
CONSUMERBENCH: Benchmarking Generative AI Applications on End-User Devices

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Abstract

The recent shift in Generative AI (GenAI) applications from cloud-only environments to end-user devices introduces new challenges in resource management, system efficiency, and user experience. This paper presents CONSUMERBENCH, a comprehensive benchmarking framework designed to evaluate the system efficiency and response time of GenAI models running on end-user devices. Unlike existing benchmarks that assume exclusive model access on dedicated GPUs, CONSUMERBENCH simulates realistic multi-application scenarios executing concurrently on constrained hardware. Furthermore, CONSUMERBENCH supports customizable workflows that simulate complex tasks requiring coordination among multiple applications. CONSUMERBENCH captures both application-level metrics, including latency and Service Level Objective (SLO) attainment, and system-level metrics like CPU/GPU utilization and memory bandwidth. Through extensive experiments, CONSUMERBENCH reveals inefficiencies in resource sharing, unfair scheduling under greedy allocation, and performance pitfalls of static model server configurations. The paper also provides practical insights for model developers and system designers, highlighting the benefits of custom kernels tailored to consumer-grade GPU architectures and the value of implementing SLO-aware scheduling strategies.

1 Introduction

The deployment landscape for Generative AI (GenAI) models is undergoing a significant transformation: once confined to hyperscale data centers equipped with powerful GPUs, these models are now increasingly being adopted on local devices such as laptops and smartphones [3, 4, 42]. This shift is primarily motivated by growing concerns over data privacy, latency, and availability under various network conditions.

Beyond simple resource constraints, end-user devices present unique challenges due to their heterogeneous application landscapes that compete for the limited hardware resources. Each application often requires specific types of GenAI models due to model performance considerations [18, 46] and varies significantly in its runtime characteristics. For example, some applications (*e.g.*, deep research agents or image generation) are long-running background processes, whereas others (*e.g.*, chatbots or live audio captioning) are short-lived tasks demanding instant response. Each of these categories imposes distinct Service Level Objectives (SLOs). Unlike cloud environments, where the different models and applications can be distributed across separate servers and dedicated GPUs, end-user devices must accommodate all models on a single, shared GPU. Consequently, end-user devices must be capable of concurrently executing the diverse models, effectively managing the limited compute, memory, network, and power resources, while consistently meeting diverse SLOs.

Existing research on GenAI inference for end-user devices [14, 15, 28] and specialized inference frameworks [16] aim to achieve target quality, latency, and throughput within platform constraints. However, these approaches typically assume that the model has dedicated, exclusive access to the

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hardware. Furthermore, existing benchmarks that evaluate the computational efficiency of GenAI models often assume that hardware resources are dedicated to a single application [44, 27, 23, 24, 49], failing to accurately represent the end-user experience when running multiple models on their devices. As a result, the complexities and opportunities associated with efficiently deploying these models in local environments, characterized by other concurrently running applications, remain unexplored.

To address this gap, we present **CONSUMERBENCH**, a comprehensive benchmarking framework that evaluates the runtime performance of user-defined GenAI applications under realistic conditions on end-user devices. Users specify the GenAI applications, models, request patterns, and SLOs (*e.g.*, latency, throughput) in a simple configuration file. **CONSUMERBENCH** then evaluates application performance against these SLOs across diverse deployment scenarios, including GPU/CPU hybrid setups, resource partitioning, and shared model deployments (*e.g.*, inference servers hosting models for multiple applications). Beyond core performance metrics, it captures system-level data such as GPU/CPU utilization, memory bandwidth, and power consumption to quantify the efficiency of on-device GenAI execution. **CONSUMERBENCH** is also the first to benchmark user-defined collaborative workflows, such as "creating a YouTube video," where multiple GenAI applications (*e.g.*, text-to-image, speech recognition, thumbnail generation) interoperate to complete complex tasks. This enables realistic testing of how resource orchestration impacts end-to-end user experience.

Through the evaluation of a diverse set of GenAI applications on a local server with a consumer-grade GPU, **CONSUMERBENCH** offers novel insights for the development of efficient infrastructure tailored to support end-user devices. **CONSUMERBENCH** reveals that greedy GPU resource allocation leads to severe starvation of lightweight applications (*e.g.*, live captioning), while static GPU partitioning reduces overall throughput due to resource underutilization. Furthermore, inference server-based model sharing fails to meet diverse application SLOs when configurations are not tailored, highlighting the need for dynamic, SLO-aware memory management and scheduling strategies as well as GPU architecture-aware kernel designs. In summary, this paper makes the following contributions:

- It highlights unique challenges in running diverse GenAI applications concurrently on end-user devices, including resource contention and unmet SLOs, that are not exposed by prior benchmarks.
- It introduces a benchmarking framework called **CONSUMERBENCH** that supports realistic multi-application workflows, tracks both application- and system-level metrics, and allows flexible configurations for evaluation on end-user devices.
- It evaluates four representative applications, reveals key system inefficiencies under different GPU sharing strategies, and offers unique insights into building efficient systems for end-user devices.

2 Related Works

2.1 LLMs on End-User Devices

Cloud inference has long been the default for GenAI applications, but recent advances in resource-efficient models [1, 2, 51], model compression [14, 15, 28], efficient runtimes [16] and edge-oriented hardware [4, 42, 3] have made credible *on-device* inference possible.

The effects of executing multiple heterogeneous GenAI applications concurrently on a single device, however, remain mostly unexplored. Some previous works attempted to construct an operating system-like abstraction for GenAI applications. AIOS schedules multi-agent, tool-augmented LLM workflows and exposes APIs for resource provisioning and state persistence [32]. MemGPT dynamically pages conversation context between CPU and GPU memory so a single chat agent can handle extremely long contexts on commodity GPUs [41]. Both projects focus on the needs of one application (or collective agents) and do not track application-level SLOs under interference. Others have studied co-locating workloads on the GPU [53, 47, 19], but they either target a cloud setting with distributed GPU clusters, or are limited to a single type of workload like DNN inference.

2.2 Benchmarks for Edge LLM Inference

Existing benchmarks for edge-class hardware, including MLPerf Inference [44], PalmBench [27], MELT [24], and others [49, 23], primarily assess latency, throughput, and energy for single-stream inference, often with exclusive hardware access. Other benchmarks [30, 17, 25, 50, 13, 33] evaluate model capabilities on local/mobile systems but lack evaluation of their system performance, such as

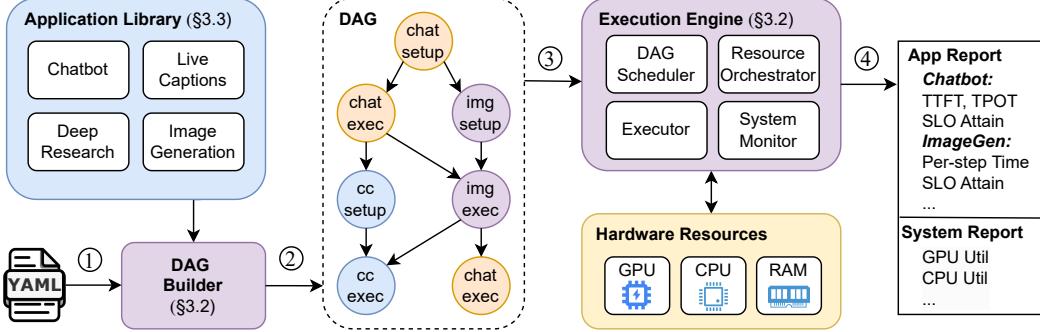


Figure 1: The overall design of CONSUMERBENCH.

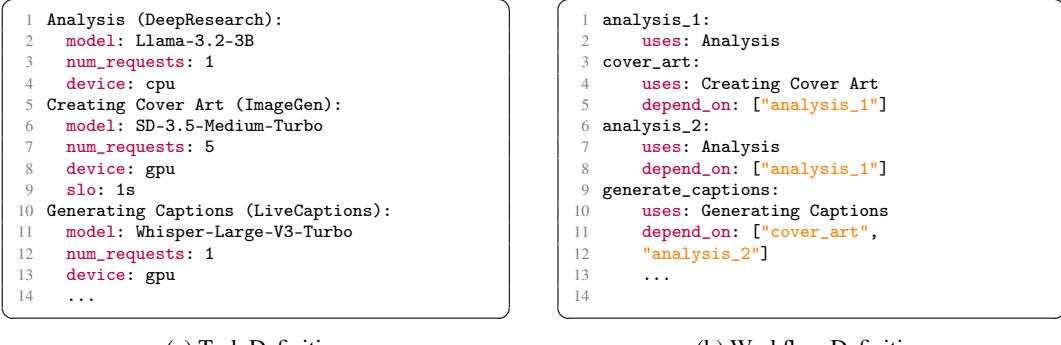


Figure 2: Example YAML configuration to define application tasks as well as user workflows.

response latency and SLO attainment. In contrast, CONSUMERBENCH benchmarks the concurrent execution of *heterogeneous* workflows comprising multiple GenAI tasks, thereby highlighting cross-application interference patterns and system inefficiencies.

3 CONSUMERBENCH

CONSUMERBENCH is a comprehensive benchmarking framework specifically designed to evaluate the runtime performance of GenAI models on end-user devices under realistic conditions.

3.1 Goals

- **G1 : Diversity of Applications.** CONSUMERBENCH supports various GenAI applications. They range from long-running background services to short-lived, latency-sensitive interactive tasks with tight SLOs, and with different modalities (*e.g.*, text-to-text, text-to-image). See §3.3.
- **G2 : Concurrent Execution and Resource Contention.** CONSUMERBENCH evaluates performance and SLO attainment when multiple applications run concurrently on shared limited hardware and use different resource orchestration strategies. This reveals resource contention and trade-offs overlooked by existing benchmarks. See §3.2.
- **G3 : System-Level Holistic Metrics.** CONSUMERBENCH collects detailed metrics such as compute utilization, memory bandwidth utilization, and power consumption. These metrics help users not only understand whether an application meets its SLO, but also diagnose why it might fail, which is crucial for improving system design and optimizing on-device deployment strategies. See §3.2.
- **G4 : Configurability and Automation.** CONSUMERBENCH allows users to easily define application scenarios and performance goals through a user-friendly configuration. It automates execution and metric collection for complex workflows. See §3.2.

3.2 Methodology

Fig. 1 shows the design overview of CONSUMERBENCH. Given a user configuration of the workflow, CONSUMERBENCH orchestrates the execution of the workflow through a graph representation. After the workflow finishes, it generates a benchmark report for SLO satisfaction and resource efficiency.

Input User Configuration (①). The input to CONSUMERBENCH is a YAML configuration file that contains the set of applications to run, their corresponding models, hardware placements (CPU, GPU, or CPU-GPU hybrid), SLOs, and input requests. The configuration can also specify dependencies between applications, allowing users to define complex multi-step workflows where one application’s output serves as input for another. Fig. 2 provides an example YAML configuration for three applications (Deep Research agent, Image Generation and Audio Captioning), illustrating dependencies and SLOs. While our SLOs focus on request latency, users can configure SLOs for other metrics.

Creating Overall Workflow (②). CONSUMERBENCH builds a directed acyclic graph (DAG) from the YAML specification. Each node represents an application instance, with edges denoting dependencies. Nodes are of three types: `setup` (application startup), `exec` (execution), and `cleanup` (resource release). CONSUMERBENCH validates the DAG to ensure that there are no cycles and that each application includes a `setup` node before any `exec` nodes. Fig. 1 includes an example DAG with three applications: Chatbot (`chat`), ImageGen (`img`), and LiveCaptions (`cc`).

Executing the Workflow (③). The execution engine uses the DAG to coordinate application execution and collect metrics.

- The **DAG scheduler** manages request scheduling, respects dependencies, and enables concurrent execution where possible, supporting complex and realistic user-defined workflows.
- The **resource orchestrator** employs various GPU management strategies to execute workflows, including greedy resource allocation, where the applications consume GPU resources as needed, and GPU partitioning, which divides GPU resources equally among running applications.
- The **executor** is responsible for loading and unloading of the GenAI models and executing user requests, obeying the DAG scheduler.
- The **system monitor** tracks system-wide resource usage during execution. GPU compute and memory bandwidth usage are monitored with the help of NVIDIA’s Data Center GPU Management (DCGM) utility¹ [10]. CPU utilization is monitored using the `stat` tool, while CPU memory (DRAM) bandwidth utilization is monitored using the `pcm-memory` utility [9]. CONSUMERBENCH monitors power consumption using NVML [37] for GPU and RAPL [22] for CPU.

Generating Benchmark Report (④). After completing all workflow tasks, CONSUMERBENCH automatically evaluates each application’s performance against the SLOs defined in the YAML configuration. It then generates a comprehensive report summarizing performance, SLO satisfaction, and resource efficiency for the entire workflow.

3.3 Supporting Diverse Applications and Models

CONSUMERBENCH provides an API that enables users to integrate their own applications with either custom or existing models, making the framework highly extensible. To evaluate a custom application, users simply implement three functions: `setup()`, to initialize the GenAI application and its model; `execute()`, to send requests to the model; and `cleanup()`, to release application resources. CONSUMERBENCH further enables multiple applications to share a single model by using a common `setup()` function, which launches a shared inference server for all participating applications. This capability is important for end-user devices as it helps minimize memory usage and startup overhead. Table 1 summarizes the four applications currently supported by CONSUMERBENCH, covering different modalities and common use cases on end-user devices.

Chatbot. This is a text-to-text generation app for chat and Q&A, featuring a simple frontend and a local backend with an OpenAI-compatible API [40]. The backend uses `llama.cpp` [16], supporting CPU-GPU co-execution and is optimized for end-user devices. SLO targets are based on human reading speed [29]: 1 second for Time to First Token (TTFT) and a generation speed of 4 tokens per second (Time Per Output Token - TPOT).

¹Although designed for datacenter GPUs, DCGM supports consumer-grade GPUs, including all GeForce GPUs.

Application	Dataset	Model	SLO
Chatbot	LMSYS-Chat-1M [55]	Llama-3.2-3B [2]	TTFT: 1s, TPOT: 0.25s
DeepResearch	HotpotQA [52]	Llama-3.2-3B [2]	N/A
ImageGen	COCO Captions [8]	SD-3.5-Medium-Turbo [48]	Step Time: 1s
LiveCaptions	Earnings-21 [12]	Whisper-Large-V3-Turbo [43]	Per-Segment Time: 2s

Table 1: Summary of dataset, model, and SLO used in each application.

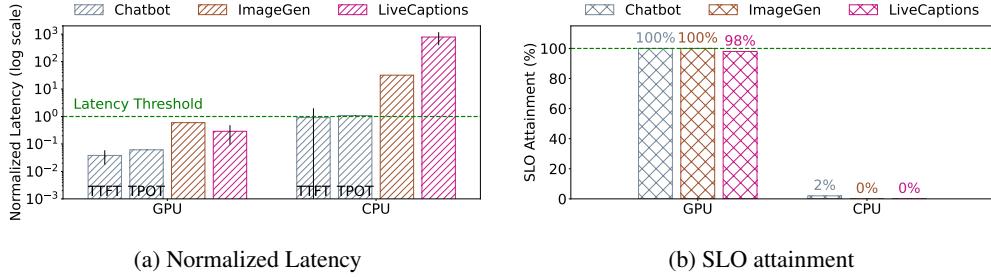


Figure 3: (a) Latencies normalized to SLO requirements and (b) SLO attainment for Chatbot, Image Generation, and Live Caption running exclusively on the GPU or CPU.

DeepResearch. This is an agentic application for complex, multi-step reasoning and fact gathering, adapting smolagent’s open-deep-research [45] and using LiteLLM [7] to interact with a local model via llama.cpp. DeepResearch operates on long contexts and functions as a persistent background application, without any SLO.

ImageGen. This is a text-to-image application with a simple frontend and a backend using stable-diffusion-webui [6] in API server mode. Motivated by research on diffusion models on resource-constrained devices [54, 26], the SLO for ImageGen is set to 1 second per denoising step.

LiveCaptions. This is an audio-to-text application for real-time scenarios [31]. The frontend chunks an audio file into segments and sends each segment to a backend adapted from whisper-online [31] to support HTTP connections. LiveCaptions can function as a latency-sensitive or background task. For the latency-sensitive case, a 2-second audio segment is sent every 2 seconds, requiring the model to generate captions for every segment as it arrives. The SLO for this scenario is thus 2 seconds. For background transcription of a large audio file (5–10 minutes), there is no SLO.

4 Experimentation

This section presents notable benchmarking results of CONSUMERBENCH. We provide additional results in the Supplementary Material.

Experimental Setup. We run experiments on a local server consisting of a single RTX 6000 GPU [36] with 24GB VRAM. The server is equipped with an Intel Xeon Gold 6126 CPU (2.60GHz, 24 cores) and 32GB of system memory (DRAM). The applications evaluated are listed in Table 1. Note that CONSUMERBENCH is not limited to the use of these applications, and users can add more applications by following the procedure in §3.3. For each application, CONSUMERBENCH samples requests from the dataset, measures per-request latency, and compares the results to the defined SLOs.

System-wide metrics. While CONSUMERBENCH monitors a range of resource utilization metrics such as compute, memory, and power (see §3.2), this section focuses on GPU compute (also called GPU utilization) for brevity. Additional metrics are detailed in the Supplementary Material. For GPU utilization, CONSUMERBENCH tracks two key metrics: SMAXT, the percentage of Streaming Multiprocessors (SMs) reserved by an application, and SMOCC, the percentage of SMs actively running kernels. If SMOCC is significantly lower than SMAXT, it indicates that the application is utilizing only a small portion of the SMs it reserves, suggesting inefficient use of GPU resources.

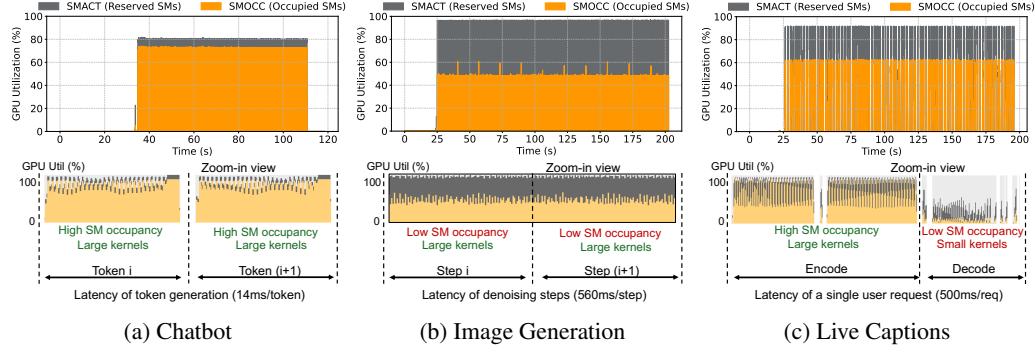


Figure 4: GPU utilization of each application running exclusively on the GPU.

4.1 Running Applications Exclusively on GPU and CPU

We establish performance bounds by running each application exclusively on the GPU (upper bound) and on the CPU (lower bound), to account for scenarios where the limited GPU memory may force applications to fall back to CPU execution. Fig. 3 shows results for our latency-sensitive applications; DeepResearch is excluded as it does not have an SLO.

Performance. When running on the GPU, all applications achieve 100% SLO attainment except for LiveCaptions, where three² out of 150 audio segments incur SLO violations. When running on the CPU, all applications experience reduced performance, though the impact varies. Chatbot narrowly misses its SLOs, while ImageGen and LiveCaptions suffer from significantly higher request latencies.

System-level metrics. Fig. 4 shows the GPU utilization when applications run exclusively on GPU. All applications reserve almost all of the GPU cores when running exclusively, shown using SMACT. However, their efficiencies are very different, indicated by SMOCC. Chatbot utilizes its resources efficiently, while ImageGen and LiveCaptions under-utilize their reserved GPU cores.

Analysis of Individual Applications. We analyze the GPU kernels launched by each application to understand their performance and GPU utilization, shown through the zoomed-in view, in Fig. 4.

- **Chatbot:** Spends majority of its time in decoding output tokens (*i.e.*, token generation). It achieves a high SMOCC (Fig. 4a) since llama.cpp customizes the thread block and grid dimensions for its kernels during prefill and decode according to the underlying GPU architecture.
 - **ImageGen:** Spends most of its time in the denoising phase, which uses an attention-based U-Net [39]. PyTorch’s generic attention kernel used by SD-3.5-Medium-Turbo requires over 150 registers per thread, limiting the number of threads that can run concurrently on each SM. This reduces SMOCC and leads to suboptimal GPU utilization (Fig. 4b).
 - **LiveCaptions:** Uses the encoder-decoder Whisper-large-v3-turbo model. The encoder phase performs parallel operations on the input audio, involving softmax and large matrix multiplications that use tens of registers per thread with a high SMOCC. The decoder phase, however, spends most time in performing matrix multiplications with much smaller kernels than Chatbot or ImageGen. This phase also involves hundreds of registers per thread and high shared memory usage, largely due to inefficient kernel implementations. These factors contribute to the low SMOCC (Fig. 4c).

4.2 Challenges and Strategies for Concurrent Execution

Concurrent execution on end-user devices leads to interference and resource contention. This section examines how latency-sensitive applications perform under various resource management strategies when all GenAI models fit in GPU memory. Scenarios with larger models are discussed in the Supplementary Material. Application latencies and GPU utilization are shown in Fig. 5a.

Greedy Resource Allocation: This is the default strategy where the kernels of every application greedily occupy GPU resources when they are scheduled, in a first-come-first-serve (FCFS) manner.

²The model was unable to identify the language used, causing the audio segment to be re-encoded and delayed.

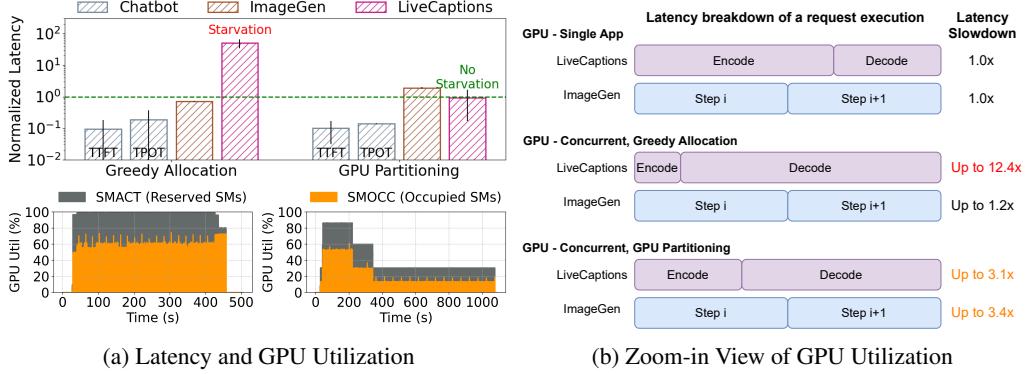


Figure 5: Application performance & GPU util using greedy resource allocation and GPU partitioning.

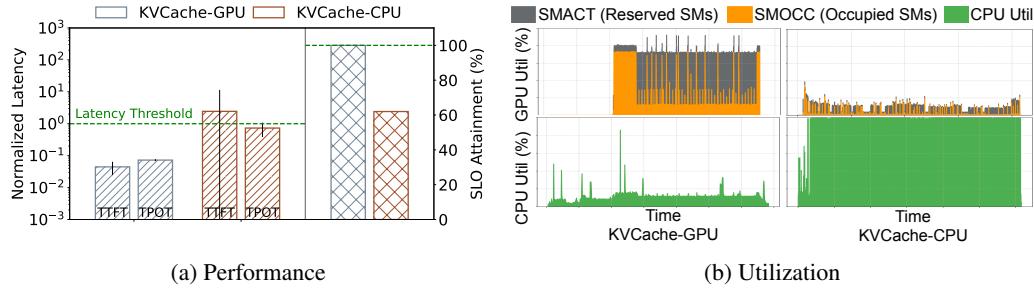


Figure 6: Comparison of Chatbot performance and resource utilization with GPU vs. CPU KV cache.

- **Performance:** ImageGen performs similarly to how it did when it ran exclusively on the GPU (§4.1). However, both Chatbot and LiveCaptions experience slowdowns. LiveCaptions suffers from starvation and performs particularly poorly, missing SLOs for almost all requests.
- **Analysis:** Greedy allocation results in unfair resource reservation, leading to starvation of some applications. A closer look at each request (Fig. 5b) reveals that LiveCaptions’ small decode kernels are stalled by ImageGen’s large kernels during concurrent execution. As a result, the decode phase in LiveCaptions runs 30× slower compared to exclusive GPU access, leading to a 12.4× increase in the average end-to-end request latency.

Static GPU Partitioning: This strategy uses NVIDIA MPS [11] to equally reserve GPU resources (33% of SMs) for each of the three latency-sensitive applications.

- **Performance:** The latency of every application degrades more gracefully compared to greedy allocation, as shown in Fig. 5a. This causes ImageGen to narrowly miss its SLOs, while LiveCaptions is able to meet its SLOs for majority of the requests.
- **Analysis:** GPU partitioning prevents stalling by enforcing equal resource reservation, resulting in predictably higher latencies for all applications (Fig. 5b). However, MPS leads to GPU underutilization by rigidly assigning 33% of GPU cores to each application, even when other partitions are idle. This inflexibility produces a staircase pattern in SMAXT/SMOCC metrics and prevents ImageGen from using available GPU resources after others finish (see GPU utilization in Fig. 5a, right). This causes ImageGen to miss SLOs despite available compute capacity.

4.2.1 Static Model Sharing via Inference Servers

Given the limited GPU memory on end-user devices, sharing a single foundation model across multiple GenAI applications with similar input-output modalities is a desirable strategy [4]. In datacenters, this is typically achieved using inference servers, but such infrastructure is generally lacking on end-user devices. In this section, we evaluate whether inference servers can effectively facilitate model sharing in local environments.

We use the locally-deployed llama.cpp inference server with the Llama-3.2-3B model to serve requests for Chatbot (latency-sensitive task) and DeepResearch (background task). To support DeepResearch’s requirement for a large context window, we configure llama.cpp with a 16GB KV cache, matching

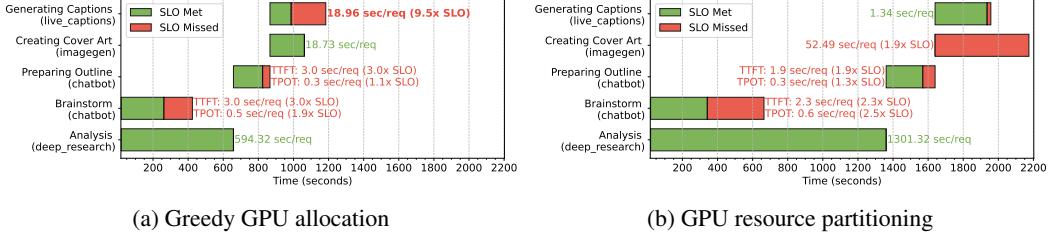


Figure 7: E2E latency & SLO attainment for content-creation workflow w/ and w/o GPU partitioning.

the model’s 128K token context window. To conserve GPU memory, we launch llama.cpp with the `--no-kv-offload` option that stores the KV cache in CPU memory (referred to as Chatbot-KVCache-CPU). In contrast, running the default Chatbot configuration with a smaller KV cache allows both applications to execute concurrently on the GPU, but forces DeepResearch to use a smaller context window, resulting in degraded output quality. Fig. 6 shows the GPU/CPU utilization and latency for both Chatbot and Chatbot-KVCache-CPU when running alongside DeepResearch.

Performance & system-level metrics: Compared to Chatbot, Chatbot-KVCache-CPU exhibits high variance in results and misses its SLO for approximately 40% of its requests. To avoid the overhead of loading the KV cache into the GPU, Chatbot-KVCache-CPU performs attention operations on the CPU, leading to high CPU utilization and correspondingly low GPU utilization.

Analysis: Inference servers use static configurations for shared models, which cannot accommodate different performance needs of multiple applications. Configuring a large KV cache for DeepResearch negatively impacts the latency of Chatbot. Hence, naively sharing models via inference servers leads to resource conflicts and suboptimal performance when applications require conflicting settings.

4.3 Real-World User Workflow

We evaluate end-user experience by simulating a digital content creation workflow with sequential and concurrent tasks: brainstorming (Chatbot-KVCache-CPU), analyzing existing content (DeepResearch), preparing scripts (Chatbot), creating cover image (ImageGen), and generating captions (LiveCaptions). DeepResearch and Chatbot-KVCache-CPU share a single model via llama.cpp to mimic real-world resource constraints. The configuration for this workflow is provided in the Supplementary Material. Fig. 7 shows latencies for workflow tasks with and without GPU partitioning.

Analysis: Greedy GPU allocation shortens the end-to-end workflow time by 45% compared to partitioning, mainly due to faster completion of DeepResearch. In contrast, GPU partitioning limits the resources for DeepResearch, causing delays for subsequent tasks. GPU partitioning, on the other hand, avoids stalling of LiveCaptions by reserving 33% of the GPU while gracefully reducing ImageGen performance by 1.8×. Thus, despite better fairness, partitioning increases total workflow runtime, highlighting a trade-off: greedy allocation risks starvation but optimizes utilization, while partitioning ensures fairness at the cost of efficiency.

4.4 Evaluation on Apple Silicon

We use CONSUMERBENCH to evaluate our applications on a MacBook M1 Pro [5] laptop with 32GB of unified memory, six performance cores, and two efficiency cores. We include its results in the Supplementary Material due to brevity, but focus on some important performance highlights. Overall, MacBook achieves a better trade-off for GPU utilization and fairness of resources for concurrent applications. However, CONSUMERBENCH reveals that the computationally intensive kernels of ImageGen and LiveCaptions suffer high slowdowns on MacBook compared to our baseline setup.

5 Insights revealed by CONSUMERBENCH

5.1 Insights for Building and Implementing Efficient Generative AI Models

Existing research on GenAI model development for end-user devices primarily focuses on reducing the memory footprint while maintaining generation quality comparable to larger models. However,

CONSUMERBENCH reveals that these methods alone are not sufficient for high system performance (such as response latency) and practical deployments on end-user devices.

Architectural Efficiency. The architecture of models should be designed to utilize GPU resources efficiently. This means avoiding characteristics that can lead to low SM occupancy, such as requiring many intermediate results that demand excessive registers or shared memory per thread. For example, using bounded activation functions could constrain the dynamic range of intermediate results, enabling lower-bit representations and reducing shared memory pressure during inference [21] (§4.1).

Implementation Awareness in Kernel Design. The implementation of models needs to be aware of the underlying GPU architecture. This includes creating kernels that leverage architectural features such as warp size and memory hierarchy, as well as optimizing for specialized components such as tensor core utilization (§4.1).

Concurrency-Aware Kernel Development. Model implementations should assume concurrent GPU execution by independent applications. Kernels should be developed in a manner that allows the GPU scheduler to achieve both high GPU utilization and fairness in resource allocations across all running applications (§4.2).

5.2 Insights for Systems and Inference Frameworks

System and infrastructure developers should provide more flexibility in how models are deployed and how resources are utilized on end-user devices.

Flexible Resource Management. Existing GPU partitioning schemes are often static. This can lead to either poor fairness in resource scheduling among competing applications or underutilization of resources. CONSUMERBENCH’s experiments reveal a significant need for advancements in system development to achieve dynamicity and flexibility in memory management (§4.2).

SLO-Aware Scheduling. Alongside dynamic memory management, there is a need for SLO-aware scheduling of requests specifically for GenAI applications running on end-user devices. This ensures applications meet their user-facing performance targets (§4.2, §4.3).

Configurable Inference Servers. Inference servers that support the sharing of a single model among multiple applications need to allow for higher configurability. This is particularly important because applications sharing a model may have different performance goals (§4.2.1). This highlights the need for servers to be more adaptable to varying application SLOs.

6 Limitations

CONSUMERBENCH currently assumes that all models are locally deployed on end-user devices and does not address scenarios like edge-cloud collaborative speculative decoding [20, 38], where a small local model collaborates with a larger datacenter model; we plan to support such cases in future work. Additionally, while not fundamental to CONSUMERBENCH, the current implementation targets laptops and servers, without support for more constrained devices like mobile phones or sensors.

CONSUMERBENCH does not evaluate GPU partitioning with CUDA Green Context [34] because it requires application-level modifications and lacks Python bindings. Moreover, CUDA Green Context is designed for resource partitioning *within* a single application, whereas CONSUMERBENCH focuses on managing contention *across* multiple applications. As a result, we expect its performance to be similar to that of greedy partitioning in our scenarios. CONSUMERBENCH does not evaluate GPU partitioning using Multi-Instance GPU (MIG), since it is not supported in consumer-grade GPUs [35].

7 Conclusion

This paper presents CONSUMERBENCH, a comprehensive benchmarking framework for evaluating GenAI applications on end-user devices. It enables users to define realistic workflows and monitors application-level metrics and system performance under concurrent execution. CONSUMERBENCH reveals inefficiencies in resource sharing and kernel scheduling, offering valuable insights to users in developing more efficient models and system optimizations tailored to end-user devices. The implementation of CONSUMERBENCH is open-sourced at <https://github.com/efeslab/ConsumerBench>.

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Appendices

A Data and Code Access

The implementation of CONSUMERBENCH, along with instructions on how to set it up and reproduce the results in the paper, is provided at <https://github.com/efeslab/ConsumerBench>.

B Additional Results

B.1 System-level Metrics for Applications Running Exclusively on GPU

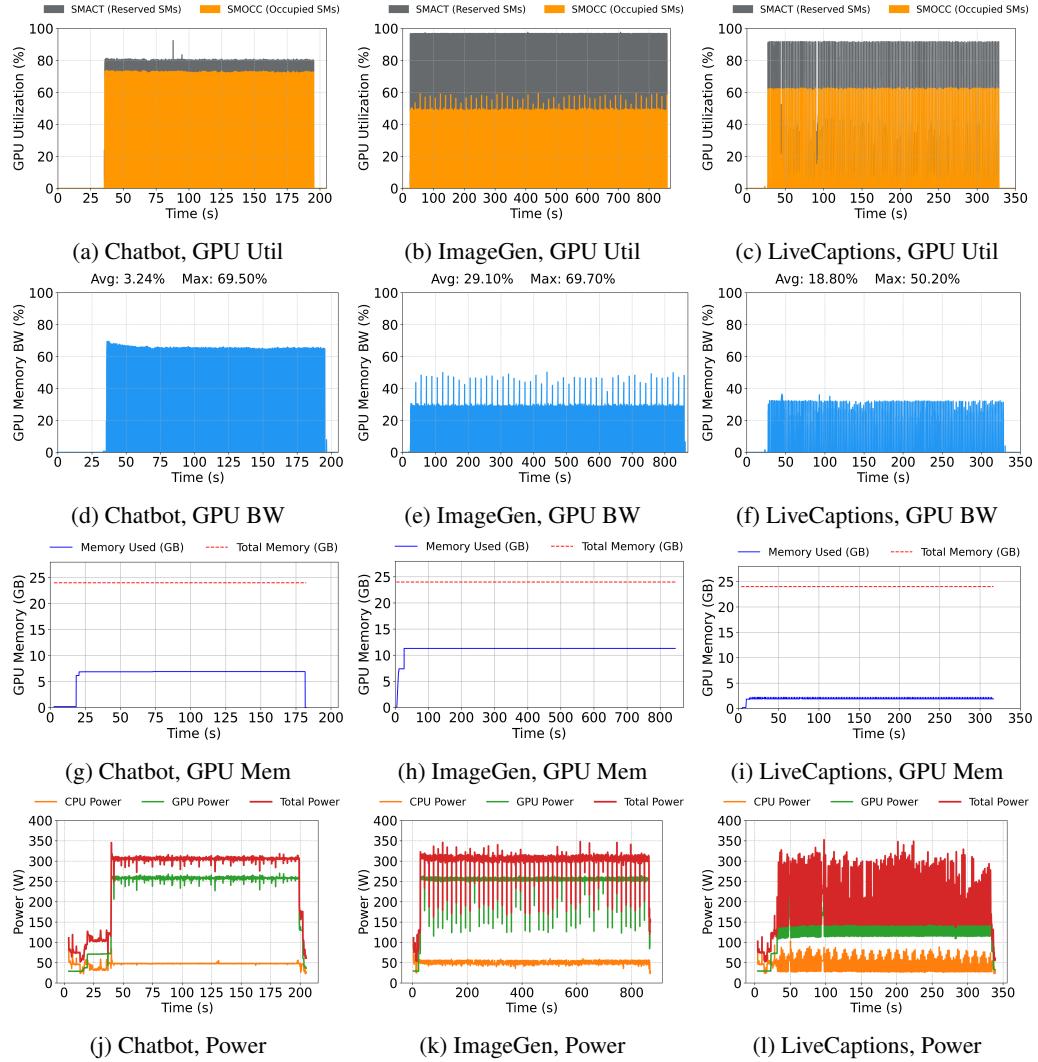


Figure 8: Running applications exclusively on the GPU.

Fig. 8 shows the GPU utilization, memory bandwidth consumption, memory utilization and power consumption when running latency-sensitive applications exclusively on the GPU as reported by CONSUMERBENCH. These are augmented results for Section 4.1 in the paper. Overall, Chatbot consumes the most GPU bandwidth, while ImageGen requires the most amount of GPU memory. All applications have a similar peak power consumption despite the difference in the GPU utilization.

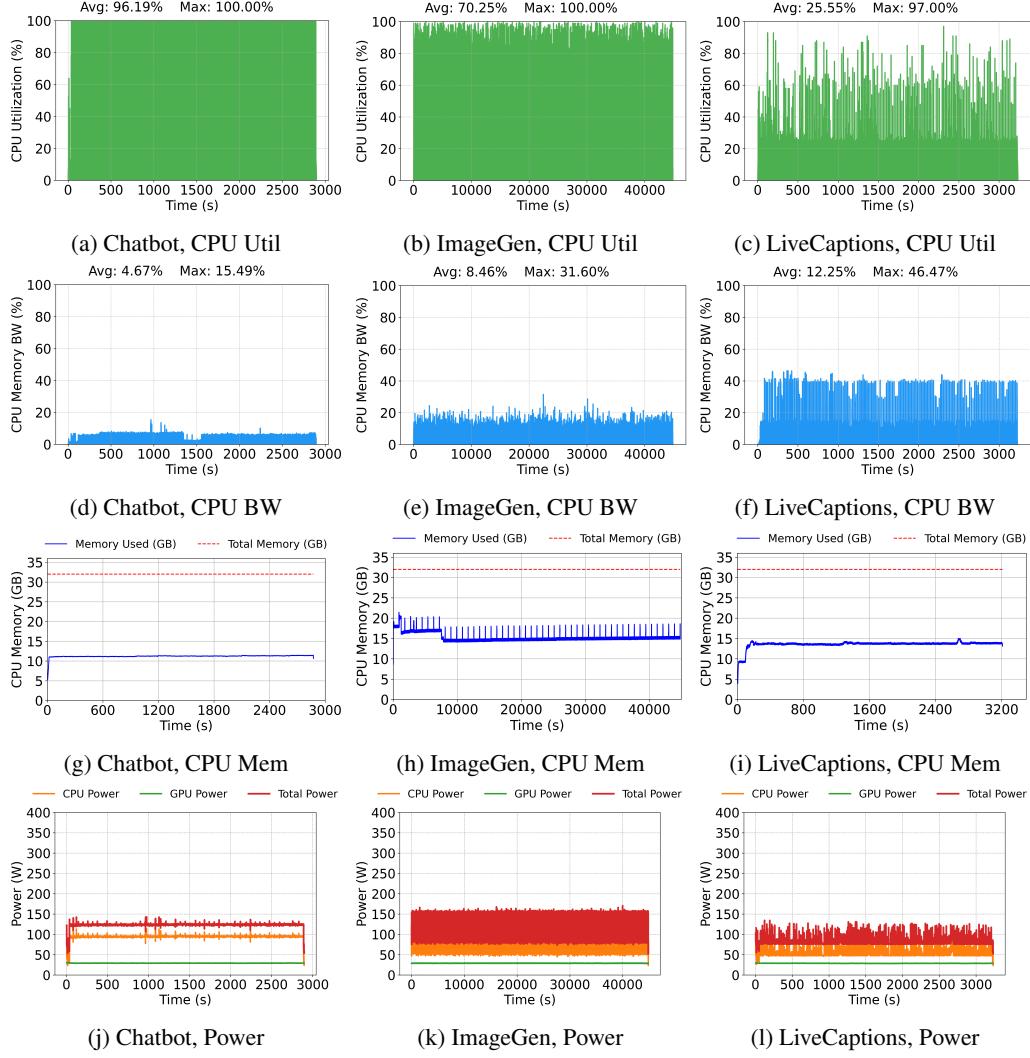


Figure 9: Running applications exclusively on the CPU.

B.2 System-level Metrics for Applications Running Exclusively on CPU

Fig. 9 shows the resource utilization when running latency-sensitive applications exclusively on CPU. These are augmented results for Section 4.1 in the paper. The applications are bottlenecked by compute as opposed to memory, evident by the high CPU utilization and low memory bandwidth consumption. Finally, applications require significantly less power when executing on CPU compared to GPU.

B.3 System-level Metrics for Concurrent Execution of Applications

Fig. 10 shows the GPU metrics and power consumption when running Chatbot, ImageGen, and LiveCaptions concurrently on the GPU. These are augmented results for Section 4.2 in the paper. Greedy resource allocation consumes more power on average compared to static GPU partitioning. This directly follows from the fact that static GPU partitioning underutilizes the GPU, as shown in Fig. 10d.

B.4 Concurrently Executing Applications with Larger Models

We use CONSUMERBENCH to evaluate the performance of applications with larger models that do not concurrently fit in the GPU memory of our server. Specifically, we change the model used in

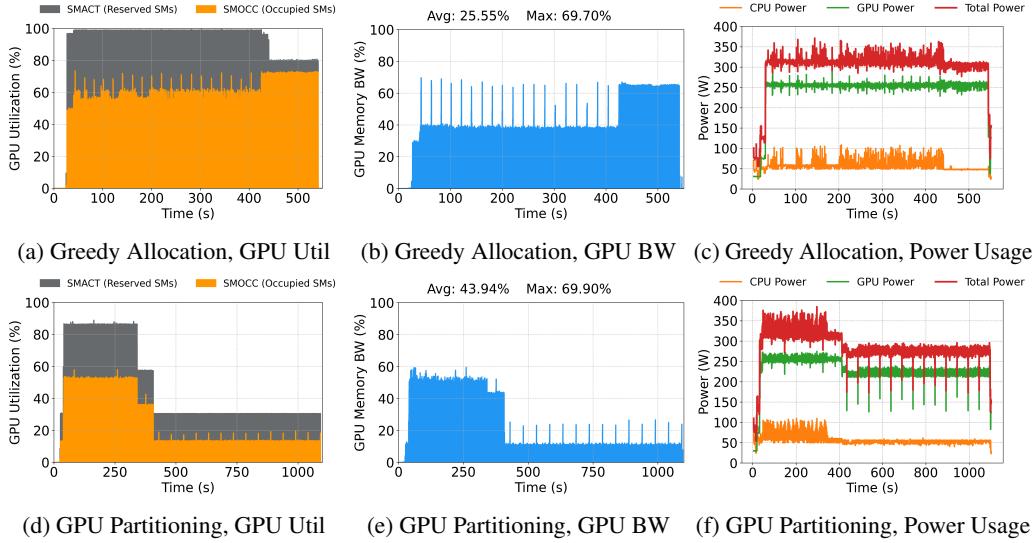


Figure 10: Running applications concurrently on the GPU.

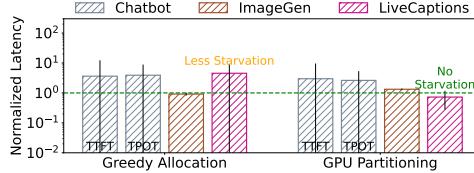


Figure 11: Normalized latency of running larger applications concurrently using greedy allocation and static GPU partitioning

Chatbot from Llama-3.2-3B to Llama-3.1-8B that requires 16GB of memory without accounting for the KV Cache. We execute the Chatbot exclusively on CPU while concurrently running ImageGen and LiveCaptions on the GPU. Fig. 11 shows the performance of the applications using greedy GPU allocation and static GPU partitioning. These are augmented results for Section 4.2 in the paper. Fig. 12 and Fig. 13 further show the GPU metrics, CPU metrics and power usage of the different GPU management strategies.

Overall, Chatbot exhibits reduced performance with the larger model compared to Llama-3.2-3B, leading to SLO violations. Although LiveCaptions also experiences SLO violations, its resource starvation is alleviated due to reduced contention when not all three applications share the GPU simultaneously. Lastly, partitioning the GPU between ImageGen and LiveCaptions effectively eliminates starvation for LiveCaptions, though it causes ImageGen to run slightly slower compared to scenarios with greedy resource allocation.

B.5 System-level Metrics for Static Model Sharing via Inference Servers

Fig. 14 and Fig. 15 show the GPU metrics, CPU metrics, and power usage of running Chatbot with static model sharing via llama.cpp. These are augmented results for Section 4.2.1 in the paper.

Chatbot-KVCache-CPU overall consumes lower GPU resources, but is bottlenecked on the CPU compute due to attention operations on the CPU, evident from the high CPU utilization. Furthermore, performing CPU computations leads to lower power consumption for Chatbot-KVCache-CPU compared to Chatbot.

B.6 System-level Metrics for Real-world User Workflow

Fig. 16 and Fig. 17 show the GPU metrics, CPU metrics, and power usage of running the digital content creation workflow using greedy GPU resource allocation and static GPU partitioning. These are augmented results for Section 4.3 in the paper.

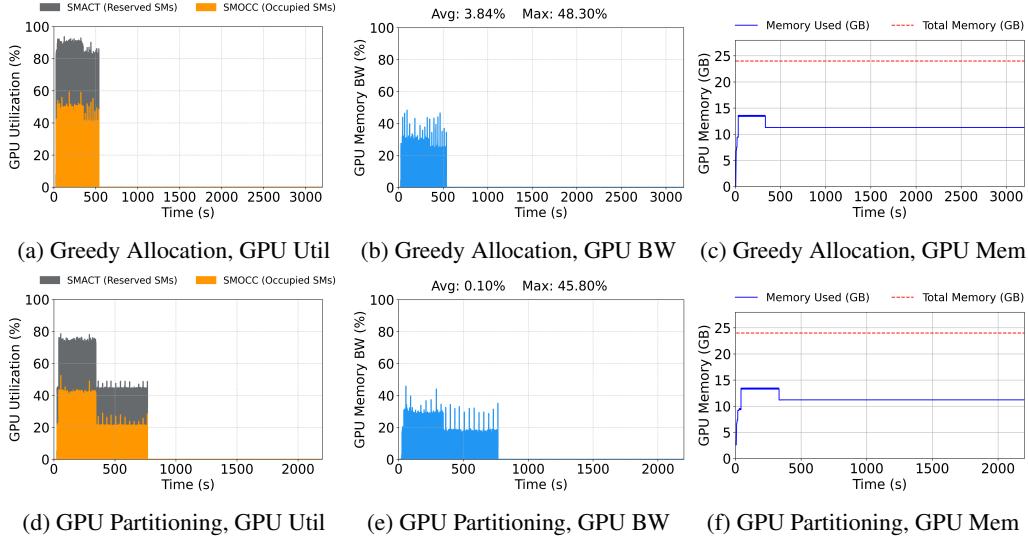


Figure 12: GPU metrics of running larger applications concurrently.

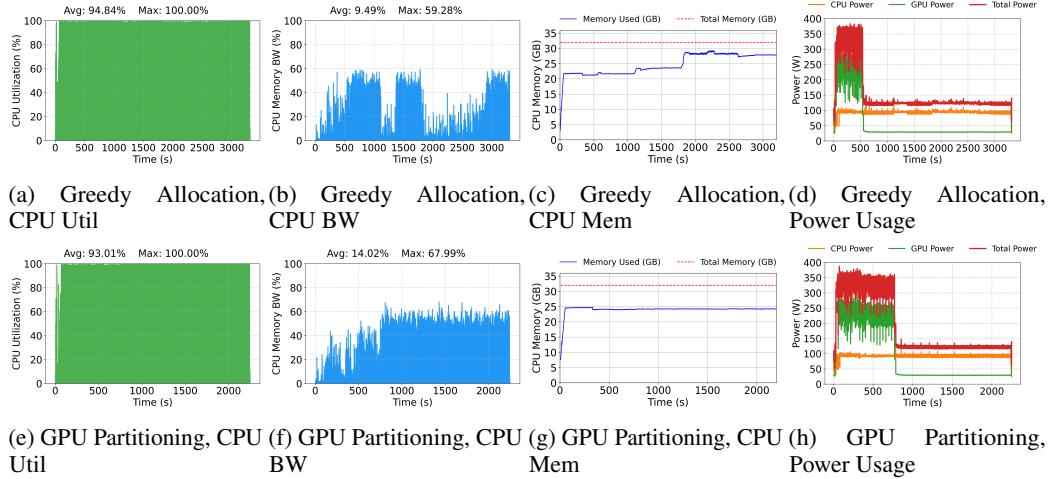


Figure 13: CPU metrics and power usage of running larger applications concurrently.

Greedy GPU resource allocation overall consumes more GPU resources, and has a higher peak power consumption compared to static GPU partitioning. However, the end-to-end time required for greedy resource allocation is 45% lower than GPU partitioning. This implies that the total power consumed in executing the digital content creation workflow is lower for greedy allocation compared to GPU partitioning.

C Apple Silicon Experiments

We conducted all experiments on an Apple MacBook Pro (M1 Pro chip) with 32GB unified memory, 6 performance cores, 2 efficiency cores, and 200GB/s memory bandwidth. These are augmented results for Section 4.4 in the paper.

System-level metrics We use the powermetrics tool of Mac to monitor GPU utilization and power consumption on Apple Silicon devices. Due to the closed-source nature of Apple’s hardware, we are unable to report additional metrics such as memory bandwidth utilization. The GPU utilization values provided by powermetrics reflect the proportion of reserved Streaming Multiprocessors (SMs), specifically SMACT. Notably, the power consumption observed on Apple Silicon is substantially lower than that of our previously evaluated Intel server with an NVIDIA GPU, which is expected given the MacBook Pro’s lower power capacity as a laptop.

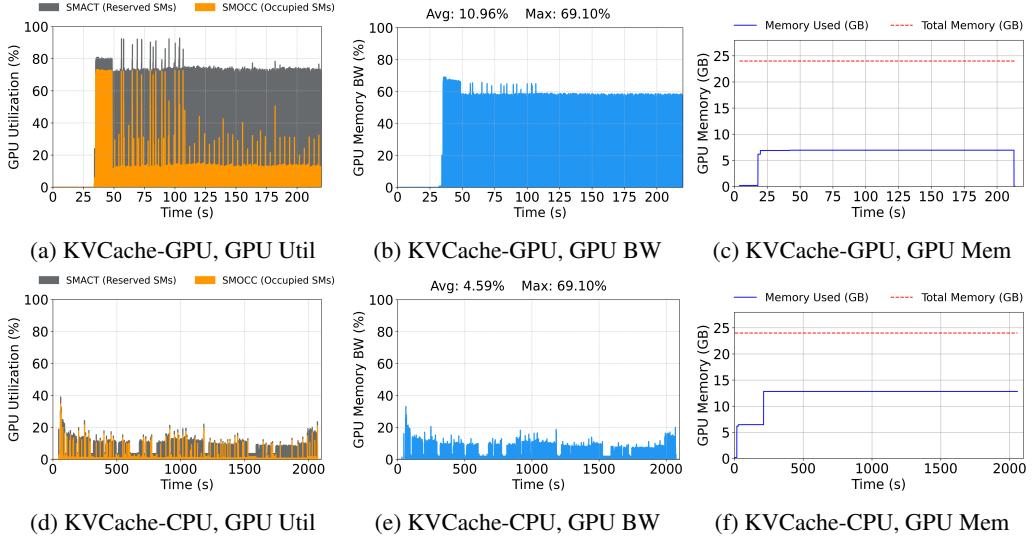


Figure 14: GPU metrics of running applications with static model sharing via inference servers.

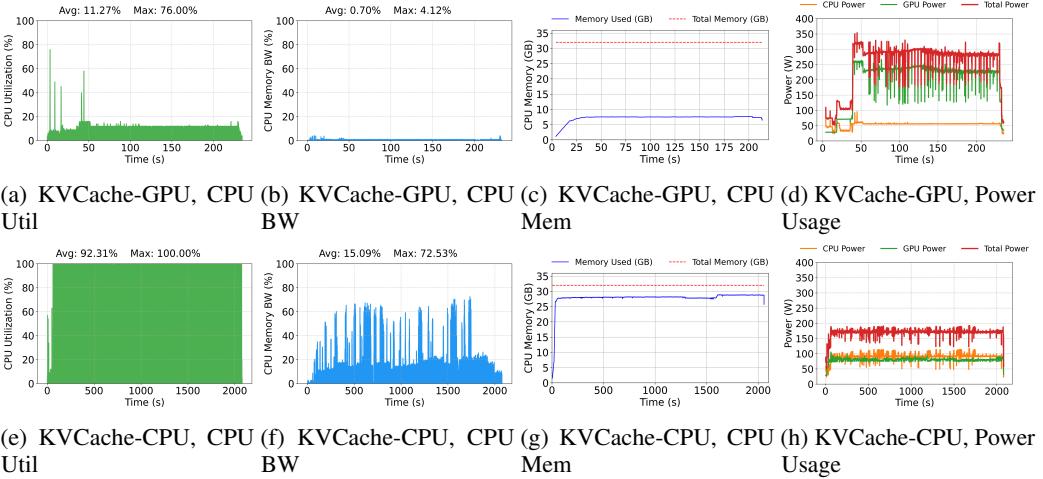


Figure 15: CPU metrics and power usage of running applications with static model sharing via inference servers.

Application Optimizations. Our GenAI optimizations for Apple Silicon include:

- **Chatbot & DeepResearch.** We configured the `llama.cpp` server with the `-metal` flag to optimize GPU kernel execution for Apple Silicon’s ARM-based architecture. The Llama-3.2-3B model runs efficiently through this Metal-accelerated backend, handling both conversational and research workloads.
- **ImageGen.** Our local image generation server uses the MPS (Metal Performance Shaders) backend, mirroring `llama.cpp`’s Apple Silicon optimizations. We employ the SD-v1-4 model instead of the NVIDIA-optimized SD-3.5-medium-turbo variant, as it demonstrates better performance on Apple’s unified memory architecture.
- **LiveCaptions.** The MLX framework accelerates our Whisper-Large-v3-turbo implementation for real-time audio processing. While maintaining model parity with our default server, we adjusted the service-level objective (SLO) to 4 seconds (from 2 seconds) and modified audio chunking intervals to accommodate Apple Silicon’s higher transcription latency.

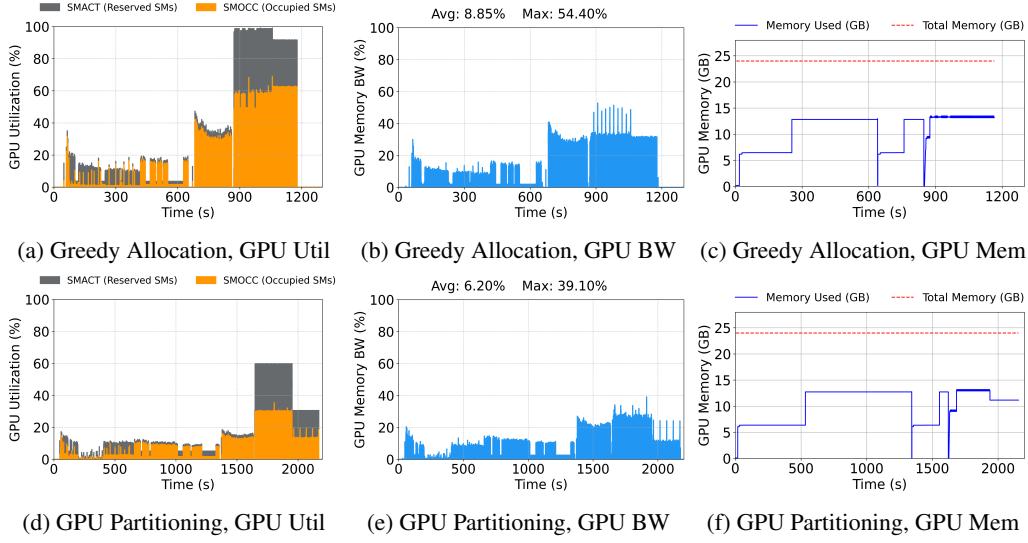


Figure 16: GPU metrics of running the digital content creation workflow.

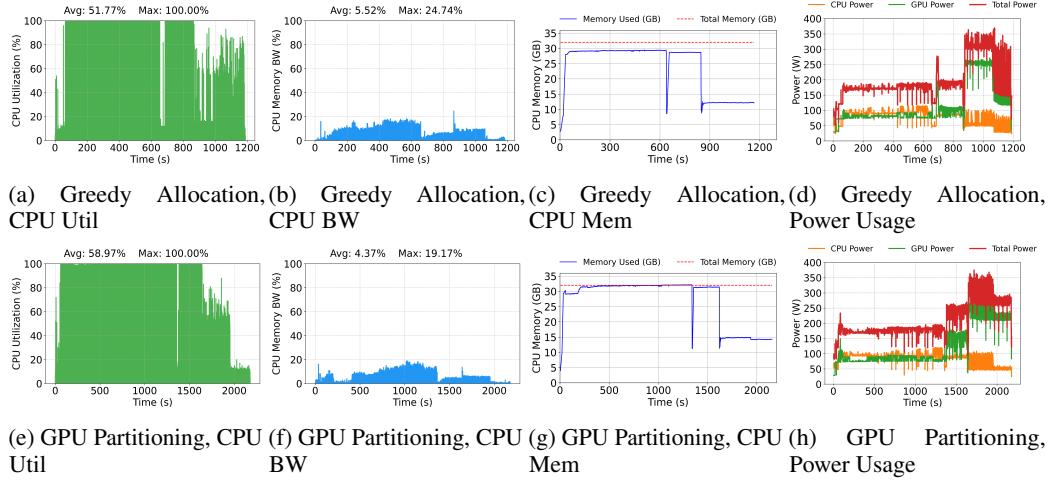


Figure 17: CPU metrics and power usage of running the digital content creation workflow.

C.1 Running Applications Exclusively vs. Concurrently

Fig. 18 shows the normalized latency and SLO attainment of the applications when they run exclusively and concurrently on the Apple Silicon. Fig. 19 further shows the GPU utilization and power usage of each scenario. When applications are run in isolation, they are able to meet their SLOs for the majority, if not all, of their requests. However, when applications are executed concurrently, we observe a different pattern compared to the Intel server setup. Specifically, ImageGen experiences a slight performance degradation, while LiveCaptions suffers a significant decline. This behavior suggests that Apple Silicon attempts to fairly schedule GPU compute resources among applications, but the scheduling is suboptimal, leading to resource starvation for LiveCaptions. Additionally, Apple Silicon does not support static GPU partitioning, and we were unable to explore alternative application configurations.

C.2 Static Model Sharing via Inference Servers

Fig. 20 shows the normalized latency and SLO attainment of running Chatbot and Chatbot-KVCache-CPU on Apple Silicon. Fig. 21(a,b) shows the GPU utilization, while Fig. 21(d,e) shows the power usage of each scenario. The performance for Chatbot-KVCache-CPU is similar on Apple Silicon compared with the Intel server. This is for similar reasons. Chatbot-KVCache-CPU does not use

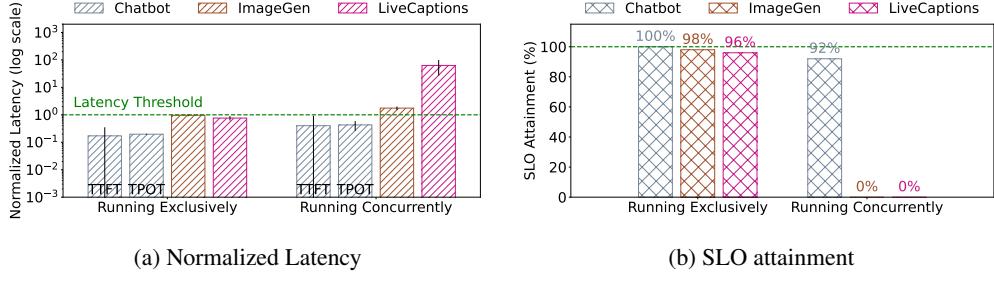


Figure 18: (a) Latencies normalized to SLO requirements and (b) SLO attainment for Chatbot, Image Generation, and Live Caption running exclusively or concurrently on the Apple Silicon.

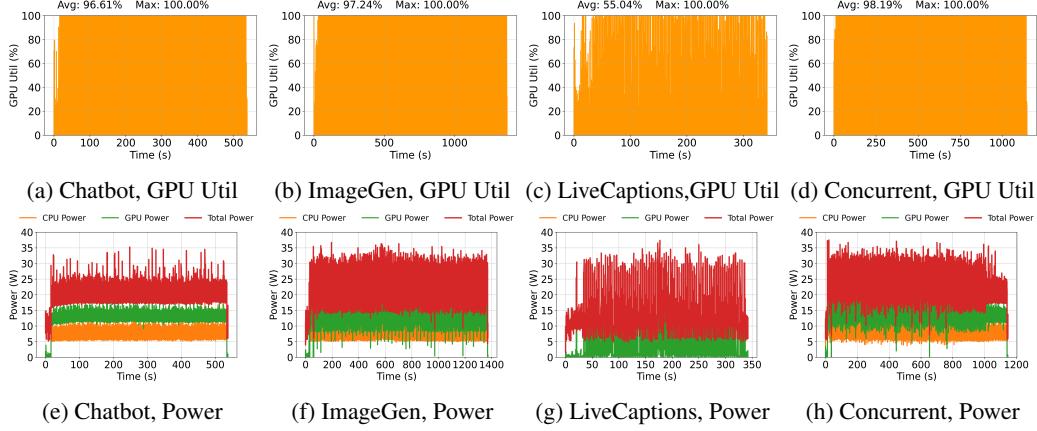


Figure 19: Metrics of running applications exclusively and concurrently on the Apple Silicon.

GPU cores for attention computation in Chatbot-KVCache-CPU, incurring slowdowns compared to Chatbot.

C.3 End-to-end Workflow

We execute the digital content creation workflow on Apple Silicon and present its performance in Fig. 22. Fig. 21c and Fig. 21f shows the GPU utilization and power usage of the workflow. This workflow demonstrates improved fairness in resource allocation on Apple Silicon. Overall, the end-to-end application latency remains comparable to that of the Intel server, while LiveCaptions experiences slightly lesser resource starvation than greedy resource allocation under Intel platform ($8\times$ in Apple Silicon compared to $9.5\times$ in Intel server). Consequently, Apple Silicon achieves a slightly more balanced trade-off between application SLO adherence and overall workflow efficiency compared to the Intel server.

D Configuration for Digital Content Creation Workflow

Fig. 23 shows the YAML configuration for the digital content creation workflow, as described in Section 4.3 in the paper.

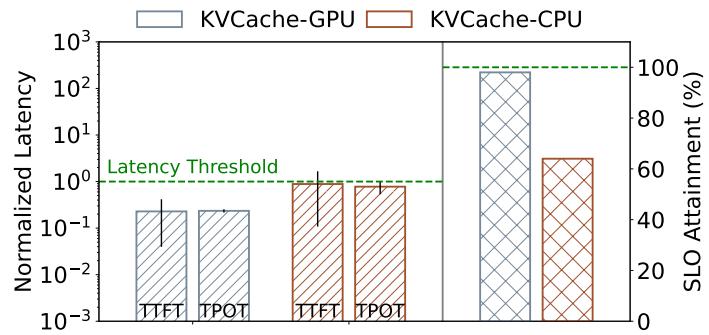


Figure 20: Normalized latency and SLO attainment for Chatbot and Chatbot-KVCache-CPU on the Apple Silicon.

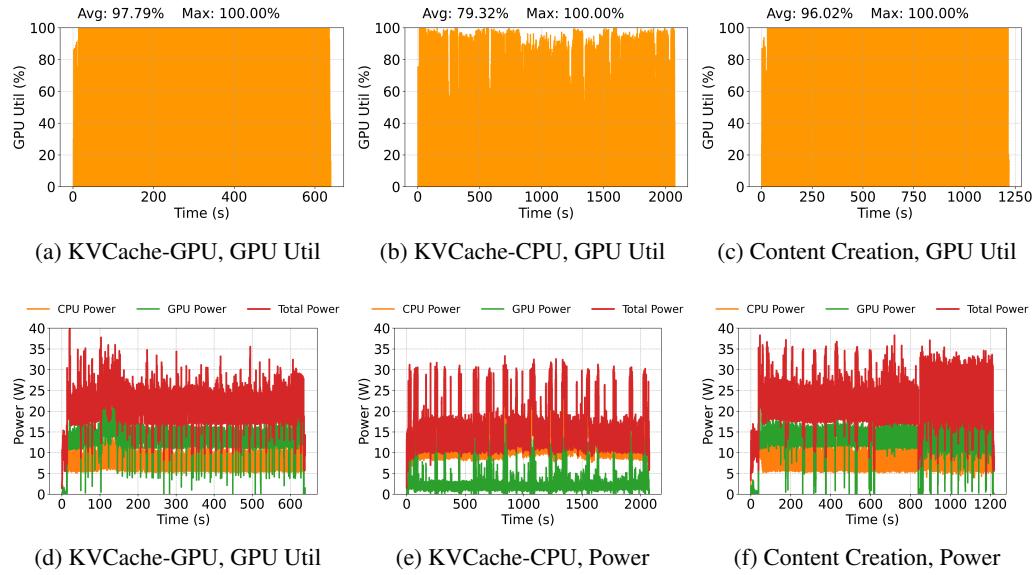


Figure 21: Metrics of running Chatbot, Chatbot-KVCache-CPU and content creation workflow on the Apple Silicon.

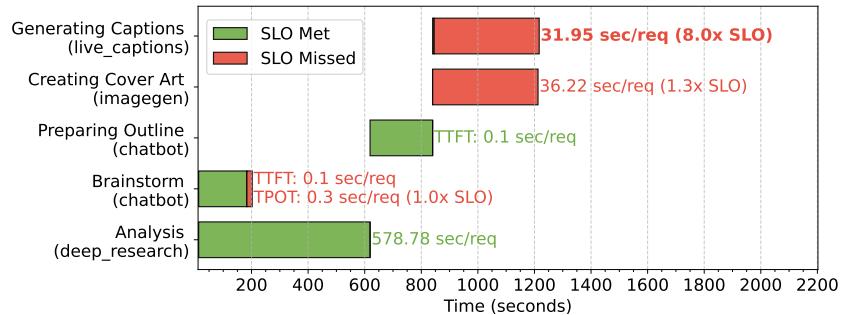


Figure 22: E2E latency & SLO attainment for content-creation workflow running on the Apple Silicon.

```

1 Brainstorm (chatbot):
2   model: openai/meta-llama/Llama-3.2-3B-Instruct
3   num_requests: 10
4   device: gpu
5   type: chatbot
6   mps: 100
7   slo: [1s, 0.25s]
8
9 Analysis (deep_research):
10  model: openai/meta-llama/Llama-3.2-3B-Instruct
11  num_requests: 1
12  device: gpu
13  type: deep_research
14  mps: 100
15
16 Preparing Outline (chatbot):
17  model: openai/meta-llama/Llama-3.2-3B-Instruct
18  num_requests: 20
19  device: gpu
20  type: chatbot
21  mps: 100
22  slo: [1s, 0.25s]
23
24 Creating Cover Art (imagegen):
25  server_model: stable-diffusion-3.5-medium-turbo
26  num_requests: 10
27  device: gpu
28  type: imagegen
29  mps: 100
30  slo: 1s
31
32 Generating Captions (live_captions):
33  num_requests: 1
34  device: gpu
35  type: live_captions
36  mps: 100
37  slo: 2s
38
39 workflows:
40   analysis:
41     uses: Analysis (deep_research)
42     background: true
43
44   brainstorm:
45     uses: Brainstorm (chatbot)
46
47   outline:
48     uses: Preparing Outline (chatbot)
49     depend_on: ["brainstorm", "analysis"]
50
51   cover_art:
52     uses: Creating Cover Art (imagegen)
53     depend_on: ["outline"]
54
55   generate_captions:
56     uses: Generating Captions (live_captions)
57     depend_on: ["outline"]
58
59

```

Figure 23: Full YAML configuration of the content creation workflow.