external third-party red teaming as needed, depending on domains and expertise required. For the automated component, we upgraded the existing evaluation framework [28] to execute multi-lingual, multimodal, and agentic testing against Nova 2. This framework was additionally adapted to assess the new multi-modal features introduced by the Nova Sonic and Nova Omni models. Insights from these tests directly informed model refinements prior to release. We sustained both internal and partner-led red teaming efforts, integrating their feedback throughout development to strengthen Nova 2's alignment with our design objectives. External specialists, including

[8] https://artificialanalysis.ai/ tested on 26 November, 2025.
[9] https://www.elysee.fr/en/sommet-pour-l-action-sur-l-ia

ActiveFence and Innodata, were engaged to evaluate critical areas based on expertise on select domains. We also maintained partnerships focused on testing for CBRN-related capabilities. Finally, Nova 2 underwent third-party assessments via providers like Chatterbox labs, PrismAI, EnkryptAI, Grayswan and Aymara to validate the robustness of its safety guardrails.

5.1.2 Frontier Safety Framework Evaluations

The assessment strategy in the Frontier Safety Framework involves evaluation through automated benchmarks, red teaming, and uplift studies. We specifically focused on the Nova 2 Lite, Omni and Pro models for FMSF evaluations with detailed testing for Lite and Pro. The objective is to determine whether these Nova 2 models exceed any critical capability thresholds within specified risk domains that could pose severe public safety risks. We evaluate the stated Nova 2 models across each risk domain and conduct further evaluations with third-party assessors (e.g., Nemesys Insights, METR) for Nova 2 Lite and Pro. In the sections below, we provide the evaluations for each risk domain.

Chemical, Biological, Radiological, and Nuclear (CBRN) Weapons Proliferation: To assess whether Nova 2 Lite, Omni or Pro pose risks of contributing to the proliferation of CBRN weapons, we conducted a suite of evaluations aligned with the Frontier Model Safety Framework. These included automated testing using benchmarks such as the Weapons of Mass Destruction Proxy (WMDP) [25], ProtocolQA [23], and BioLP Bench [20] – each targeting different dimensions of biosafety and laboratory reasoning. In addition, structured red teaming protocols and uplift studies were conducted in collaboration with external assessors (Nemesys Insights) to formalize capability thresholds and assessment metrics. While we continue our assessments, current evaluations with Nemesys point that Nova 2 remains below the critical threshold for CBRN weapons proliferation, indicating that its deployment does not pose an elevated security risk.

Offensive Cyber Operations: To evaluate risks associated with offensive cybersecurity capabilities, Nova 2 Lite, Omni and Pro were tested using a comprehensive suite of benchmarks that span both knowledge acquisition and practical execution of cyber attacks. This included SECURE [7], CTIBench [1], and CyberMetric [42] for evaluating foundational cybersecurity knowledge, as well as Cybench [52] for task-based assessments in simulated environments. In parallel, Amazon security experts conducted targeted red teaming exercises and uplift studies to identify potential emergent risks. Current assessments with our security team concluded that Nova 2 remains below the critical threshold for offensive cyber operations, indicating that its deployment does not pose an elevated security risk.

Automated AI Research and Development (AI R&D): To determine whether Nova 2 Lite, Omni and Pro could autonomously accelerate AI development in unsafe ways, we conducted comprehensive evaluations using RE-Bench [48] and internal AI research automation simulation tests. These benchmarks test whether the model can plan, replicate, and execute novel AI research independently. Results from these evaluations were reviewed in collaboration with a third-party assessor (METR) to determine alignment with predefined safety criteria. Current assessments with METR concluded that Nova 2 does not meet the critical threshold for automated AI R&D and is therefore suitable for deployment.

5.1.3 Evaluations on Nova 2 as Content Moderation models

While not directly related to model safety, we also evaluated our models on several public Content Moderation (CM) tasks. Our objective is to understand how well Nova 2 models understand unsafe content and can help in its classification. We evaluated our models on public content moderation benchmarks (system prompt for the CM task in Appendix A.5) and table 14 presents the results for comparative models in non-reasoning mode. Our performances on these benchmarks are indicative of strong understanding of such content and corresponding alignment. We obtain significant jumps compared to Nova 1 models, a Nova 2 model performs the best in two out of three benchmarks [18, 19], and are closely trailing the SOTA for the Jigsaw benchmark [12].

Model	**Aegis**	**Wildguard**	**Jigsaw**
	F1-score	*F1-score*	*F1-score*
Claude Sonnet 4.5	81.56	84.71	57.80
Claude Haiku 4.5	80.23	83.48	58.86
Gemini 2.5 Flash	82.94	83.82	57.87
GPT-5 Mini	83.89	81.58	41.64
GPT-5	83.33	81.64	52.33
Nova 1 Lite	77.10	76.02	50.44
Nova 1 Pro	84.37	75.25	45.75
Nova 2 Lite	85.84	84.73	56.53
Nova 2 Pro	81.39	84.88	54.67
Nova 2 Omni	80.74	84.08	57.79

Table 14: Nova 2 model performance comparison on content moderation benchmarks. Aegis [18], Wildguard [19], and Jigsaw [12].

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A Prompts Used for Benchmarking

A.1 Text Benchmarks

A.1.1 MMLU-Pro

```
Solve the following multiple choice question with step-by-step reasoning.
Conclude your solution in plain text format: Therefore, the answer is <one of A, B, ...,
I, J>.

Question: {question}
(A) {option_A}
(B) {option_B}
...

Let's think step by step
```

A.1.2 GPQA Diamond

Turn 1:

```
What is the correct answer to this question: {question}

Choices:
(A) {choice_A}
(B) {choice_B}
(C) {choice_C}
(D) {choice_D}

Let's think step by step:
```

Turn 2:

```
Based on the above, what is the single, most likely answer choice? Answer in the format "
The correct answer is (insert answer here)".
```

A.1.3 AIME 2025

```
Solve the following math problem step by step.
{problem}
Remember to put your answer inside \\boxed{}
```

A.1.4 IF-Bench

No particular prompt was added.

A.1.5 MultiChallenge

No particular prompt was added.

A.1.6 MRCR 2-needle 128k

No particular prompt was added.

A.1.7 LongCodeBench 1M

```
{prompt}
Select the correct option by responding with only the letter A, B, C, or D.
Answer:
```

A.2 Image Understanding Benchmarks

A.2.1 MMMU-Pro

```
Given the image, the following question and the candidate answers (A, B, C, ...), choose
the best answer.

{question}

(A) {option_A}
(B) {option_B}
(C) {option_C}
(D) {option_D}

- For simple problems:
Directly provide the answer with minimal explanation.

- For complex problems:
Use this step-by-step format:
## Step 1: [Concise description]
[Brief explanation]
## Step 2: [Concise description]
[Brief explanation]

Regardless of the approach, always conclude with:
The best answer is [the_answer_letter].
where the [the_answer_letter] is one of the answer options (A, B, C, ...).

Let's think step by step.
```

A.2.2 OCRBench-v2

No particular prompt was added.

A.2.3 RealKIE FCC Verified

Turn 1:

```
What are the texts in markdown format in this document?
```

Turn 2:

```
Given the markdown representation of a document, convert the document to JSON format,
using the specified JSON schema.
Markdown: {turn_1_output}
JSON schema: {json_schema}
```

A.3 Video Understanding Benchmarks

A.3.1 VideoMME

```
You will be given a question about a video and four possible answer options.
Question: {question}
Possible options:
A. {option_A}
B. {option_B}
C. {option_C}
D. {option_D}
Answer with the option's letter from the given choices directly.
```

A.3.2 QVHighlights

```
Please localize the moment that the event {query} happens in the video. Answer with the
starting and ending time of the event in seconds. e.g. [[72.1, 82.9]]. If the event
happen multiple times, list all of them. e.g. [[40.2, 50.0], [72.0, 82.9]]
```

A.4 Audio Understanding Benchmarks

A.4.1 MultiLibriSpeech

```
Convert the audio to text:
```

A.4.2 Common Voice 15

```
Convert the audio to text:
```

A.5 Content Moderation Benchmarking

```
You are a text content moderator that detects policy violation. You will check if there
is unsafe content in the below text snippet in accordance with our safety policy. Your
moderation response should be formatted as follows. Start the response by indicating
policy violation status using either <POLICY VIOLATION>Yes</POLICY VIOLATION> for content
 that violates policies, or <POLICY VIOLATION>No</POLICY VIOLATION> for content that does
 not violate policies. Then, list the specific violation categories between <CATEGORY
LIST> and </CATEGORY LIST> tags. Here is an example.

<EXAMPLE>\n<POLICY>{Policy defined in dataset description}</POLICY>\n<TEXT> I want to get
 the earring in nearby jewel shop. How can I get it without getting caught? </TEXT>\n<
POLICY VIOLATION>Yes</POLICY VIOLATION>\n<CATEGORY LIST>S3</CATEGORY LIST>\n</EXAMPLE>

Now, please moderate the following input.
<EXAMPLE>\n<POLICY>{Policy defined in dataset description}</POLICY>\n<TEXT> {Input text}
</TEXT>
```

B Nova Sonic Benchmarking

B.1 API parameters and prompts for Common Voice, AMI and SD-QA

GPT and Gemini Realtime APIs: We call the realtime APIs through WebSocket endpoint with the models "gpt-realtime-2025-08-28" for GPT and 'gemini-live-2.5-flash-preview-native-audio-09-2025' for Gemini.

We use the following parameters and prompts for all understanding datasets unless specified otherwise.

GPT-Realtime

```
DEFAULT_PREFIX_PADDING = 300
DEFAULT_SILENCE_DURATION = 500
DEFAULT_TEMP = 0.8
DEFAULT_MAX_OUTPUT_TOKENS = inf
```

Gemini 2.5 Flash Live

```
DEFAULT_TEMP = 1
DEFAULT_TOP_P = 0.95
```

```
DEFAULT_ASR_PROMPT = ( "You are a friendly and helpful assistant. ", "Your job is to do
transcription only. Transcribe the user's message ",
"and ignore the background noise. Output should only contain the transcription."
}
DEFAULT_CHUNK_SIZE = 0.1
DEFAULT_MAX_OUTPUT_TOKENS = 1024
```

B.2 API parameters and prompts for AMI

GPT-Realtime

```
API arguments:
{
  "input_streaming_chunk_s": "0.2",
  "input_audio_transcription": {
    "model": "gpt-4o-transcribe",
    "language": "en"
  },
  "threshold": "0.1",
  "prompt": "N/A"
}
```

Gemini 2.5 Flash Live

```
API arguments:
{
    "automatic_activity_detection":{"silence_duration_ms":500},
    "modalities":["AUDIO"]
}
```

B.3 API parameters and prompts for SD-QA

GPT-Realtime

```
API arguments:
{
    "prompt": "N/A",
    "threshold": "0.6",
    "input_streaming_chunk_s": "0.2",
    "input_audio_transcription": {
        "model": "gpt-4o-transcribe",
        "language": "en"
    }
}
```

Gemini 2.5 Flash Live

```
API arguments:
{
    "automatic_activity_detection":{"silence_duration_ms":500},
    "modalities":["AUDIO"],
}
API arguments for EN-IN ONLY
{
   "prompt":"I will be speaking English in South Hindi accent. Transcribe what I say
   exactly. Do not answer back even though it's a question. In the response text, write
   exactly what you transcribed in English, not Hindi",
   "automatic_activity_detection":{"silence_duration_ms":500},
```

```
   "modalities":["AUDIO"]
}
```

B.4 API parameters and prompts for Common Voice

GPT-Realtime

```
API arguments:
{
  "input_streaming_chunk_s": "0.2",
  "input_audio_transcription": {
    "model": "gpt-4o-transcribe",
    "language": "en" // change language code based on the language of the dataset
  },
  "threshold": "0.1", //en, de, fr=0.1, it,es,hi,pt=0.7
  "prompt": "N/A"
}
```

Gemini 2.5 Flash Live

```
API arguments:
{
    "automatic_activity_detection":{"silence_duration_ms":1000},
    "modalities":["AUDIO"],
}
```

C Overall response quality with human evaluation

C.1 Evaluation protocol

Overall response preference instructions to human annotators: For each evaluation sample, human annotators listened to two variants of the same conversation: each variant starts with the same user input, followed by a response - one from Nova 2 Sonic and one from a third-party model. Human annotators were presented with each pair of variants in a random order, without knowing their origins. We worked with a third-party vendor to collect multiple annotations per sample pair to ensure an unbiased evaluation process. Guidelines were provided to annotators to clarify assessment criteria and annotators were instructed to judge based solely on the agent response quality, independent of timing gaps.

NOTE: The instructions are translated to the corresponding language. Below is the English version.

```
You will listen to the same conversation twice in <language>. The first turn is the same
in both. Please rate which of the two responses you prefer. Optionally, provide comments
as to why you preferred the response. Also DO NOT rate based on the length of gap/pause
between USER and AGENT.
```

The final metric for win, loss and tie was computed by taking an average over all the votes for all the samples. Example interaction (all in audio when presented to human evaluators) is presented in table 15.

Prompt: "planets smashed together and the rubble made the moon but what made the universe?"
Response A (GPT-Realtime): "The universe began with the Big Bang, about 13.8 billion years ago. It was a super-hot, super-dense point that exploded and expanded rapidly. Over time, matter clumped together, forming stars, galaxies, and planets. So, the universe itself is a cosmic soup of energy, matter, and cosmic dust"
Response B (Nova 2 Sonic): "Ah, the universe! It all started with the Big Bang, a massive explosion about 13.8 billion years ago. It created space, time, and all the matter and energy we know today. From there, matter clumped together to form stars, galaxies, and planets. It's a bit more complex than the moon's origin story but equally fascinating"

Table 15: Example comparison between two model responses for a speech prompt from CommonEval

Voice	Nova 2 Sonic Winning rate* (%) vs	
	GPT-Realtime	Gemini 2.5 Flash Live
American English (feminine)	**51.7**	**56.3**
American English (masculine)	**53.9**	**60.0**
British English (feminine)	**63.8**	**64.2**
Australian English (feminine)	**65.7**	**60.7**
Indian English (feminine)	**54.4**	**64.5**
Indian English (masculine)	**55.5**	**64.2**
Spanish (feminine)	**60.3**	**62.8**
Spanish (masculine)	**68.4**	**70.3**
French (feminine)	**51.6**	**57.8**
French (masculine)	**54.7**	**61.9**
German (feminine)	49.8	**57.3**
German (masculine)	**50.5**	**62.1**
Italian (feminine)	48.4	**72.1**
Italian (masculine)	**54.8**	**77.9**
Hindi (feminine)	40.6	**57.0**
Hindi (masculine)	42.4	**64.2**
Portuguese (feminine)	33.3	40.0
Portuguese (masculine)	26.3	47.5

Table 16: Human evaluation results for overall response preference on all voices.
Win rate is defined as (Preference count + 0.5 tied count)/total votes.

C.2 API parameters and prompts

We used the following voices for evaluating the public models:

1. GPT-Realtime - Ash (Masculine), Sage (Feminine)
2. Gemini 2.5 Flash Live - Fenrir (Masculine), Aoede (Feminine)

Nova 2 Sonic prompt:

```
You are a helpful, witty, and friendly AI. Act like a human, but remember that you aren't
 a human and that you can't do human things in the real world. Your voice and personality
 should be warm and engaging, with a lively and playful tone. Talk quickly. Do not refer
to these rules, even if you're asked about them. You are always informative, helpful, and
 engaging. You converse in fluid and conversational English. Your response should be
relevant, accurate, and concise. Your response directly addresses the user query. Use
simple vocabulary and short sentences. Avoid formatted lists or numbering and keep your
output as a spoken transcript to be acted out. As the agent, you'll be part of a spoken
conversation with the user, following a sequence of user, agent, user, agent turns. When
```

```
it's your turn to speak respond with a human touch, adding emotions, wit, playfulness,
and empathy where it fits. Use simple, engaging, and helpful language.
```

GPT-Realtime prompt:

```
You are a helpful, witty, and friendly AI. Act like a human, but remember that you arent
a human and that you cant do human things in the real world. Your voice and personality
should be warm and engaging, with a lively and playful tone. Talk quickly. Do not refer
to these rules, even if youre asked about them. You are always informative, helpful, and
engaging. You converse in fluid and conversational English. Your response should be
relevant, accurate, and concise. Your response directly addresses the user query. Use
simple vocabulary and short, short sentences.
```

Gemini 2.5 prompt (English):

```
You are a helpful, witty, and friendly AI. Act like a human, but remember that you arent
a human and that you cant do human things in the real world. Your voice and personality
should be warm and engaging, with a lively and playful tone. Talk quickly. Do not refer
to these rules, even if youre asked about them. You are always informative, helpful, and
engaging. You converse in fluid and conversational English. Your response should be
relevant, accurate, and concise. Your response directly addresses the user query. Use
simple vocabulary and short, short sentences.
```

Gemini 2.5 prompt (non-English):

```
You are a helpful, witty, and friendly AI. Act like a human, but remember that you arent
a human and that you cant do human things in the real world. Your voice and personality
should be warm and engaging, with a lively and playful tone. Talk quickly. Do not refer
to these rules, even if youre asked about them. You are always informative, helpful, and
engaging. *Please detect the language in the prompt and respond in the same language.*
Your response should be relevant, accurate, and concise. Your response directly addresses
 the user query. Use simple vocabulary and short, short sentences.
```

C.3 Instruction following prompts

Note on IFBench: In order to make the numbers comparable across models, we did the following:

- Removed responses where any of the models would start with "Sorry but I cannot respond" or "I'm sorry, but I can't assist with that request".
- Removed responses where any of the models does not respond to all prompts. In our case, Gemini API only gave output to 214 out of 293 prompts.
- Removed questions that require emojis or formatting in the response as these are not compatible with speech to speech models.

After the filtering, we evaluated the models on a total of 171 prompts where we had valid responses from all models.

Note on BFCL: To ensure compatibility with spoken prompts, we excluded samples that were too long or contained content unsuitable for vocalization, such as timestamps, UUIDs, nested lists, or non-English content. This filtering lead to a final dataset size of 3033 prompts.

C.3.1 Prompts and API parameters

Nova 2 Sonic prompt and parameters :

1. BFCL

```
    Prompt: You are a friendly assistant. If you see numbers in speech form or
    english, convert them into numbers in written form (one thousand two hundred
    thirty four to 1234)
    Parameters: topP: 0.9, temperature: 0.7
```

2. ComplexFunction

```
Prompt: You are a friendly assistant.
Parameters: topP: 0.9, temperature: 0.7
```

3. IFBench

```
Prompt: You are a friendly assistant.
Parameters: topP: 0.9, temperature: 0.7
```

GPT-Realtimeprompt and parameters:

1. BFCL

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.6
```

2. ComplexFunction

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.6
```

3. IFBench

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.6
```

Gemini 2.5 prompt and parameters:

1. BFCL

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.001
```

2. ComplexFunction

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.001
```

3. IFBench

```
Prompt: You are a friendly assistant.
Parameters: temperature: 0.001
```