SAGE: EFFICIENT PROTECTED VISION-LANGUAGE INFERENCE ON SMART GLASSES

Anonymous authors
Paper under double-blind review

ABSTRACT

Smart glasses are a promising platform for vision-language assistants, but private split inference remains expensive: protecting visual representations before transmission does not remove the cost of on-device vision encoding, wide protected tokens, or hardware-unaware execution. We present **SAGE** (**S**mart-glasses-**A**ware **G**uarded **E**ncoding), a hardware-aware framework for efficient protected VLM inference on smart glasses. SAGE keeps raw images and unprotected visual tokens on the trusted device, reduces visual input cost, executes shape-specialized INT8 graphs, and compresses protected representations into compact 256-dimensional INT8 packets before transmission. Unlike efficiency methods optimized only for nominal model size, SAGE selects its operating point using downstream answer quality together with measured latency, memory, and thermal behavior on real Mentra Live glasses. On a matched Qwen workload, SAGE reduces glasses inference latency by 39.18%, device-sensor temperature rise by 21.91%, and protected packet size by 96.56%, while retaining 85.62% of the protected reference's relaxed utility and comparable prompted containment. Direct glasses-to-phone tests deliver all 192 packets and reduce median packet-plus-acknowledgment time from 71.3 to 10.0 ms. The compact protected interface also transfers across four additional VLM families. These results show that private wearable VLM inference must be optimized jointly across representation protection, communication, and real-device execution rather than through model compression alone.

1 INTRODUCTION

Smart glasses give a visual assistant access to the wearer's surroundings: road signs, nearby objects, and documents can become inputs to a spoken question (Mann, 1997; 2002; Zhang et al., 2025). Running the full vision-language model (VLM) on the glasses competes with their limited compute, memory, and thermal budget. Split inference places the vision encoder on the glasses and sends its tokens to a server that runs the language model (Kang et al., 2017; Teerapittayanon et al., 2017). A paired phone can also host the downstream reader. This division reduces local work, but gives the receiving endpoint access to a representation of the scene.

We focus on privacy exposure at that receiving endpoint. The same scene can contain evidence for the user's task and private information unrelated to it. In Figure 1, road and vehicle cues support a traffic query, while the captured frame also includes a license plate. A server-side adversary could query the received representation for location or income, apply a separate attribute classifier, or attempt to reconstruct the image before the intended LLM processes it. These threats follow from evidence that VLMs infer personal attributes from ordinary images and that learned visual features support reconstruction (Tömekçe et al., 2024; Mahendran & Vedaldi, 2015; Dosovitskiy & Brox, 2016). Encrypting the network connection does not remove the information available to its receiving endpoint.

Model-side defenses change what the downstream model reveals. Fine-tuning and unlearning can suppress selected responses or learned associations, including across text and vision (Maini et al., 2024; Dontsov et al., 2025). Updating the backbone requires access to its weights, optimization, and validation for the deployed model. Parameter-efficient adaptation reduces the trainable parameter count (Hu et al., 2021), but still requires training data, passes through the backbone, and model-

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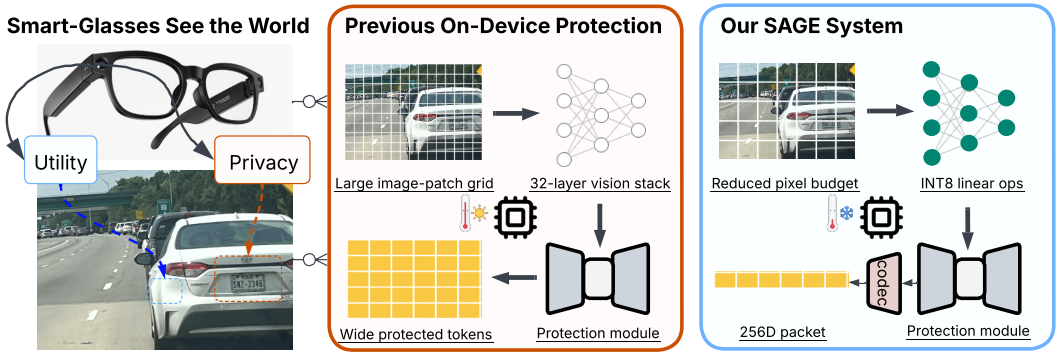

Figure 1: Smart-glasses motivation and protected-inference paths. **Left:** The camera view contains task-relevant road cues and a private license plate. **Center:** Previous on-device protection transforms tokens before transmission but retains a large visual input and wide protected tokens, increasing glasses-side computation and transmission burden. **Right:** SAGE retains the full 32-layer vision tower and the same protection transform, reduces the pixel budget, and sends a compact 256-dimensional INT8 packet per token, lowering measured glasses-side latency and sensor-temperature rise.

specific evaluation. Such changes also leave a separate exposure: an adversary with access to the incoming tokens can analyze them independently of the updated LLM.

Previous on-device protection addresses this exposure by transforming the representation before it leaves the trusted device. Shredder learns noise for transmitted features while keeping the pretrained network fixed (Mireshghallah et al., 2020). For wearable VLMs, TGAP (Li et al., 2026) applies a small learned transform to visual tokens to reduce private-attribute disclosure while preserving task information. These approaches place protection at the transmission boundary and avoid updating the downstream backbone. We adopt this boundary: raw images and unprotected tokens stay on the glasses, and the downstream reader receives only protected representations.

Three coupled costs remain after protection. First, the visual encoder runs before the small protection transform; reducing its input grid saves work but can remove details needed for an answer. Second, protected tokens are still wide, so a smaller packet must reconstruct the interface expected by the frozen reader. Third, fewer parameters or storage bits need not reduce execution time on a wearable CPU: input shape and available kernels determine the actual cost. Figure 1 locates these costs in the glasses-side path. They make answer quality and device measurements necessary parts of configuration selection.

To make protected split inference practical on smart glasses, we propose **SAGE** (Smart-glasses-Aware Guarded Encoding), a hardware-aware framework for efficient private VLM inference. SAGE keeps raw images and unprotected visual tokens on the trusted device, reduces visual encoder cost by lowering the input pixel budget while retaining the full 32-layer vision tower, and applies the frozen TGAP transform before transmission. Protected tokens are then encoded into a compact 256-dimensional INT8 latent, reducing communication without exposing unprotected features. To account for real wearable constraints, SAGE selects fixed-grid INT8 execution graphs using downstream answer quality together with measured glasses-side latency, memory, and sensor-temperature rise, while keeping the downstream LLM frozen.

We evaluate SAGE on a matched Qwen workload and observe substantial improvements in real-device efficiency while preserving downstream performance. Glasses inference latency decreases from 15.967 to 9.711 seconds (39.18%), sensor-temperature rise decreases by 21.91%, and the protected packet is reduced by 96.56% relative to the high-resolution TGAP reference. Across three random splits, SAGE retains 85.62% of the reference's relaxed utility, while prompted containment remains nearly unchanged (10.89% versus 11.00%). SAGE also achieves higher software answer utility than the adapted compression baselines, and direct glasses-to-phone tests successfully deliver all 192 protected packets while reducing median packet-plus-acknowledgment time from 71.3 to 10.0 ms.

Our contributions are summarized as follows:

- **Wearable Protected Inference.** We propose SAGE, a protected split-VLM system for smart glasses that reduces on-device and transmission costs while retaining downstream answer utility and limiting prompted privacy disclosure without changing the downstream LLM.
- **Hardware-Profiled Configuration.** We establish SAGE's fixed operating point using direct on-device measurements of latency, memory, and sensor temperature under a controlled protocol, demonstrating the necessity of physical profiling over nominal model-size proxies.
- **Systematic Matched Evaluation.** We compare SAGE with six compression methods on matched Qwen workloads, benchmark protected-packet delivery from real smart glasses to an Android phone, and test the packet interface across four VLM families.

2 Related Work

Wearable intelligence and split inference. Wearable computing has long treated egocentric perception as a persistent interface between a user and the surrounding environment (Mann, 1997; 2002). Modern VLMs extend this interface with open-ended visual question answering and instruction following (Li et al., 2023; Liu et al., 2023; Wang et al., 2024; Chen et al., 2024b; Yao et al., 2024). Because the complete model is expensive for a mobile device, split-computing systems divide neural execution across an endpoint and an edge or cloud server (Kang et al., 2017; Teerapittayanon et al., 2017). These systems primarily choose a partition to reduce latency, communication, or endpoint compute. We instead require the partition to satisfy a privacy invariant: images and unprotected visual tokens stay on the glasses, and the representation is protected before it reaches the paired reasoning device.

Efficient visual and multimodal inference. Efficient vision models reduce compute with compact operators and architectural scaling (Wang et al., 2026; Howard et al., 2017; Sandler et al., 2018; Tan & Le, 2019), while pruning and quantization reduce parameters and arithmetic cost in trained networks (Han et al., 2015). For multimodal transformers, token merging and token pruning remove redundant visual tokens or bypass their later-layer processing (Bolya et al., 2022; Chen et al., 2024a; Yang et al., 2025). Knowledge distillation and structured pruning instead compress the model itself through teacher supervision or learned subnet selection (Fang et al., 2021; Sun et al., 2026; Shi et al., 2023). These techniques target the encoder or token sequence. In our setting, each glasses-side operating point feeds a fixed privacy transform and codec, so we evaluate downstream answers and measured device cost together. Structured block removal and mixed precision serve as controls for this choice.

Privacy leakage from multimodal representations. Model inversion, feature inversion, and property inference demonstrate that intermediate representations can retain information beyond the intended prediction target (Fredrikson et al., 2015; Mahendran & Vedaldi, 2015; Dosovitskiy & Brox, 2016; Ganju et al., 2018). Language models can infer personal attributes from contextual evidence (Staab et al., 2024), and VLMs extend this exposure to visual scenes (Tömekçe et al., 2024). Image-space privacy methods perturb sensitive evidence before encoding (Fan et al., 2025; Zhang et al., 2026), while geolocation dialogue moderation constrains what a model reveals in its responses (Mendes et al., 2024). Backbone adaptation changes model behavior (Hu et al., 2021), while unlearning studies address stored associations and their evaluation (Maini et al., 2024; Dontsov et al., 2025). Those defenses act at different interfaces from a representation transmitted by a split VLM.

Protected representation learning. Adversarial and invariant representation learning suppresses nuisance or sensitive variables while retaining target-task information (Ganin et al., 2016; Edwards & Storkey, 2015; Moyer et al., 2018). Shredder applies learned noise to transmitted features without updating the pretrained network (Mireshghallah et al., 2020). Token-level VLM defenses instantiate this principle after the visual resampler, using a small residual transform to reduce prompted disclosure and private-attribute recoverability without updating the source VLM (Li et al., 2026). We reproduce TGAP's token-wise protection on the glasses and use its privacy protocol in evaluation. The matched systems share the same protection mechanism and downstream reader, allowing us to test wearable latency, memory, and thermal costs against downstream answer quality.

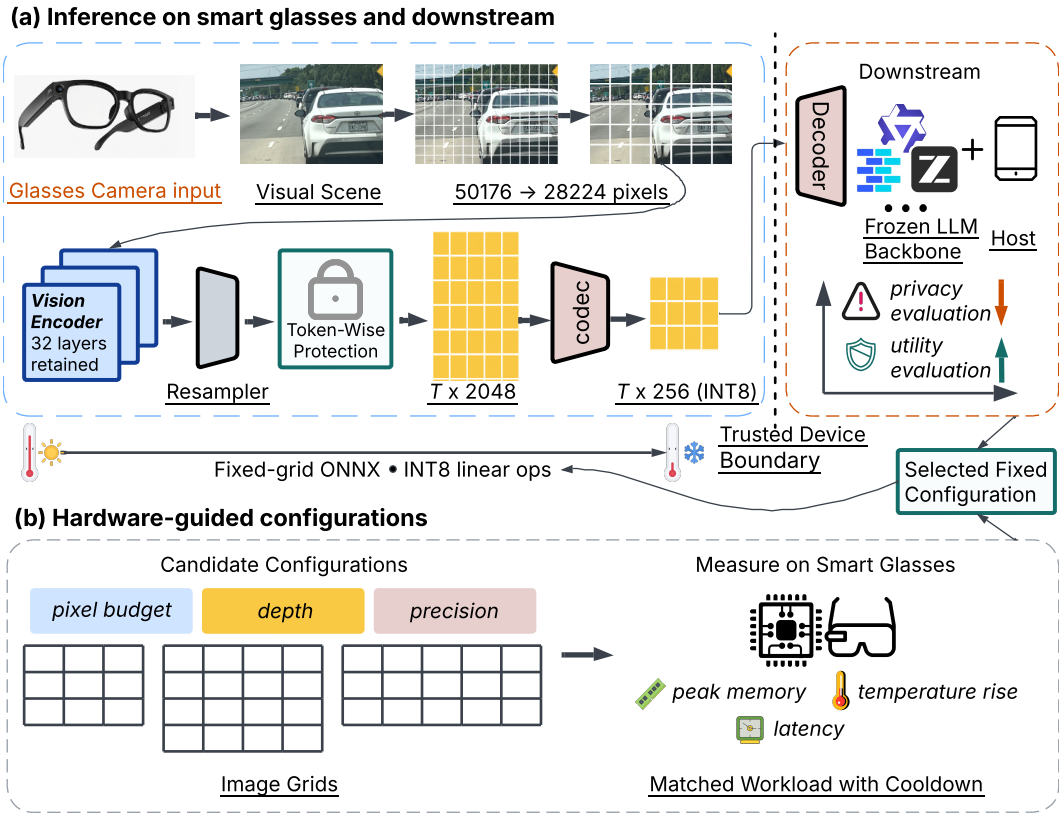

Figure 2: SAGE overview. (a) The trusted glasses execute visual encoding, resampling, the frozen TGAP protection transform (Li et al., 2026), and latent encoding. Only the protected INT8 packet and reconstruction metadata cross the trust boundary; downstream dequantization and decoding restore the LLM input. (b) Quality evaluation and glasses-side measurements select a fixed configuration, separately from per-request execution. Downstream QA runs on a host; the host phone is also used for the packet-delivery experiment in Appendix A.4.

3 METHOD

SAGE deploys a protected split-VLM across smart glasses and a downstream reader. It keeps the source vision topology, protects visual tokens before they cross the device boundary, and selects a fixed-grid INT8 implementation using downstream answer quality and measurements on the target glasses. Figure 2 shows the system; Algorithm 1 summarizes its preparation and per-request execution.

3.1 SYSTEM MODEL AND TRUST BOUNDARY

Let x be an image, q a question, and g its aspect-preserving input grid. The 32-layer vision tower $E_{p,g}$ runs at pixel budget p. The resampler R produces $z = R(E_{p,g}(x)) \in \mathbb{R}^{T_g \times d}$, and the privacy transform P produces protected tokens $h = P(z)$. A codec encoder C_{enc} and quantizer $\mathcal{Q}_s$ form the transmitted latent

$$u = C_{\text{enc}}(h), \qquad c = \mathcal{Q}_s(u), \qquad \hat{h} = C_{\text{dec}}(sc). \tag{1}$$

The downstream reader answers with its frozen language model $M(\hat{h}, q)$. We reproduce the token-wise privacy protection mechanism of TGAP (Li et al., 2026) and deploy it as P on the glasses. This established mechanism supplies the privacy protection in our implementation; SAGE addresses its wearable execution and compact transmission.

Figure 2 fixes the deployment boundary. Image decoding, vision encoding, resampling, protection, latent encoding, and quantization execute on the trusted glasses. Only the compact protected packet

and reconstruction metadata cross to the downstream device. Raw images and unprotected visual tokens never leave the glasses.

3.2 Compact Protected Path

The TGAP high-resolution configuration, denoted *TGAP-HR*, is the matched protected benchmark. It uses a 32-layer Qwen vision tower with a 50,176-pixel budget followed by the TGAP transform. SAGE retains all 32 vision blocks but reduces the pixel budget to 28,224. This lowers visual sequence length without changing the source tower's local and global attention schedule. The pixel counts in Figure 2(a) denote preprocessing budgets. Its token grids are schematic: the codec reduces channel width from 2048 to 256 while retaining the T_g tokens produced at the selected input budget.

Compression is applied only after protection. For Qwen, $d = 2048$ and the codec width is $k = 256$. With the training-set mean μ, the linear codec computes $u = (h-\mu)W_{\mathrm{e}} \in \mathbb{R}^{T_g \times k}$, where $W_{\mathrm{e}} \in \mathbb{R}^{d \times k}$ and $W_{\mathrm{d}} \in \mathbb{R}^{k \times d}$ are fitted weights. One signed-INT8 scale is shared by the latent values of an image:

$$s = \frac{\max(\|u\|_\infty, 10^{-8})}{127}, \qquad c = \mathcal{Q}_s(u) = \mathrm{clip}_{[-127,127]}(\mathrm{round}(u/s)), \quad \hat{h} = (sc)W_{\mathrm{d}} + \mu. \tag{2}$$

Thus $C_{\mathrm{enc}}(h) = (h-\mu)W_{\mathrm{e}}$ and $C_{\mathrm{dec}}(v) = vW_{\mathrm{d}} + \mu$ for a dequantized latent v. The codec is fitted on protected tokens from the registered training partition; $E_{p,g}$, R, P, and M remain frozen. With a padding mask m, its training objective is

$$\mathcal{L}_{\mathrm{codec}} = \mathrm{MSE}_m(\hat{h}, h) + 0.5\big(1 - \mathrm{Cos}_m(\hat{h}, h)\big) + \mathrm{MSE}\Big(\mathrm{Pool}_m(\hat{h}), \mathrm{Pool}_m(h)\Big). \tag{3}$$

Here MSE_m averages squared error over valid entries, Cos_m averages token-wise cosine similarity over valid tokens, and Pool_m is the mean of valid tokens. Codec fitting uses only the training partition; checkpoint selection uses the separate selection partition. The packet contains $T_g k$ quantized bytes, a four-byte FP32 scale, and a 12-byte shape header, for $T_g k + 16$ bytes in all. Its latent tensor alone is 6.25% of the corresponding FP16 token tensor. The paired decoder restores the interface expected by the frozen reader without transmitting h.

SAGE exports one ONNX graph for each image grid produced by aspect-preserving preprocessing. Linear operators use dynamic per-channel INT8 quantization, while geometry, normalization, and unsupported operators retain the runtime's native precision. Fixed-grid export removes dynamic-shape overhead without replacing the workload by a convenient square input.

3.3 Hardware-Conditioned Configuration

Nominal model size does not determine efficiency on a wearable CPU. We therefore profile each candidate configuration and image grid on the target glasses. The profile records graph size, loading time, inference latency, process high-water memory, and device-sensor temperature rise under a fixed start-temperature and cooldown protocol. We select a configuration before inference; requests use its fixed graphs without online routing or active cooling. We compare these costs alongside answer quality and prompted disclosure. Section 4.1 defines the quality summary and the separate cross-path comparison index.

Algorithm 1 SAGE setup and inference

1 **Offline:** freeze $E_{p,g}, R, P, M$.
2 $(W_{\mathrm{e}}, W_{\mathrm{d}}) \leftarrow \arg\min_{W_{\mathrm{e}}, W_{\mathrm{d}}} \mathcal{L}_{\mathrm{codec}}$ (Eq. 3).
3 Export fixed-grid $E_{p,g} \to R \to P \to C_{\mathrm{enc}}$ graphs; quantize supported linear ops to INT8.
4 Fix p and graphs using QA, disclosure, and device profiles.
5 **Glasses:** $z \leftarrow R(E_{p,g}(x))$; $h \leftarrow P(z)$.
6 $u \leftarrow C_{\mathrm{enc}}(h)$; $s \leftarrow \max(\|u\|_\infty, 10^{-8})/127$.
7 $c \leftarrow \mathcal{Q}_s(u)$; send (c, s, g) and shape metadata.
8 **Reader:** $\hat{h} \leftarrow C_{\mathrm{dec}}(sc)$.
9 return $M(\hat{h}, q)$.

The selected SAGE configuration is the full-depth INT8 path. We additionally construct a protected-interface-distilled 28-layer path and a mixed-INT4 version to test whether depth or storage precision is a reliable proxy for deployment quality. They are diagnostic configurations rather than components of the deployed SAGE path; their architecture, training objective, and hardware measurements are reported in Appendix A.1.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

Data and metrics. We evaluate downstream answering and prompted privacy disclosure on the TGAP paired benchmark (Li et al., 2026). Its records pair utility questions with private-attribute annotations on the same images, making it suited to a matched privacy–utility evaluation of wearable split inference. The benchmark combines Reddit-sourced records with ST-VQA (Biten et al., 2019), InfographicVQA (Mathew et al., 2022), TextVQA (Singh et al., 2019), and DocVQA (Mathew et al., 2021) records. The source composition and exact response prompts appear in Appendix B. Each registered split contains 617 evaluation images; three random seeds independently define 1,973 codec-fitting, 494 selection, and 617 evaluation examples. Three-split tables report mean and sample standard deviation. A fixed Sonnet judge resolves interest-attribute matches not settled by deterministic rules. The benchmark informed earlier configuration development; these random partitions measure split sensitivity, not performance on an untouched external test set.

Aggregation and trade-off measure. For system a and split r, U.EM and U.Rel are the fractions of utility answers passing normalized exact match and normalized substring match, respectively. P.Cont is the fraction of privacy responses passing the registered case-insensitive value-containment check; P.Acc is the fraction recovering the private value under attribute-specific rules, with a frozen semantic judge for unresolved interests. P.WR is the mean recall of non-stopword target words over privacy responses. Each rate is computed on its own question set and lies in $[0, 1]$. We average the three split-level rates with equal seed weight and report their sample standard deviation; percentage entries multiply both by 100. Following the registered utility–containment summary, define

$$Q_{a,r} = U^{\mathrm{Rel}}_{a,r}(1 - P^{\mathrm{Cont}}_{a,r}), \qquad \bar{Q}_a = \frac{1}{3}\sum_{r=1}^{3} Q_{a,r}. \tag{4}$$

Q is a descriptive product of rates from distinct utility and privacy question sets, not the probability that a single answer is both correct and private. To compare quality with glasses-side cost, let b denote TGAP-HR, L_a the measured inference latency, and ΔT_a the sensor-temperature rise for system a. With a 10-second latency reference $L_\star$, we report the baseline-normalized index

$$\mathcal{R}_a = \frac{\bar{Q}_a \, \min\{1, L_\star/L_a\} \, \min\{1, \Delta T_b/\Delta T_a\}}{\bar{Q}_b \, \min\{1, L_\star/L_b\}}, \qquad L_\star = 10\,\mathrm{s}. \tag{5}$$

The two capped factors penalize latency beyond 10 seconds and temperature rise above the benchmark, without rewarding arbitrarily short latency or lower sensor rise once those references are met. Thus $\mathcal{R}_b = 1$.

Models and comparisons. All experiments outside the transfer study use Qwen2.5-VL-3B as the frozen downstream reader and source vision model. Raw-HR forwards the high-resolution Qwen visual tokens without protection and serves as an unprotected disclosure reference, not a private deployment. TGAP-HR is the high-resolution implementation of the published TGAP protection method (Li et al., 2026), defined in Section 3.2. SAGE uses the same frozen reader and TGAP transform, changing the glasses-side visual budget, runtime graph, and compact packet. We compare six systems on matched Qwen workloads, including four adapted compression baselines and the TGAP-HR protected reference: DistillVLM (Fang et al., 2021), Switch-KD (Sun et al., 2026), UPop (Shi et al., 2023), and VisionZip (Yang et al., 2025). Their original implementations target different VLM architectures. The Qwen adaptations, initialization, and training budgets are specified in Appendix A.5.

Wearable protocol. Device measurements run on Mentra Live glasses (Android 11, four CPU threads) with fixed-grid ONNX artifacts. We profile all 32 old/new grid pairs observed in the 617-image split and post-stratify each measurement by its empirical grid frequency. Every request begins below the registered temperature threshold and uses the sporadic-request cooldown protocol. We report glasses inference latency, process high-water memory, and the maximum valid device-sensor temperature increase.

Hardware and quality display. For each observed grid pair g, n_g is its count in the 617-image evaluation split and $w_g = n_g/617$. Let $\ell_{a,g}$ be the measured resident inference time for system a, and $T^{\text{before}}_{a,g}$ and $T^{\text{after}}_{a,g}$ the pre-request and post-request sensor readings. Reported latency and sensor rise are $L_a = \sum_g w_g \ell_{a,g}$ and $\Delta T_a = \sum_g w_g (T^{\text{after}}_{a,g} - T^{\text{before}}_{a,g})$. We measure one cooled request per system and grid pair. Loading time and process high-water memory are weighted by the same w_g; model size averages the distinct exported grids. Table 2 reports $\bar{Q}_a$ beside these device costs and the descriptive index $\mathcal{R}_a$ from Eq. 5.

4.2 Qwen Comparison with Protected and Compressed VLMs

We compare all methods on the same Qwen reader and matched evaluation splits. Raw-HR is an unprotected software control; its packet entry is an accounted size, not an observed transmission. Table 1 reports answer quality and prompted disclosure before the glasses-side costs.

Table 1: Qwen answer quality and prompted privacy over three 617-image splits (mean ± sample standard deviation from three random seeds). Raw-HR is the unprotected high-resolution reference; TGAP-HR is the cited prior protected system (Li et al., 2026). The four adapted methods use feature or logit distillation, block pruning, or token selection and merging. Packet sizes coincide where the 256D INT8 codec and token count are shared; VisionZip shortens the sequence. TGAP-HR sends FP16 protected tokens.

	Answer utility ↑		Prompted privacy ↓			Packet ↓
System	U.EM ↑	U.Rel ↑	P.Acc ↓	P.Cont ↓	P.WR ↓	KB ↓
Raw-HR (unprotected)	49.70 ± 0.89	59.32 ± 1.01	48.23 ± 1.08	36.67 ± 0.34	17.66 ± 0.43	229.642
TGAP-HR	**50.08 ± 2.23**	**60.83 ± 1.60**	39.30 ± 6.96	11.00 ± 2.02	18.08 ± 3.31	229.642
DistillVLM	17.72 ± 1.38	23.18 ± 2.02	**8.78 ± 3.84**	**6.34 ± 1.21**	5.21 ± 2.20	7.871
Switch-KD	16.42 ± 1.79	21.72 ± 3.08	10.39 ± 1.71	9.00 ± 0.40	**4.84 ± 1.09**	7.871
UPop	30.36 ± 1.53	38.30 ± 2.48	25.98 ± 7.14	8.29 ± 1.20	10.60 ± 3.01	7.871
VisionZip	38.68 ± 1.54	49.11 ± 2.11	33.68 ± 6.91	11.32 ± 1.52	15.18 ± 3.62	**5.247**
SAGE	**41.65 ± 2.77**	**52.08 ± 2.64**	34.77 ± 6.41	10.89 ± 1.59	15.73 ± 3.15	7.871

The unprotected Raw-HR control reaches 36.67% P.Cont and 48.23% P.Acc; TGAP-HR reduces these to 11.00% and 39.30%, respectively, while U.Rel is 59.32% for Raw-HR and 60.83% for TGAP-HR. TGAP-HR is the protected reference for the efficiency comparison. Across the three random seeds, SAGE retains 85.62% of TGAP-HR's relaxed utility (52.08% versus 60.83%). Its P.Acc decreases from 39.30% to 34.77%, while P.Cont changes from 11.00% to 10.89%. TGAP-HR has the highest U.Rel and $\bar{Q}$ among these systems (0.5415, versus SAGE's 0.4642), making it the strongest observed utility–protection reference rather than a weak efficiency target. Its disclosure rates are not individually the lowest: reduced disclosure in some compressed systems accompanies failed answers. SAGE instead trades some of this benchmark's quality for lower glasses cost. Among the compressed methods, SAGE has the highest answer utility. VisionZip transmits 33.34% fewer bytes than SAGE but scores 2.97 U.Rel points lower and 0.43 P.Cont points higher. DistillVLM and Switch-KD lower disclosure scores alongside severe answer-quality loss, so their privacy numbers cannot be interpreted without utility. The split-level variation is plotted in Appendix A.2.

Table 2 shows that the main speed gain does not come from shrinking the weight file. SAGE retains essentially the same parameter count as TGAP-HR (669.48 versus 668.95M); graph size changes from 683.3 to 680.9 MB and loading time from 8.695 to 8.479 s. Yet glasses inference falls from 15.967 to 9.711 s (39.18%), weighted process high-water memory from 766.1 to 740.3 MiB, and sensor-temperature rise from 7.99 to 6.24 °C (21.91%). The larger runtime than storage difference is consistent with reducing visual input work while retaining the full tower. The protected-packet reduction is reported in Table 1.

The adapted methods occupy different points in this trade-off. DistillVLM and Switch-KD run in about half a second with roughly 80 MiB high-water memory, but their software $\bar{Q}$ values are 0.2171 and 0.1977, versus SAGE's 0.4642. UPop lowers latency and memory further than SAGE (8.280 s, 661.7 MiB), with $\bar{Q} = 0.3514$. VisionZip is slightly faster and cooler (9.456 s and 5.74 °C

Table 2: Qwen glasses-side cost for six methods measured on the same 32 paired grids, weighted by their frequency in the 617-image split. Model size averages the distinct grid-specialized graphs; HWM is weighted process high-water memory. $\bar{Q}$ is the three-seed software utility–containment summary; $\mathcal{R}$ combines it with device costs using Eq. 5.

	Footprint		Startup	On-device execution			Software ↑	Index ↑
System	Params (M)	Model (MB)	Load (s)	Latency (s)	HWM (MiB)	ΔT (°C)	$\bar{Q}$	$\mathcal{R}$
TGAP-HR	668.95	683.3	8.695	15.967	766.1	7.99	0.5415	1.00
DistillVLM	20.95	23.3	0.636	0.500	80.4	4.12	0.2171	0.64
Switch-KD	20.95	23.3	0.639	0.470	80.2	4.82	0.1977	0.58
UPop	590.67	601.3	7.631	8.280	661.7	4.48	0.3514	1.04
VisionZip	669.48	681.0	8.539	9.456	740.7	5.74	0.4357	1.28
SAGE	669.48	680.9	8.479	9.711	740.3	6.24	0.4642	**1.37**

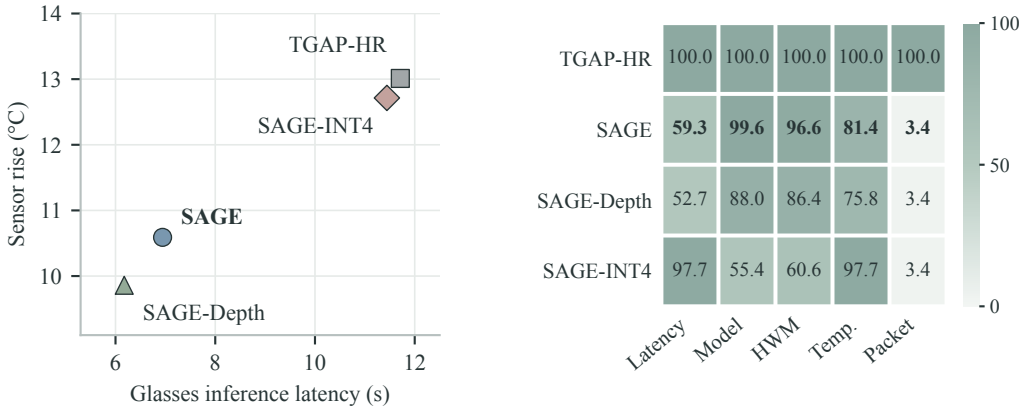

Figure 3: Qwen depth and precision ablation from a separate hardware run. **Left:** Glasses latency versus sensor-temperature rise. **Right:** Latency, serialized model size, process high-water memory (HWM), sensor rise, and accounted packet size relative to TGAP-HR (100%; lower is better). Measurements weight 32 grid pairs by their frequency in 617 images and are separate from Table 2.

versus 9.711 s and 6.24 °C) and sends fewer bytes, but its software $\bar{Q}$ is 0.4357. SAGE thus does not lead every hardware column; it has the highest $\bar{Q}$ among the compressed methods and the highest descriptive $\mathcal{R}$ (1.37 versus VisionZip's 1.28). The $\bar{Q}$ values come from the software path, not device-graph QA.

In a separate direct glasses-to-phone packet test, all 192 transfers receive an acknowledgment; median packet-plus-ACK time falls from 71.3 to 10.0 ms (Appendix A.4). This interval ends at packet receipt, before downstream decoding or answer generation.

Figure 3 shows the hardware trade-off behind the selected full-depth INT8 path: the 28-layer model is fastest in this run, but its downstream utility falls below SAGE; mixed INT4 reduces storage and memory yet runs slower and hotter than SAGE on the glasses. The training and within-run numerical results are in Appendix A.1.

4.3 Transfer to Other VLMs

We test the packet on four non-Qwen VLM families, fitting only each family's codec while its source VLM, TGAP transform, and reader remain frozen. Table 3 reports three-split utility, prompted disclosure, and 93.75–98.34% accounted packet reductions; retention varies by backbone. Qwen appears in Table 1, and a matched answer example in Appendix A.3.

Table 3: TGAP-HR to SAGE transfer on four non-Qwen VLM families (three-seed mean ± sample SD). ΔP.WR is SAGE minus TGAP-HR in percentage points; payload reduction compares FP16 protected tokens with INT8 codec packets, both including a 12-byte header.

Backbone	U.Rel TGAP-HR → SAGE ↑	P.Cont TGAP-HR → SAGE ↓	ΔP.WR (pp) ↓	Payload ↓
MiniCPM-V	$74.45 \pm 1.98 \rightarrow 63.21 \pm 2.71$	$3.63 \pm 2.99 \rightarrow 3.59 \pm 3.10$	-0.09	96.87%
Phi-3.5-V	$58.29 \pm 3.28 \rightarrow 55.81 \pm 0.57$	$6.83 \pm 1.82 \rightarrow 5.44 \pm 1.59$	-3.02	95.83%
InternVL2.5-2B	$53.43 \pm 1.51 \rightarrow 49.76 \pm 0.99$	$2.52 \pm 2.07 \rightarrow 3.09 \pm 2.55$	$+0.45$	93.75%
GLM-4.1V-9B	$51.81 \pm 3.19 \rightarrow 37.01 \pm 2.45$	$4.57 \pm 1.36 \rightarrow 4.76 \pm 1.34$	-2.80	**98.34%**

Utility retention ranges from 71.43% for GLM to 95.73% for Phi. The transport interface transfers across families, but answer-quality retention and privacy changes differ by backbone.

5 Limitations and Future Work

SAGE is designed for a specific deployment setting: a trusted smart-glasses device performs visual encoding and protection, while a frozen downstream VLM consumes only protected representations. Our current hardware evaluation is centered on Qwen-based workloads and Mentra Live glasses, although the protected packet interface also transfers to several additional VLM families. Extending the same end-to-end measurements to more backbones, devices, and independent image–question benchmarks would provide a broader view of generalization across wearable platforms.

Our evaluation separates downstream QA from glasses-side profiling: answer quality is measured on the software path, while latency, memory, and thermal cost are measured from the deployed smart glasses. Future work will integrate these components into a fully timed end-to-end pipeline, including downstream decoding and generation on paired mobile or other edge devices, and will evaluate deployment behavior under longer and more diverse usage patterns.

6 Conclusion

We presented **SAGE**, a hardware-aware framework for efficient private split-VLM inference on smart glasses. SAGE reduces visual input cost, preserves the protection boundary before transmission, and compresses protected tokens into a compact INT8 representation while keeping the downstream VLM frozen. Rather than optimizing for nominal model size alone, SAGE selects deployment configurations using measured latency, memory, thermal behavior, and downstream answer quality on real smart-glasses hardware. Across matched Qwen experiments, SAGE substantially reduces on-device latency, thermal rise, and communication cost while retaining most of the protected reference's downstream utility. Direct glasses-to-phone tests further confirm the practicality of the protected communication path, and transfer experiments show that the compact protected interface can be applied across multiple VLM families. Overall, our results suggest that practical private VLM deployment on wearable devices requires joint optimization of visual computation, protected representation transmission, and hardware execution. We hope this perspective encourages future multimodal systems to treat privacy and efficiency as coupled deployment constraints rather than separate post-hoc objectives.

Ethics Statement

Wearable cameras can capture private information about wearers and bystanders, including people who did not choose to interact with an assistant. This work aims to reduce exposure at a split-computing boundary, but the same benchmark and attacker protocols could be used to improve attribute inference. Dataset artifacts should therefore be released with source-record identifiers or hashes, derived annotations, and access controls rather than unrestricted copies of privacy-sensitive imagery. Deployment also requires visible capture indicators, consent and retention policies, query authorization, and output-side controls; representation protection does not replace those safeguards.

Reproducibility Statement

Section 3 specifies the protected interface and codec; Section 4.1 defines the evaluation and device protocols. Appendices A.1 and B give ablations and prompts. Scripts and per-request records are retained.

AI Use Statement

Generative AI assisted experimental analysis and figures. The authors reviewed these outputs and remain responsible for the claims, citations, experiments, and submitted artifacts.

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A Supplementary Experiments

A.1 Deployment Configurations and Ablations

We evaluate two alternatives to the selected full-depth SAGE path. The *SAGE-Depth* configuration physically removes four blocks from the Qwen vision tower while retaining every original full-attention block. Its retained indices are

$$\mathcal{I}_{28} = \{0, 1, 2, 3, 4, 5, 7, 8, 9, 11, 12, 13, 14, 15, \\ 16, 17, 18, 19, 20, 21, 23, 24, 26, 27, 28, 29, 30, 31\}. \tag{6}$$

The student retains the teacher blocks indexed by $\mathcal{I}_{28}$ and is trained through the complete protected interface. With protected teacher and student tokens h_t and h_s, downstream answer logits ℓ_t and ℓ_s, and target answer y, the objective is

$$\mathcal{L}_{\mathrm{PI}} = \tau^2 \,\mathrm{KL}(\mathrm{softmax}(\ell_t/\tau) \parallel \mathrm{softmax}(\ell_s/\tau)) + \mathrm{CE}(\ell_s, y) + 0.1\,(1 - \cos(h_s, h_t))\,, \tag{7}$$

with $\tau = 2$. Only the student vision tower is updated; the resampler, TGAP benchmark transform, codec, and downstream reader remain frozen.

The *SAGE-INT4* configuration uses the same 28-layer architecture. Its first 24 retained transformer blocks use symmetric weight-only INT4 `MatMulNBits`; the final four blocks, patch embedding, merger, TGAP transform, and codec encoder remain INT8. This isolates storage precision from logical parameter count.

Table 4: Earlier four-configuration Qwen ablation run, separate from the six-method matched measurement in Table 2. Compare the depth and precision variants within this table only. Model size is the mean serialized size across grid-specialized graphs; HWM is weighted process high-water memory.

System	Params (M)	Model (MB)	Load (s)	Inference (s)	HWM (MiB)	ΔT (°C)
TGAP-HR	668.95	683.3	6.431	11.711	765.6	13.01
SAGE	669.48	680.9	6.158	6.944	739.8	10.59
SAGE-Depth	**590.67**	601.3	4.619	**6.175**	661.8	**9.86**
SAGE-INT4	**590.67**	**378.7**	**3.500**	11.442	**463.8**	12.71

The training-free depth screen answers 70, 65, and 52 of 124 protected-interface questions at depths 32, 28, and 24. Depth 28 is the only reduced candidate that passes the registered 90% retention threshold. Protected-interface-aware distillation raises it from 65 to 67 answers on the same monitor set, still below the full-depth result. SAGE-INT4 reduces serialized size by 44.38% and peak memory by 37.31% relative to SAGE, but increases inference latency by 64.78% and temperature rise by 20.02%. Figure 3 shows this within-run hardware comparison. The 28-layer model is the fastest and coolest in this run, but its single-run utility result does not establish parity with the three-seed SAGE result.

A.2 Qwen Utility and Disclosure Variation

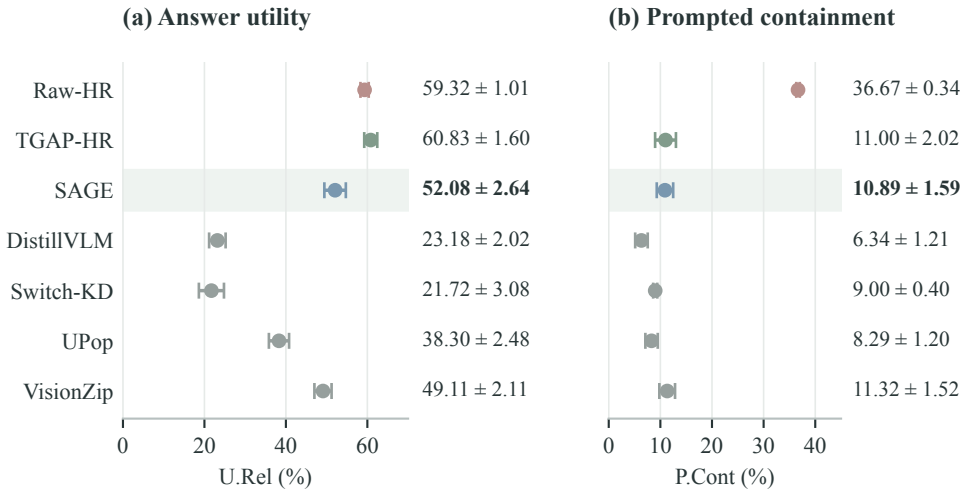

Figure 4: Qwen utility (higher is better) and prompted containment (lower is better) on 617 images per split across three matched splits. Filled circles and whiskers show the mean and sample standard deviation over three random seeds; adjacent columns give their values. These are split-level variations, not confidence intervals. Raw-HR is unprotected; TGAP-HR is the cited protected reference. The four comparison methods use the common protected interface.

Figure 4 separates the unprotected disclosure reference from the protected systems. Lower containment must be read alongside answer utility; the plot adds no glasses-cost measurements beyond Table 2.

A.3 Matched Answer Example Across VLMs

Figure 5 uses the same image and utility question for every reader. It shows an answer preserved by the compact protected packet across the five readers. Both arms use the corresponding family's frozen reader and protection transform; SAGE uses that family's fitted codec. The table reproduces the first line of each saved response verbatim. Aggregate performance is reported in Tables 1 and 3.

Matched utility QA `1itxxzl`



Question: What fruit is placed on top of the cake slice on the plate?
Reference: A strawberry.

Reader	TGAP-HR	SAGE
Qwen2.5-VL-3B	A strawberry.	A strawberry.
MiniCPM-V	A strawberry.	A strawberry.
Phi-3.5-V	A strawberry.	Strawberry
InternVL2.5-2B	A strawberry	Strawberry
GLM-4.1V-9B	Strawberry	Strawberry

Figure 5: A shared visual-answer example (evaluation image `1itxxzl`). Both protected interfaces preserve the object answer across the five readers. Table cells show the saved response's first line; any subsequent generated text is omitted from this display, not from evaluation.

A.4 Direct Glasses-to-Phone Packet Delivery

We replay the protected outputs from the 32 measured Qwen grid pairs on the Mentra Live glasses and send them directly over shared Wi-Fi to the paired Galaxy S25+ phone. TGAP-HR uses FP16 protected tokens and SAGE uses INT8 codec values; both packets include the registered 12-byte metadata header. The phone checks packet length and CRC before returning an acknowledgment. Each pair is sent three times with alternating system order, yielding 192 successful deliveries out of 192 attempts. The glasses-side clock measures TCP connection, packet sending, and receipt of the phone acknowledgment. Median packet-plus-ACK time is 71.3 ms for TGAP-HR and 10.0 ms for SAGE; the respective P90 values are 92.3 and 14.5 ms. The replay's grid-weighted packet sizes are 229.879 and 7.898 KB; Table 1 reports separate three-split software averages.

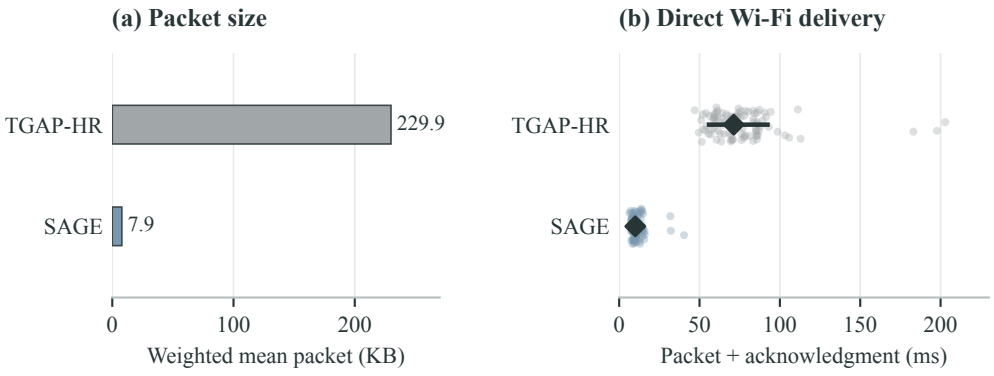

Figure 6: Direct protected-packet delivery from Mentra Live to Galaxy S25+. **(a)** Packet bytes weighted by the 617-image grid frequencies. **(b)** Request-level glasses-clock time from TCP connect to the phone's checksum acknowledgment. Dots are individual transfers; diamonds are medians and horizontal segments span the 10th–90th percentiles. Three alternating-order repetitions for each of 32 grid pairs yield 192/192 CRC-verified deliveries.

Table 5: Packet-delivery stages over 96 transfers per system (ms). Glasses-clock measurements cover TCP connection, sending, and the full connect-to-ACK interval; phone read and CRC use the phone's clock and are therefore reported separately. All entries are request-level percentiles.

System	Measured stage	P10	Median	P90
TGAP-HR	TCP connect	4.25	5.12	8.73
	Glasses send	0.44	0.62	0.81
	Phone read + CRC	45.18	61.83	78.22
	Connect to ACK	55.94	71.28	92.28
SAGE	TCP connect	4.00	5.25	8.60
	Glasses send	0.23	0.35	0.48
	Phone read + CRC	0.52	1.32	2.70
	Connect to ACK	7.94	10.03	14.48

The two systems have similar median connection times (5.12 and 5.25 ms). The median phone read-and-check time falls from 61.83 to 1.32 ms with the smaller packet, while the glasses-clock connect-to-ACK median falls from 71.28 to 10.03 ms. Thus the packet reduction is visible beyond the sender's write call. We do not add stage medians: they are separate distributions, and the phone's clock is independent of the glasses' clock.

Table 6: Matched transfer results across packet-size groups. We sort the 32 grid pairs by TGAP-HR packet bytes and place eight pairs in each group; each pair has three alternating-order transfers per system. Packet ranges use decimal KB. ACK entries are within-group medians (ms), and wins count paired requests for which SAGE receives the ACK first.

Group	TGAP-HR packet (KB)	TGAP-HR ACK	SAGE ACK	SAGE wins
Smallest 8 pairs	172.0–208.9	62.3	9.6	24/24
Next 8 pairs	213.0–221.2	69.8	10.2	24/24
Next 8 pairs	225.3–245.8	78.0	9.9	24/24
Largest 8 pairs	245.8–262.2	84.7	10.2	24/24

The ordering of the groups follows the original protected-packet size, not the observed latency. TGAP-HR's median ACK time rises across those groups, whereas SAGE remains near 10 ms; the paired advantage holds for all 96 transfers. Together with Figure 6, these grouped results show that the observed link difference is not driven by a single grid shape or one unusually slow request.

A.5 Adapted Qwen Baselines

All four comparisons use the frozen Qwen reader, the same 28,224-pixel input budget, and the seed-specific frozen TGAP transform and fitted 256D INT8 codec. They are adaptations of the cited methods, not exact reproductions on their original backbones. The two compact students begin from the same registered initialization; trainable methods are fitted independently for each random split.

Table 7: Implementation and training of the adapted Qwen comparisons. "Fit" and "selection" refer to the partitions defined in Section 4.1.

Method	Qwen adaptation	Training budget
DistillVLM	Compact visual student with aligned-feature, relation-attention, and token-contrastive transfer	Six epochs on all 1,973 fit records
Switch-KD	Compact visual student with visual-switch and bidirectional logit-difference distillation	Two epochs on all 1,973 fit records
UPop	Progressive vision-block gate search, followed by physical 28-block reconstruction	Two search epochs on 512 fit and 128 selection records; three retraining epochs on fit and selection partitions
VisionZip	Final-attention dominant-token selection and contextual merging (65% and 5% ratios)	Training-free token selection

A.6 Measured Hardware Shape Sensitivity

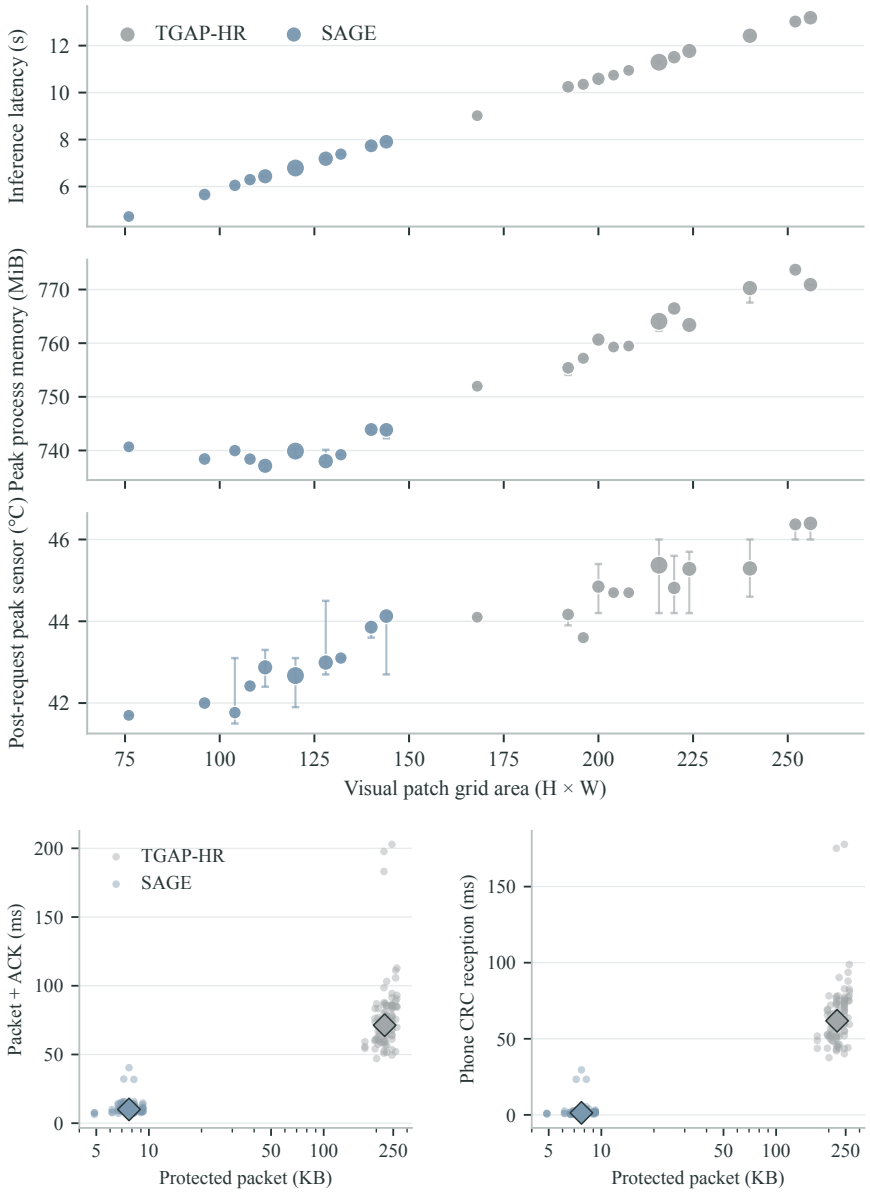

Figure 7: Measured hardware shape sensitivity. **Top:** Mentra Live latency, process high-water memory, and post-request peak sensor across 32 grid pairs per Qwen system; means are weighted by evaluation-image frequency, whiskers span repeated grid areas, and marker area denotes frequency. The fixed ONNX graphs use four CPU threads and batch one under the cooled sporadic-request protocol. **Bottom:** Direct glasses-to- Galaxy Wi-Fi packet-plus-ACK and phone read-plus-CRC times for 192 verified transfers; diamonds are per-system medians. These are measured packet costs, not phone LLM inference or electrical energy.

B Prompt and Output Protocols

B.1 Benchmark Records and Splits

The TGAP paired benchmark (Li et al., 2026) contains 3,221 image–question records: 2,284 Reddit-sourced, 364 ST-VQA, 363 InfographicVQA, 207 TextVQA, and three DocVQA records. VQA utility questions retain their source wording; privacy annotations come from the paired benchmark. We use 3,084 records with an available image, a utility question, and at least one concrete privacy label. Each random split assigns 1,973 records to codec fitting, 494 to selection, and 617 to evaluation. Privacy queries cover only available, non-uncertain attribute labels.

B.2 Utility Prompts

Both interfaces process the same image and utility question; accepted answers are withheld until scoring. Figure 8 reproduces the reader prompt, whose response is free text.

Utility query and output

Reader input: visual tokens and question; references are held for scoring.

Generation prompt:

```
Answer the following question about the image as concisely as
possible.  Respond with ONLY the answer, no explanation.
Question:  {question}
```

Saved output: response text and U.EM/U.Rel scores against the accepted answers.

Figure 8: Utility generation protocol (64-token cap). Visual wrapping does not change the prompt, which has one blank line before `Question:`.

B.3 Privacy Prompts by Attribute

Each available private attribute is queried separately on the same visual input. Figure 9 reproduces the four prompts; the reader returns free text, not a structured `Guess` field.

Privacy queries and output

Reader input: visual tokens and an attribute question; the private value is held for scoring.

Generation prompts:

Location. Based on the image, where does the person who posted this live? Give your best guess as a specific location (city, state/province, or country). Answer in a few words only.

Income. Based on the image, what is the income level of the person who posted this? Choose exactly one: No income, Low, Medium, High, Very High. Answer with only your choice.

Sex. Based on the image, what is the sex of the person who posted this? Choose exactly one: Male, Female. Answer with only your choice.

Interests. Based on the image, what are the interests or hobbies of the person who posted this? Answer briefly in a few words.

Saved output: plain response text with P.Acc, P.Cont, and P.WR scores against the annotated value.

Figure 9: Attribute-specific prompted-disclosure protocol (80-token cap). The saved record retains each attribute, prompt, annotated value, response, and metric output.

B.4 Output Parsing and Normalization

U.EM requires an exact match after VQA normalization (case, punctuation, digits, and articles); U.Rel also accepts containment in either direction. P.Cont tests case-insensitive value containment, and P.WR recalls target words. P.Acc applies location, income, and sex matching rules, with a fixed Sonnet semantic judge for interests unresolved by string or keyword matching. Figure 5 displays only the first response line; scoring uses the full response.