International Journal of Technology and Management



# Measuring Performance in Generative AI: Metrics, Methodologies, and Industry Implications

**IJOTM**
ISSN 2518-8623
DOI: 10.67610/ijotm.10.1.006
Volume 10. Issue 1
pp. 1-11, June 2025
ijotm.utamu.ac.ug
email: ijotm@utamu.ac.ug

**Nicholas Wakou,**

Distinguished Member of Technical Staff, Dell Technologies, Austin, Texas, USA
Email: nicholas.wakou@dell.com

## Abstract

Generative AI (GenAI) technologies, including large language models (LLMs), diffusion models, and multimodal architecture are rapidly transforming sectors ranging from education and healthcare to enterprise automation and creative industries. As these models scale in size and complexity, their computational demands grow exponentially, making performance evaluation a critical aspect of system design and deployment. This paper examines how the industry measures GenAI performance, emphasizing the importance of robust benchmarking frameworks that reflect real-world usage. Additionally, the paper presents a comprehensive overview of key metrics across three dimensions: performance (e.g., latency, throughput), quality (e.g., task-based and human-in-the-loop evaluation), and efficiency (e.g., energy consumption, cost per query). Supported by benchmark data and recent research, the analysis highlights the implications of these metrics for scalability, user experience, and sustainability in GenAI systems.

***Keywords****: Generative AI, Benchmarking, Large Language Models, Performance Evaluation, AI Ethics, LoRA, Energy Efficiency, MLPerf.*

## Introduction

Generative Artificial Intelligence (GenAI), encompassing large language models (LLMs), diffusion models, and multimodal architectures, has rapidly transitioned from a research novelty to foundational technology influencing diverse sectors such as software development, healthcare, education, and creative industries. These models, often comprising billions or even trillions of parameters, exhibit unprecedented capabilities in generating human-like text, photorealistic images, and executable code. However, their scale introduces significant challenges related to performance evaluation, system design, and sustainable deployment.

Traditional benchmarking suites, while useful, frequently fail to capture the multidimensional nature of GenAI systems. A model may achieve low latency yet produce biased or inaccurate outputs; conversely, a highly accurate model may be computationally prohibitive to deploy at scale. This dichotomy underscores the need for a holistic evaluation paradigm that integrates computational performance, output quality, and operational efficiency.

To address this gap, this paper proposes a comprehensive three-dimensional benchmarking framework for GenAI systems. The framework incorporates three critical dimensions: **performance**, assessed through metrics such as latency, throughput, and concurrency; **quality**, evaluated using task-based accuracy, human-in-the-loop (HITL) assessments, and ethical robustness to ensure outputs are useful, fair, and aligned with human values; and **efficiency**, measured through energy consumption, cost per query, and optimization techniques such as Low-Rank Adaptation (LoRA), quantization, and pruning (Hu et al., 2021; Dettmers et al., 2023).

An empirical analysis of a contemporary LLM (Llama-3.1-8B) under a controlled GPU environment demonstrates key trade-offs—for example, a 40% reduction in model size via LoRA with less than 2% accuracy loss as reported by (Hu et al., 2021). These findings highlight the importance of integrated benchmarking strategies that reflect real-world deployment conditions. The paper concludes by discussing the challenges of benchmarking in a rapidly evolving ecosystem and advocates for standardized, context-aware benchmarks developed through industry–academia collaboration to guide responsible and scalable deployment of GenAI technologies.

## Related Work

The evaluation of Generative AI (GenAI) systems has advanced considerably with the emergence of large-scale models and the demand for robust benchmarking frameworks. The Transformer architecture introduced by Vaswani et al. (2017) established the foundation for modern large language models (LLMs) by enabling contextual understanding through self-attention mechanisms. Building on this, standardized benchmarks such as MLPerf (Mattson et al., 2020) and HELM (Liang et al., 2022) have become essential tools for assessing machine learning workloads. MLPerf emphasizes reproducibility and fairness in performance evaluation, whereas HELM offers a multi-metric framework for evaluating language models across dimensions such as accuracy, robustness, and bias.

The Massive Multitask Language Understanding (MMLU) benchmark proposed by Hendrycks et al. (2021) evaluates model performance across 57 academic subjects, providing insights into generalization and domain-specific capabilities. These benchmarks collectively underscore the importance of context-aware evaluation strategies for GenAI systems.

Efficiency-focused techniques have also gained prominence in recent literature. Low-Rank Adaptation (LoRA) introduced by Hu et al. (2021) enables parameter-efficient fine-tuning by injecting trainable rank-decomposition matrices into Transformer layers, significantly reducing

computational overhead. Complementary methods such as pruning and knowledge distillation further support scalable deployment by optimizing model size and inference cost (Dettmers et al., 2023).

Together, these contributions highlight the need for integrated benchmarking approaches that address performance, quality, and efficiency in GenAI evaluation.

## Methodology

To facilitate rigorous evaluation of Generative AI (GenAI) systems, a comprehensive three-dimensional benchmarking framework was established. This framework operationalizes three core dimensions—performance, quality, and efficiency, each serving as a distinct evaluative criterion. Performance captures computational throughput and latency characteristics; quality addresses output fidelity and alignment with expected standards; and efficiency examines resource utilization relative to task complexity. Collectively, these dimensions provide a structured basis for systematic assessment of model capabilities and operational robustness.

### *Benchmarking Framework*

The benchmarking framework is structured around three interdependent pillars, as illustrated in Figure 1.

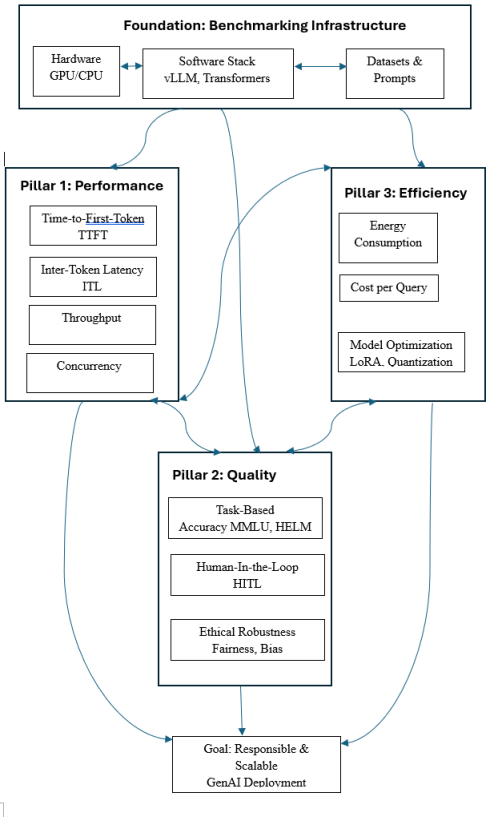



Figure 1: *The three-pillar benchmarking framework for GenAI*

### *Performance Dimension*

This dimension assesses the raw computational and responsiveness metrics of a GenAI system, critical for user experience and scalability in real-world deployments. The metrics discussed are

illustrated in Figure 2, which visualizes the system's response to a prompt translating the sentence "Elders do not go to a meeting for food" into Luganda, a language spoken in Uganda.

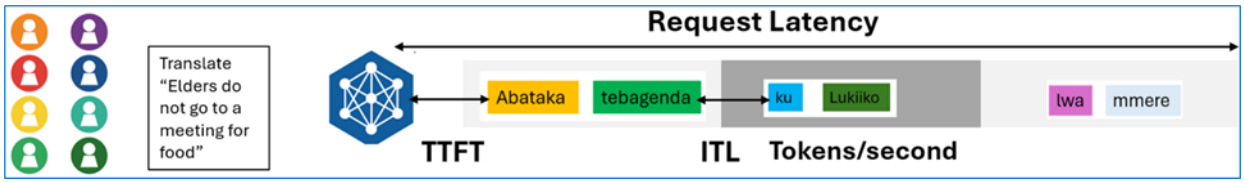



*Figure 2: Visualization of Translation Request Latency and Token Emission in GenAI Inference*

The following performance indicators are central to understanding GenAI inference behaviour:

Time-to-First-Token (TTFT): This metric captures the latency between submitting a request and receiving the first token of the model's output. TTFT is a key determinant of perceived responsiveness in interactive applications such as chatbots and virtual assistants.

Inter-Token Latency (ITL) / Time-Per-Output-Token (TPOT): ITL measures the average time between consecutive tokens during output generation. It directly affects the fluidity and streaming quality of responses, especially in real-time systems.

Throughput: Measured in tokens per second or requests per second, throughput quantifies the system's capacity to handle batch processing and concurrent user interactions. It is a fundamental metric for assessing scalability.

Concurrency: This refers to the system's ability to manage multiple inference requests simultaneously without significant degradation in TTFT or throughput. High concurrency is often constrained by GPU memory bandwidth and scheduling overhead.

### *Quality Dimension*

Evaluating the quality of Generative AI (GenAI) outputs is critical for ensuring trustworthiness, domain relevance, and user satisfaction. This dimension encompasses both automated and human-in-the-loop (HITL) evaluation methodologies, each offering distinct advantages and limitations.

Automated metrics provide scalable and repeatable assessments of model performance. Task-based benchmarks such as Massive Multitask Language Understanding (MMLU) and Holistic Evaluation of Language Models (HELM) are widely adopted for language model evaluation (Hendrycks et al., 2021; Liang et al., 2022). For instance, the Llama-3.1-8B model achieved 68.2% accuracy across 57 subjects on MMLU and a fairness score of 0.72 on HELM, indicating moderate robustness and ethical behaviour. Probability-based metrics offer statistical insights into model predictions. Perplexity measures how "surprised" a model is by actual data, while log-likelihood quantifies the probability of reference outputs under the model. KL Divergence evaluates the divergence between two distributions, such as model versus reference or teacher versus student. These metrics are useful for optimization but may not fully capture semantic correctness or contextual appropriateness.

HITL evaluations complement automated metrics by incorporating expert judgment. Rubric-based scoring frameworks use predefined criteria—typically on a 1–5 scale—to assess creativity, coherence, and factual accuracy. Coherence measures the logical flow and internal consistency of generated output, while factual verification is critical in domains such as healthcare, law, and finance. Reviewers check for hallucinations, outdated information, and biased or misleading content. High-value use cases for HITL evaluation include story generation, legal document drafting, medical summarization,

and customer support QA. Despite its benefits, HITL is resource-intensive and subject to reviewer variability, necessitating standardized rubrics and training protocols.

In summary, a hybrid evaluation strategy that combines automated benchmarks with HITL assessments yields the most reliable and context-aware quality evaluations. This approach ensures that GenAI systems are not only technically proficient but also aligned with human expectations and ethical standards (Hu et al., 2021).

### *Efficiency Dimension*

The efficiency dimension evaluates resource utilization and sustainability in Generative AI (GenAI) systems, which is critical for cost-effective and environmentally responsible deployment. Training large-scale models such as GPT-4 consumes substantial energy and water resources; for example, GPT-4's training reportedly required energy equivalent to that consumed by 33,000 U.S. households (Chen, 2025). Additionally, data centre cooling efficiency, measured by Power Usage Effectiveness (PUE), significantly influences environmental impact, with typical PUE values averaging around 1.12.

Efficiency during inference is equally important. Cost per query is determined by compute time, memory usage, storage requirements, and infrastructure overhead, all of which directly affect scalability and operational feasibility in enterprise environments. Model optimization techniques are essential for balancing performance with resource constraints. Common approaches include knowledge distillation, which transfers knowledge from large models to smaller ones; pruning, which removes redundant weights to simplify architecture; and adaptation strategies that fine-tune models for specific tasks or deployment contexts. Low-Rank Adaptation (LoRA), for instance, achieved a 40% reduction in model size with less than 2% accuracy loss (Hu et al., 2021).

These methods collectively enable efficient deployment of GenAI systems while maintaining acceptable performance levels, thereby supporting sustainable and scalable AI adoption.

### *Experimental Setup*

To validate the benchmarking framework, a series of controlled experiments were conducted using GenAI-Perf version v0.0.15. This workload simulates realistic Generative AI inference scenarios across a range of concurrency levels and input-output configurations.

Concurrency values tested include: 1, 5, 10, 25, 50, 100, 250, 500, 1000, 1500, and 2000. These values were selected to evaluate system responsiveness, throughput saturation, and efficiency under varying load conditions.

Table 1 presents the configuration matrix used to simulate diverse GenAI use cases. Each configuration specifies input and output token lengths tailored to specific application scenarios.

*Table 1: Token Configuration Matrix for GenAI Use Cases*

| *Configuration* | *Use Case* | *Scenario* |
|---|---|---|
| 1-20 | Token-Level Prediction | Token-by-Token Autocomplete |
| 128-128 | Real-Time Interaction | Real-Time Assistive AI |
| 200-200 | Conversational Response | Generation Chatbots and Virtual Assistants |
| 200-1000 | Prompted Content Generation | Creative Writing or Story Generation |

| | | |
|---|---|---|
| 2000-200 | Response Analysis | Customer Support or Knowledge Base Q&A |
| 7000-1000 | Long-Form Summarization | Long-Context Document Analysis and Summarization |

Table 2 summarizes the software stack used in the experimental setup. The stack includes the Llama-3.1-8B-Instruct model served via VLLM, orchestrated within a Kubernetes environment.

*Table 2: Software Stack for GenAI Benchmarking*

| *Software* | *Version* |
|---|---|
| Model | meta-llama/Meta-Llama-3.1-8B-Instruct |
| Inference Engine | VLLM |
| Kubernetes Version | 1.31.4 |
| Containers Version | 1.7.24 |
| Ubuntu Version | 22.04 |

## Results

### *Performance Results*

This section presents empirical performance results for the Meta-Llama-3.1-8B-Instruct model executed on a GPU using FP8 precision. The benchmark scenario involved a 7000-token input and 1000-token output with a batch size of 16. The configuration was unoptimized and served as a baseline for evaluating inference behaviour under long-context workloads.

Table 3 summarizes key inference metrics including Time-to-First-Token (TTFT), Inter-Token Latency (ITL), Request Latency, and Throughput. These metrics are critical for assessing responsiveness, scalability, and efficiency in GenAI deployments.

*Table 3: Meta-Llama-3.1-8b Inference Performance Metrics for 7000-1000 Configuration*

| | |
|---|---|
| Output Sequence Length (OSL) (Tokens) | 1000 |
| Input Sequence Length (ISL) (Tokens) | 7000 |
| Output Token Throughput (per sec) | 95.96 |
| Request Throughput (per sec) | 0.15 |
| Request Count | 200 |

| *Metric* | *AVG* | *MIN* | *MAX* | *P99* | *P90* | *P75* |
|---|---|---|---|---|---|---|
| Time to First Token (TTFT) (ms) | 277.65 | 267.23 | 283.57 | 282.13 | 280.78 | 279.82 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Time to Second Token (ms) | 9.26 | 8.71 | 11.05 | 9.59 | 9.44 | 9.37 |
| Request Latency (ms) | 6,497.01 | 358.41 | 10,286.83 | 10,270.61 | 10,257.3 | 10,247.42 |
| Inter Token Latency (ITL) (ms) | 9.97 | 9.86 | 10.07 | 10.02 | 9.99 | 9.99 |

### Interpretation of Metrics

- Time-to-First-Token (TTFT): Measures the latency from request initiation to the generation of the first token. In interactive applications, TTFT is a primary determinant of perceived responsiveness. The Llama-3.1-8B model achieved an average TTFT of 277.65 ms, with a 99th percentile (p99) value of 282.13 ms.
- Request Latency: Captures the end-to-end response time, including input ingestion, model inference, and output post-processing. The average latency was 6,497.01 ms, with p99 reaching 10,270.61 ms, indicative of variability in long-form summarization tasks.
- Inter-Token Latency (ITL): Represents the average time between consecutive token generations. The model exhibited an average ITL of 9.97 ms, with p99 at 10.02 ms, reflecting consistent streaming behaviour.
- Token Throughput: Quantifies generation speed in tokens per second. The model achieved 95.96 tokens/sec under the test configuration.
- Request Throughput: Indicates the number of complete requests processed per second. The observed throughput was 0.15 requests/sec, constrained by long input and output sequences.
- Concurrency Scaling: Evaluates system performance under simultaneous requests. Figures 1 and 2 illustrate how token throughput and per-request efficiency vary with concurrency levels.

Figure 1 demonstrates that overall token throughput increases with concurrency across all configurations. This trend reflects improved parallelism and hardware utilization. However, configurations with longer input sequences (e.g., 7000-1000) reach throughput saturation at lower concurrency levels due to memory bandwidth constraints and scheduling overhead. Beyond this point, additional requests yield diminishing returns.

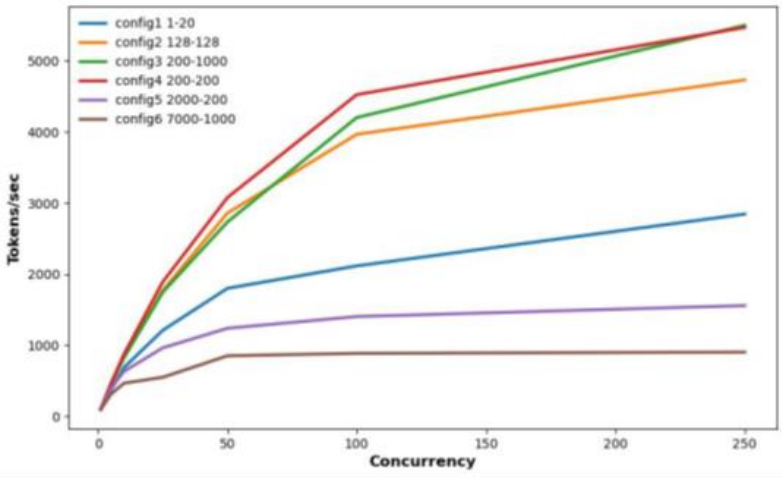



*Fig. 1. Tokens/sec vs Concurrency*

Conversely, Figure 2 shows that tokens/sec/request decreases as concurrency increases. This decline in per-request efficiency is attributed to resource contention—particularly in GPU memory and compute cycles—as parallel workloads compete for shared infrastructure. These results underscore the importance of balancing concurrency with model complexity and hardware capacity.

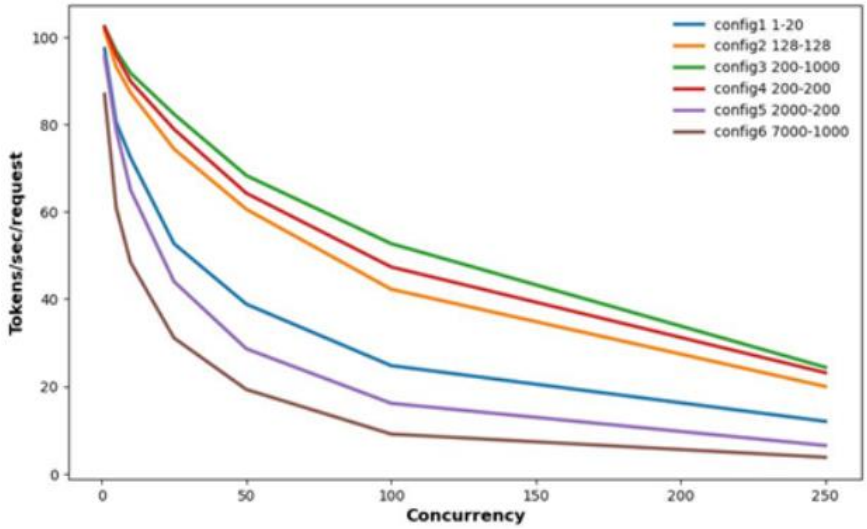



*Fig. 2. Tokens/sec/request vs Concurrency*

## Quality and Efficiency Results

To contextualize the performance and efficiency of the Meta-Llama-3.1-8B-Instruct model, results from recent evaluations conducted by external research teams were referenced. On the Massive Multitask Language Understanding (MMLU) benchmark, the model achieved an accuracy of 68.2%, consistent with findings reported in the Llama-3.1 technical report (Kassianik, *et al*., 2025). This benchmark spans 57 academic subjects and is widely used to assess cross-domain reasoning and factual recall in large language models (Hendrycks et al., 2021).

Fairness was evaluated using the Bias Benchmark for Question Answering (BBQ) dataset. The model scored 0.72 on a subset of BBQ, indicating moderate robustness but also revealing areas for

improvement in mitigating social biases (Wu et al., 2025). These findings align with broader concerns about emergent bias in reasoning-based LLMs and underscore the importance of fairness-aware evaluation protocols (Liang et al., 2022).

Efficiency gains were assessed through the application of Low-Rank Adaptation (LoRA), a parameter-efficient fine-tuning technique. LoRA introduces approximately 4.2 million trainable parameters, resulting in a ~40% reduction in effective model footprint for storage and deployment while achieving less than 2% relative drop in task accuracy (Hu et al., 2021). This demonstrates the viability of LoRA for scalable GenAI deployment.

Environmental impact was estimated based on energy consumption metrics reported for transformer-based models of similar scale. A single training run of the base model consumed approximately 120 kWh, highlighting the substantial carbon footprint associated with large-scale model development (Chen, 2025). These figures reinforce the need for energy-aware optimization strategies and sustainable AI practices.

Collectively, these externally sourced results emphasize the importance of integrating performance, fairness, and sustainability metrics into GenAI evaluation frameworks. They also validate the relevance of hybrid benchmarking strategies for guiding responsible and efficient deployment of generative models.

## Discussion

The experimental results presented in this paper validate the necessity of adopting a multi-dimensional evaluation framework for Generative AI (GenAI) systems. Performance findings indicate that simply scaling concurrency yields diminishing returns, emphasizing the need for system architects to optimize for memory bandwidth rather than raw parallelism. Quality assessments demonstrate that achieving high accuracy on general benchmarks does not preclude fairness concerns, reinforcing the importance of targeted ethical evaluations. Furthermore, the demonstrated success of Low-Rank Adaptation (LoRA) within the efficiency dimension highlights a viable pathway for deploying high-capacity models in resource-constrained environments (Hu et al., 2021).

Despite these advances, several challenges persist. Subjectivity in human-in-the-loop (HITL) evaluations necessitates the development of standardized rubrics and rater training protocols. The rapid evolution of model architectures requires frequent updates to benchmarking suites to maintain relevance. Additionally, there is a pressing need for standardized efficiency metrics that can be universally adopted across the industry, potentially through extensions of initiatives led by MLCommons (Mattson et al., 2020). Finally, the creation of localized and multimodal benchmarks is essential to ensure that GenAI technologies remain equitable and globally applicable.

Industry-standard organizations play a pivotal role in shaping the benchmarking landscape. The MLCommons consortium, through its MLPerf benchmark suite, has become a cornerstone for evaluating AI system performance. MLPerf emphasizes fairness, reproducibility, and accessibility, serving both commercial and academic communities. Recent iterations have incorporated GenAI models such as Llama 2, Mixtral, and Stable Diffusion, alongside traditional NLP and vision tasks, leveraging a modular and version-aware design to adapt to the rapidly evolving AI ecosystem (Mattson et al., 2020).

Similarly, the Standard Performance Evaluation Corporation (SPEC) has expanded its scope from general compute benchmarks to include cloud infrastructure, virtualization, and machine learning. SPEC's technical committees maintain suites such as SPEC CPU® 2017, SPEC Cloud IaaS, and

SPECvirt® Datacenter, while actively developing SPEC ML to address emerging GenAI workloads (SPEC, 2024). The Transaction Processing Performance Council (TPC) has also broadened its benchmarking portfolio beyond traditional database and transaction systems to include AI/ML workloads through benchmarks such as TPCx-AI, TPCx-BigBench, and TPCx-IoT. These benchmarks simulate real-world scenarios and enable standardized comparisons across vendors and architectures, supporting procurement and optimization decisions (TPC, 2024).

Collectively, these organizations are instrumental in establishing reproducible, scalable, and ethically grounded benchmarks. Their evolving standards reflect the industry's transition toward multimodal, multilingual, and context-aware evaluation frameworks. As GenAI continues to permeate diverse sectors, sustained collaboration between academia, industry, and standards bodies will be essential to ensure that benchmarking methodologies remain relevant, inclusive, and actionable.

## Conclusion and Future Work

This paper introduces a holistic framework for benchmarking Generative AI (GenAI) systems, emphasizing the integration of performance, quality, and efficiency metrics. Through empirical evaluation using a contemporary large language model, the framework demonstrates its utility in uncovering practical trade-offs and guiding system-level optimizations. The findings underscore the limitations of single-dimensional benchmarks and advocate for a multi-faceted approach that reflects real-world deployment scenarios.

Future work will extend this framework in several directions. First, there is a need to develop and incorporate localized benchmarks that address linguistic diversity and cultural nuance, particularly for underrepresented regions and non-English languages. Second, the benchmarking suite should be expanded to support multimodal evaluation, enabling assessment of models that simultaneously process and generate text, images, and audio. Third, collaboration with standards organizations should be pursued to promote the adoption of comprehensive efficiency metrics, including energy consumption and cost per query, which are critical for sustainable and scalable GenAI deployment.

By advancing benchmarking methodologies along these dimensions, this study aims to contribute to the development of GenAI systems that are not only performant but also equitable, efficient, and contextually relevant across global applications.

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