WearerText: Benchmarking Wearer-Centered Scene Text Understanding in AI-Glasses Videos

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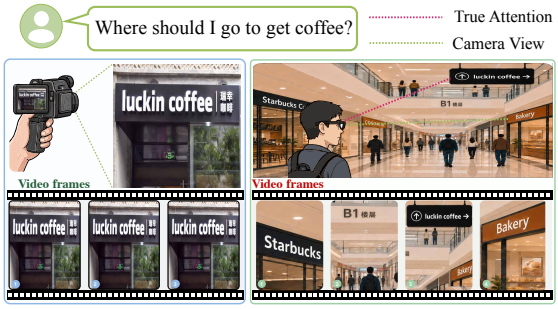
Abstract

Recent MLLMs have shown promise in scene-text-aware video understanding, yet their ability to understand scene text from the wearer's perspective in AI-glasses videos remains underexplored. AI-glasses videos are passively captured without a camera-frame preview, limiting the wearer's ability to adjust framing during recording. As a result, relevant text may be unstable, and the recorded view may not fully reflect the wearer's attention. The challenge is thus not merely to read visible text, but to identify and read the right text given the wearer's position, viewpoint trajectory, and goal. To systematically evaluate this capability, we introduce **WearerText**, a benchmark for **Wearer**-Centered Scene **Text** Understanding, comprising 1,101 real-world AI-glasses videos and 15,336 QA pairs spanning 13 tasks. These tasks are organized into a three-level diagnostic hierarchy: *L1 Text Perception*, *L2 Contextual Understanding*, and *L3 Wearer-Grounded Reasoning*, targeting unstable text perception, wearer-view alignment, and goal-oriented text reasoning, respectively. To ensure reliable construction and evaluation, we develop MAH-V, a multi-agent hybrid verification pipeline for QA construction, and propose VerEval, a Verified-evidence metric for open-ended Evaluation. Benchmarking 20 recent MLLMs shows that current models still struggle with wearer-centered scene text understanding, particularly on tasks requiring wearer-view alignment and goal-oriented text reasoning.[1]

1 Introduction

Recent multimodal large language models (MLLMs) have shown impressive progress in scene-text-aware video understanding (Feng et al., 2025; Shi et al., 2026). However, their ability to understand scene text from the wearer's perspective in AI-glasses videos remains largely underexplored. This capability is important for everyday applications such as shopping, transportation, and travel navigation, and is particularly valuable for assistive technologies for people with visual impairments (Waisberg et al., 2024; Xiao et al., 2025; Karakostas et al., 2024).



(a) Videos with a camera-frame preview

(b) AI-glasses Videos without a camera-frame preview

Figure 1: Access to a camera-frame preview changes the nature of video text understanding. (a) With a camera-frame preview, the operator can adjust framing to keep target text stable and centered. (b) AI glasses passively capture the wearer's first-person view without such a preview, making relevant text less stable and less aligned with the wearer's attention.

AI-glasses videos differ fundamentally from videos recorded with a live camera-frame preview. They are passively captured from the wearer's first-person perspective, without showing the wearer how the scene is actually framed by the camera. As illustrated in Figure 1, natural head movements can therefore cause relevant text to appear off-center, fragmented, or only briefly visible. Moreover, the captured camera view may not align with the wearer's visual attention: multiple text regions may appear in the scene, while only some are relevant to the wearer's position, evolving viewpoint, and goal. *The challenge is thus not merely to read visible text, but to identify and read the right text given the wearer's position, viewpoint trajectory, and goal.* We refer to this problem as *wearer-centered scene text understanding*.

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[1] https://aprilyapingzhang.github.io/WearerText/

Proceedings of the 2026 Conference on Empirical Methods in Natural Language Processing, pages 49653–49669
October 24-29, 2026 ©2026 Association for Computational Linguistics

Table 1: Comparison of WearerText with existing text-aware video benchmarks. **Video Source** indicates how the video data was obtained: web-sourced videos have unconstrained original capture conditions, while device-captured videos (dashcam, head-mounted camera, AI glasses) are passively recorded from a fixed first-person viewpoint without viewfinder framing. **Targeted Challenges**: ✓ indicates the benchmark *explicitly evaluates* this challenge as a first-class axis (dedicated task split or metric); ✗ indicates the phenomenon may occur in the data but is not isolated for evaluation. **Construction**: *Manual* = human-only annotation; *Hybrid* = LLM-assisted with human verification; **MAH-V** = our multi-agent–hybrid verification with factual and logical consistency checks. **Evaluation**: *String* = exact/F1 string match; *LLM-judge* = single-model semantic judgment; **VerEval** = our verified-evidence metric scoring factual grounding *and* reasoning consistency.

Benchmark	Video Source	Targeted Challenges (Evaluation Axes)			Scale		Construction	Evaluation
		Unstable Text (Viewpoint)	Wearer-View Alignment	Goal-Oriented Text Evidence	# QA	Videos Number		
Web-sourced video (capture conditions unconstrained)								
M4ViTeVQA (Zhao et al., 2022)	Web video	✗	✗	✗	2,103	7,620	Manual	String
VideoOCR (Fei et al., 2025)	Web video	✗	✗	✗	2,961	1,028	Manual	String
MME-VideoOCR (Shi et al., 2026)	Web video	✗	✗	✗	2,000	1,464	Manual	String
VidText (Yang et al., 2025)	Web video	✗	✗	✗	2,857	939	Manual	String
Real-world device capture (passive, no viewfinder feedback)								
RoadTextVQA (Tom et al., 2023)	Dashcam (driving)	✗	✗	✓	1,052	3,222	Manual	String
EgoTextVQA (Zhou et al., 2025)	Head-mounted (driving, home)	✓	✗	✓	7,064	1,507	Manual	LLM-judge
WearerText (Ours)	**AI glasses (shopping, tourism, transit)**	✓	✓	✓	**15,336**	**1,101**	**MAH-V**	**VerEval**

Wearer-centered scene text understanding requires three complementary capabilities that existing text-aware video benchmarks rarely isolate as distinct evaluation axes (Table 1). (1) *unstable text perception* requires recognizing and localizing text that may be off-center, fragmented, or only briefly visible under natural head motion. (2) *wearer-view alignment* requires identifying relevant text among competing text regions based on the wearer's current position and view. (3) *goal-oriented text reasoning* requires selecting, linking, and reasoning over textual evidence across frames based on the wearer's goal and evolving viewpoint. Together, these capabilities form a natural progression from unstable text perception to wearer-view grounding and goal-oriented reasoning, enabling more precise diagnosis of model failures.

To address this gap, we introduce **WearerText**, a benchmark for *wearer-centered scene text understanding* in real-world AI-glasses videos. WearerText contains 1,101 videos and 15,336 QA pairs spanning 13 tasks organized into a three-level diagnostic hierarchy: *L1 Text Perception* targets unstable text recognition and localization; *L2 Contextual Understanding* evaluates wearer-view alignment of relevant text within the surrounding scene; and *L3 Wearer-Grounded Reasoning* evaluates goal-oriented reasoning over the wearer's viewpoint trajectory and temporal text evidence. For reliable QA construction, we develop MAH-V, a multi-agent hybrid verification pipeline. For open-ended evaluation, we further propose VerEval, a verified-evidence metric that assesses factual grounding and reasoning consistency.

Benchmarking 20 recent MLLMs shows that wearer-centered scene text understanding remains far from solved. While current models handle basic text perception reasonably well, performance drops sharply on tasks requiring wearer-view alignment and goal-oriented reasoning over temporal text evidence. These results show that this setting is not a simple extension of video OCR (Shi et al., 2026): models must not only read text across frames, but also determine which text is relevant to the wearer's evolving viewpoint and goal. Our contributions are as follows:

- We formulate scene text understanding in AI-glasses videos as a *wearer-centered* problem and introduce **WearerText**, a benchmark of 1,101 real-world AI-glasses videos and 15,336 QA pairs spanning 13 tasks in a three-level diagnostic hierarchy covering unstable text perception, wearer-view alignment, and goal-oriented text reasoning.
- We propose MAH-V, a closed-loop Generate → Verify → Refine pipeline that combines multi-agent hybrid verification with human review, and VerEval, a verified-evidence metric for reliable open-ended evaluation.
- We benchmark 20 MLLMs and find that even the best models score only 46.2 on L3.3 and

38.9 on L3.6, revealing substantial gaps in wearer-centered scene text understanding.

2 Related Work

Visual Text Understanding. Visual text understanding has evolved from robust scene text recognition and VQA (Zhang et al., 2021; Singh et al., 2019; Biten et al., 2019) to layout-aware document analysis, image translation, and multimodal benchmarks across multilingual, scientific, and wearable settings (Zhang et al., 2026, 2025d; Liang et al., 2025; Zhang et al., 2025b; Li et al., 2026; Zhang et al., 2025c; Chang et al., 2025). Among wearable benchmarks, WearVQA (Chang et al., 2025) is the most closely related, but focuses on general VQA over single wearable images. In contrast, WearerText targets scene text understanding in dynamic AI-glasses videos, where models must handle unstable text, align textual evidence with the wearer's view, and reason according to the wearer's goal.

Egocentric Video Understanding. Egocentric benchmarks study visual understanding from a first-person perspective and are closely related to wearable assistance. WearVQA (Chang et al., 2025) evaluates wearable-image understanding, while EgoTextVQA (Zhou et al., 2025) extends text-aware VQA to head-mounted videos from driving and indoor activities. However, existing egocentric benchmarks do not explicitly decompose scene text understanding into unstable text perception, wearer-view alignment, and goal-oriented reasoning over changing viewpoints. WearerText focuses on this wearer-centered setting, where the relevance of textual evidence depends on the wearer's position, viewpoint trajectory, and goal.

Text-Centric Video Understanding. Several benchmarks evaluate text-aware video understanding (Zhao et al., 2022; Wu et al., 2021; Reddy et al., 2020; Zhou et al., 2025; Wu et al., 2023). RoadTextVQA (Reddy et al., 2020) focuses on driving scenes from vehicle-mounted cameras, while M4-ViTeVQA (Zhao et al., 2022) covers diverse YouTube videos. More recent benchmarks, including MME-VideoOCR (Shi et al., 2026) and VidText (Yang et al., 2025), further evaluate OCR-related capabilities in videos. These benchmarks primarily assess text recognition and understanding from the recorded video itself, but do not systematically evaluate whether models can identify text relevant to the wearer as the viewpoint changes.

Table 1 summarizes these differences. Unlike prior text-aware and egocentric benchmarks, WearerText is built from real-world AI-glasses videos and organizes evaluation into a three-level diagnostic hierarchy.

3 WearerText

In this section, we present the design rationale and construction pipeline for WearerText, which supports scalable construction and verifiable annotation for wearer-centered scene text understanding.

3.1 Hierarchical Task Design

To systematically evaluate AI-glasses text understanding, we organize WearerText into a three-level hierarchy with 13 tasks (Table 2). The hierarchy follows the key capabilities discussed above: unstable text reading, wearer-view alignment, and goal-oriented text evidence reasoning. **L1: Text Perception** evaluates whether models can recognize and localize unstable or briefly visible text in dynamic AI-glasses videos. **L2: Contextual Understanding** tests whether models can ground relevant text within the wearer's surrounding context, including dense signage, multilingual text, slogans, and scene-level semantics. **L3: Wearer-Grounded Reasoning** further examines whether models can reason over viewpoint trajectories and temporal text evidence to support goal-oriented assistance, such as navigation and viewpoint-motion understanding. Together, these levels provide a diagnostic framework for identifying where current MLLMs fail across perception, contextual grounding, and wearer-centered reasoning.

3.2 Data Construction Pipeline

To support scalable and grounded benchmark construction, we design an integrated pipeline that includes video collection, layout-aware reference text grounding, and hierarchical question–answer generation, as illustrated in Figure 2.

AI-glasses Video Collection To capture the structural complexity of real-world interactions, we utilize RayNeo AI Glasses to acquire a raw video dataset $\mathcal{V}$ consisting of 1,101 egocentric sequences. Each sequence, recorded at 30 FPS with a duration of 5–10 seconds, captures short interaction primitives such as approaching an object or scanning a menu. Our reasoning tasks therefore target goal-oriented selection of text evidence within these clips. For each video $v \in \mathcal{V}$, we simultaneously record a corresponding high-resolution global image I_g to serve as a stable spatial reference for

Table 2: Hierarchy of Wearer-Centered Scene Text Understanding Tasks and Examples in WearerText.

Task ID	Task Name	Task Definition	Examples
Level 1: Text Perception. *Can the model* SEE *and* LOCALIZE *unstable visible text in dynamic AI-glasses videos?*			
L1.1	Dynamic Text Recognition (DTR)	Transcribe scene text from unstable egocentric views with head motion and viewpoint changes.	"I was walking fast and missed the phone number on that red sign. Can you tell me what it was?"
L1.2	Dynamic Text Localization (DTL)	Locate queried text regions in dynamic frames and describe where they appear in the observed scene.	"Where is the floor and unit number located on the billboard?"
Level 2: Contextual Understanding. *Can the model* GROUND *relevant text in the wearer's surrounding context?*			
L2.1	Query-Guided Text Extraction (QTE)	Select and extract relevant information from dense environmental text according to the user's query.	"How many years has this 'Dianmao' restaurant been specializing in Peking Duck?"
L2.2	Confirmation (CF)	Verify the user's prior belief or memory using current visual-textual evidence.	"The sign says 'Floor 4'. I'm in the mall now; this shop is on the 4th floor, right?"
L2.3	Cross-Lingual Understanding (CLU)	Interpret abbreviations, symbols, pinyin, or multilingual identifiers within the physical context.	"What does 'DIANMAO' at the top of the sign represent in this context?"
L2.4	Situated Semantic Interpretation (SSI)	Interpret the semantic meaning of slogans, signs, or brand descriptions beyond literal recognition.	"What does the slogan 'Unmatched in Beijing, Renowned Everywhere' imply about this brand?"
L2.5	Wearer-Centered Situational Inference (WSI)	Infer scene-level attributes or venue suitability by grounding text in the wearer's current situation.	"Based on the style and the '20-year' claim, is this a good place to treat friends to authentic local food?"
Level 3: Wearer-Grounded Reasoning. *Can the model* REASON *and* ASSIST *according to viewpoint trajectories and user goals?*			
L3.1	History-Conditioned Intent Inference (HII)	Infer the wearer's current intent by combining previous scene-text observations with the current view.	"I'm tempted by the duck but have a meeting soon. Are there any 'fast-eating' sets mentioned?"
L3.2	Action-Trajectory Intent Prediction (AIP)	Interpret the wearer's view trajectory to predict latent goals or possible next actions.	"I looked at the coffee shop sign and then the arrow sign. Am I trying to find the coffee shop?"
L3.3	Structured Text Synthesis (STS)	Integrate structured textual sources, such as menus, or floor boards, while preserving their layout logic.	"Translate the entire list of stores on this directory into English for me."
L3.4	Spatio-Temporal Navigation Reasoning (STN)	Provide action guidance by integrating current location, target text, and movement cues over time.	"I see the 'Floor 4' ad now. What is the fastest way for me to get to the actual store from here?"
L3.5	Goal-Oriented Comparison (GOC)	Compare text-described options across the video and select the one that matches the wearer's goal.	"Considering both 'Professionalism' and 'Price', is this shop a better choice than a fast-food outlet?"
L3.6	Viewpoint Trajectory Description (VTD)	Describe how the wearer's viewpoint changes over time relative to text-bearing signs or directories.	"Describe how my viewpoint changed."

ground-truth text extraction. Detailed scenario coverage, sub-domains, and wearable-video condition statistics are provided in Appendix A and Table 5.

Layout-aware reference text grounding. Given the global image I_g, we construct a reference text T_{ref} to serve as the factual anchor for subsequent question generation and verification. Specifically, we first apply OCR to obtain a raw token set $T_{\text{raw}} = \text{OCR}(I_g)$. To preserve the semantic reading order, we employ an LLM-based layout-aware transformation that reorganizes T_{raw} into T_{layout} using spatial coordinates (x, y, w, h). Finally, human verification is performed to produce a high-quality "gold-standard" reference text T_{ref}.

Hybrid hierarchical QA generation. Based on (v, T_{ref}) pairs and the predefined three-level task hierarchy, we generate question–answer instances as candidate pairs (q_i, a_i), where q_i denotes a wearer-centered question and a_i denotes its reference answer. We use a hybrid strategy, $\mathcal{D}_{\text{hybrid}} = \mathcal{D}_{\text{auto}} \cup \mathcal{D}_{\text{man}}$. The automatic branch $\mathcal{D}_{\text{auto}}$ leverages MLLMs for scalable synthesis, while the manual branch $\mathcal{D}_{\text{man}}$ provides expert-curated instances to complement automated generation with greater diversity and quality assurance. This hybrid design aims to balance large-scale coverage with reasoning-oriented question diversity.

3.3 MAH-V: Multi-Agent–Hybrid Verification

The reliability of task construction is critical for evaluating situated reasoning. We introduce the **M**ulti-**A**gent–**H**ybrid **V**erification (MAH-V) pipeline, which combines a committee of specialized agents $\mathcal{A} = \{A_{\text{fact}}, A_{\text{logic}}, A_{\text{consistency}}, A_{\text{refine}}\}$ with a final human-verification stage to filter $\mathcal{D}_{\text{hybrid}}$. The agent committee runs the multi-agent quality control stage shown in Figure 2, and its output is reviewed by expert annotators as described at the end of this section.

Fact Checker Agent. The Fact Checker A_{fact} assesses the factual accuracy of each candidate pair $(q_i, a_i) \in \mathcal{D}_{\text{hybrid}}$. Given the video v and the verified reference text T_{ref}, it produces a structured

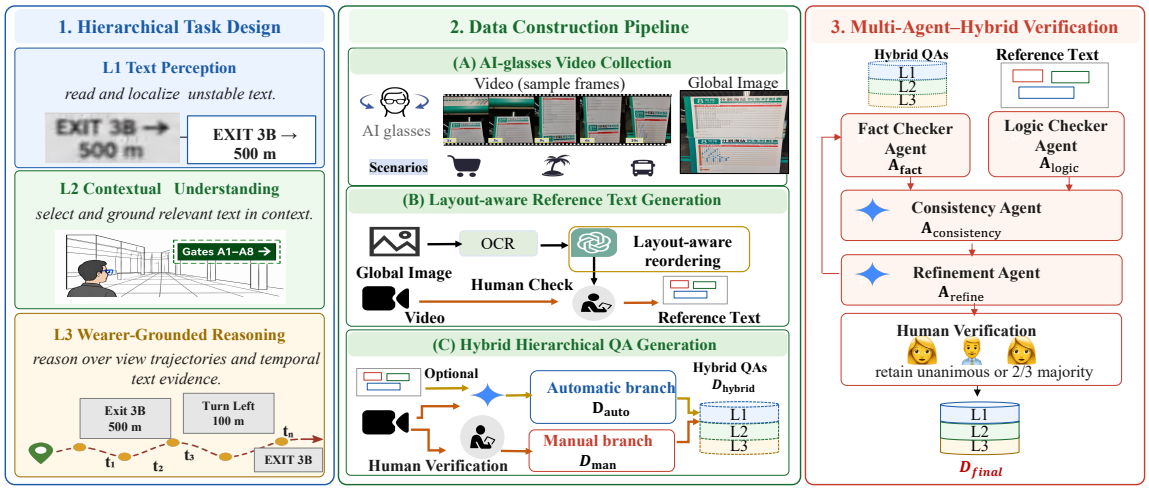

Figure 2: Overview of the WearerText construction pipeline. We first define a three-level hierarchy for AI-glasses text understanding, then collect videos and generate layout-aware reference text and hybrid QA pairs. The multi-agent–hybrid verification pipeline then performs data quality control and refinement before final human validation.

factual assessment:

$$S_{fact} = A_{\text{fact}}(q_i, a_i, v, T_{\text{ref}}). \quad (1)$$

Here, $S_{fact} = (s_{fact}, \mathcal{R}_{fact})$, where $s_{fact} \in [0, 1]$ is the factuality score and $\mathcal{R}_{fact}$ contains concrete revision suggestions. The agent checks whether factual elements in the question and answer, particularly numerical values and entities, are supported by the video and T_{ref}. Candidates with $s_{fact} < \tau$ are marked for refinement, while $\mathcal{R}_{fact}$ identifies unsupported content and provides actionable suggestions for correcting the question or answer.

Logic Checker Agent. The Logic Checker A_{logic} evaluates whether the reasoning process is grounded in the wearer-centered video context along three criteria. First, it assesses sequence necessity, determining whether temporal visual evidence is required to answer the question. Second, it performs indexical alignment by linking spatial references such as "the sign on the left" to specific video segments, ensuring that spatial descriptions are grounded in the wearer's viewpoint. Finally, it verifies temporal causality by checking that the textual cues supporting the answer have appeared in the observed video evidence, preventing reasoning that relies on unavailable information.

Consistency Agent. To improve the correctness of the generated data, the Consistency Agent $A_{\text{consistency}}$ performs cross validation. It detects contradictions between the factual evidence retrieved by A_{fact} and the reasoning logic proposed by A_{logic}. For example, if A_{fact} confirms a bus departs at "10:30" but A_{logic} infers a wait time based on "10:35", $A_{\text{consistency}}$ identifies the mismatch and generates a conflict report $\mathcal{R}_{\text{conf}}$.

Refinement Agent. The Refinement Agent A_{refine} serves as the final improvement step. Rather than simply discarding failed pairs, it uses the descriptive feedback and conflict reports $\{\mathcal{R}_{\text{conf}}, S_{fact}\}$ to improve the final QA pairs: $(q_i', a_i') = A_{\text{refine}}(q_i, a_i, \mathcal{R}_{\text{conf}}, S_{fact})$.

Human Verification and Final Dataset. After multi-agent verification, the refined QA pairs are passed to expert human annotators for final validation. Three domain experts independently review each sample, assessing both factual accuracy and logical coherence. Only samples achieving unanimous approval or majority consensus (2 out of 3) are retained in the final benchmark. This human-in-the-loop validation achieves an inter-annotator agreement of $\kappa = 0.89$, indicating high consistency in our quality assessment protocol.

3.4 VerEval: Verified-Evidence Evaluation

We propose **Ver**ified-Evidence **Eval**uation (**VerEval**), which adapts the MAH-V agent architecture for open-ended answer evaluation. While MAH-V uses OCR reference text for quality control during benchmark construction, VerEval directly compares model predictions with ground truth. VerEval uses three scoring agents. The *Fact Scorer* produces S_{fact} by checking whether factual anchors such as numbers, timestamps, and entities match the visual evidence and ground truth. The *Logic Scorer* produces S_{logic} by evaluating whether the answer's reasoning is compatible

with spatio-temporal constraints in the video. The *Consistency Scorer* then produces $S_{consist}$ by jointly reviewing the fact and logic judgments, their justifications, and the model answer. Thus, $S_{consist}$ is the output of the consistency-scoring prompt, not a renamed factuality score.

We use S_{fact} as an intermediate diagnostic signal, but exclude it from the final aggregate because its evidence is already checked by the consistency scorer and because the held-out human-alignment study showed lower discrimination for the raw fact score than for $S_{consist}$ and S_{logic}. The final VerEval score is therefore

$$S_{overall} = \lambda_1 \cdot S_{consist} + \lambda_2 \cdot S_{logic}. \quad (2)$$

In this paper, we set $\lambda_1 = 0.9$ and $\lambda_2 = 0.1$, selected on held-out human-judged samples; detailed weighting results are provided in Appendix D.3. We report the alignment between VerEval and human judgment in Figure 3, and provide all three scoring prompts in Appendix C.3.

4 Experiments

Data Statistics. We summarize dataset characteristics—scenario coverage, QA and video language distribution, and the test/train split—in Appendix Table 5, which illustrates the dataset's diversity across scenes and text settings.

Model Evaluation. We evaluate 5 closed-source API-based models (GPT-5.2 (OpenAI, 2025), Gemini-3-Pro (Google, 2025), Claude-Opus-4.5 (Anthropic, 2025), Qwen3-VL-PLUS (Bai et al., 2025a), Seed-1.6 (ByteDance, 2025)) and 15 advanced open-source MLLMs (InternVL3.5-8B/38B (Wang et al., 2025), Qwen2.5-VL-3B/7B/32B (Bai et al., 2025b), Qwen3-VL-4B/8B/32B (Bai et al., 2025a), GLM-4.6V-Flash-9B, GLM-4.6V-106B-A12B(Team et al., 2025), VideoLLaMA3-7B (Zhang et al., 2025a), MINICPM-V-4.5 (Yu et al., 2025), LLaVA-NeXT-Video-7B (Zhang et al., 2024), VideoR1-7B (Feng et al., 2025), MOLMO-2-8B (Clark et al., 2026)).

4.1 Main Results

Alignment Between VerEval and Human Judgment. We evaluate VerEval on 390 QA pairs annotated by three experts and finalized by majority vote as *Correct* or *Wrong*. We compare against SAS, a transformer-based semantic answer similarity metric (Risch et al., 2021), and ANLS, a normalized edit-similarity metric widely used in scene-text VQA (Biten et al., 2019). As shown in Figure 3, our VerEval Score aligns more closely with human judgments. It yields a larger Correct–Wrong mean gap (0.402 vs. 0.112/0.094). These results indicate that VerEval provides a more reliable evaluation signal than ANLS and SAS for open-ended wearer-centered scene text understanding. We therefore report the main leaderboard with VerEval scores in Table 3, while detailed ANLS and SAS results are provided in Appendix Tables 6 and 7. VerEval produces scores on the raw [0,1] scale; we multiply them by 100 when reporting results for readability in Tables.

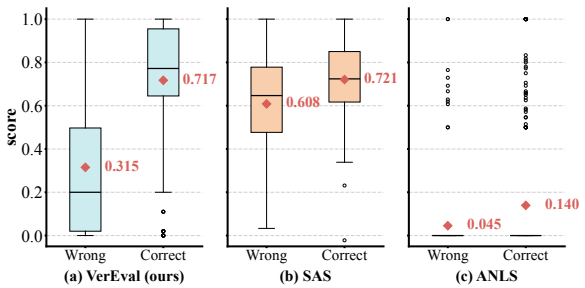

Figure 3: Distribution of automated metric scores grouped by human judgment (Wrong vs. Correct). (a) VerEval. (b) SAS. (c) ANLS. Red diamonds indicate mean values. The larger separation for VerEval indicates stronger alignment with human.

Capability Boundaries of Mainstream MLLMs. As detailed in Table 3, strong closed-source models such as GPT-5.2 and Gemini-3-Pro obtain the highest overall scores in our evaluation (73.1 and 72.9 respectively), but clear limitations remain in *Structured Text Synthesis (L3.3 STS)* and *Viewpoint Trajectory Description (L3.6 VTD)*. Specifically, the best scores in these two categories are 46.2 (Gemini-3-Pro) and 38.9 (Qwen3-VL-PLUS), indicating a substantial drop relative to *Dynamic Text Recognition (L1.1 DTR)*. The results suggest that moving from unstable text perception to goal-oriented text evidence selection remains challenging for current MLLMs.

Effectiveness of Training with Scalable Verified Data. To test whether MAH-V data is useful beyond benchmark construction, we fine-tune Qwen2.5-VL-7B on (v1) unverified LLM-generated data and (v2) MAH-V-verified data—both drawn from videos disjoint from the test split—and compare against the zero-shot baseline (v0). Table 4 shows that v1 gains on L1/L3 but loses 1.2% on L2 *Contextual Understanding*, whereas v2 improves every level (+3.7% L1, +1.8% L2, +0.5% L3). Multi-agent verification therefore both

Table 3: Overall VerEval scores. **Bold** indicates the best, Underline indicates the second best.

Model	L1: Perception		L2: Understanding					L3: Wearer-Grounded Reasoning						Overall
	L1.1 DTR	L1.2 DTL	L2.1 QTE	L2.2 CF	L2.3 CLU	L2.4 SSI	L2.5 WSI	L3.1 HII	L3.2 AIP	L3.3 STS	L3.4 STN	L3.5 GOC	L3.6 VTD	AVG
Closed-source Models														
GPT-5.2	84.5	**77.7**	72.4	74.2	**85.8**	**73.0**	**82.4**	**81.2**	**82.6**	45.1	**73.6**	**83.2**	34.4	**73.1**
Gemini-3-Pro	**91.4**	75.8	**82.7**	**82.8**	83.2	70.2	81.6	77.1	79.5	**46.2**	73.1	80.6	23.0	72.9
Claude-Opus-4.5	86.9	71.6	76.2	77.4	72.3	60.5	80.1	75.2	79.2	44.8	71.3	75.7	35.9	69.8
Qwen3-VL-PLUS	89.1	76.7	73.3	74.0	79.6	66.4	82.4	73.9	78.1	43.8	70.4	78.6	**38.9**	71.2
Seed-1.6	84.0	70.4	71.8	75.0	61.1	63.3	60.2	58.6	54.3	46.0	55.4	57.6	35.1	61.0
Open-source Models														
InternVL3.5-8B	54.4	49.6	43.9	50.4	57.0	28.1	49.6	40.4	25.5	7.9	43.3	35.3	21.4	39.0
InternVL3.5-38B	68.5	54.8	38.3	53.6	54.2	32.8	50.5	42.3	36.3	16.2	42.6	44.3	11.2	42.0
Qwen2.5-VL-3B	65.9	52.1	48.2	59.5	61.8	29.3	51.6	49.0	47.9	15.2	41.0	44.1	7.5	44.1
Qwen2.5-VL-7B	69.0	55.8	58.4	59.5	73.3	43.3	69.1	56.6	66.1	52.3	50.8	17.8	22.9	53.5
Qwen2.5-VL-32B	73.2	64.6	54.3	67.2	73.9	42.1	71.9	63.1	70.8	30.0	58.8	62.9	21.4	58.0
Qwen3-VL-4B	72.6	57.7	53.3	60.2	72.0	38.7	64.2	58.2	58.4	20.6	50.5	48.8	19.8	51.9
Qwen3-VL-8B	74.6	66.6	55.2	60.8	75.2	43.6	57.3	50.1	56.8	26.2	42.3	42.0	19.3	51.5
Qwen3-VL-32B	76.5	70.1	62.2	68.3	78.1	56.1	77.4	74.5	72.2	28.3	62.1	68.3	27.8	63.2
GLM-4.6V-Flash-9B	58.3	56.9	58.0	51.9	51.3	36.1	41.3	36.0	35.0	19.2	36.5	35.0	11.1	40.5
GLM-4.6V-106B-A12B	73.7	64.6	61.2	58.5	67.7	47.6	55.1	48.3	52.0	27.2	46.8	39.6	25.2	51.4
MINICPM-V-4.5	76.5	63.3	62.7	69.6	46.6	48.4	60.5	53.5	50.6	22.2	46.2	46.0	9.5	50.4
Open-source Video Models														
VideoLLaMA3-7B	51.1	55.0	47.1	52.8	53.8	28.5	49.0	43.1	50.0	13.9	39.7	42.7	4.9	40.9
LLaVA-NeXT-Video	8.6	18.3	10.6	18.3	32.9	7.5	21.6	17.0	19.8	2.6	15.1	21.5	2.1	15.1
VideoR1-7B	66.0	51.0	42.7	58.4	66.4	38.3	61.6	55.7	62.4	24.2	49.6	54.4	24.6	50.4
MOLMO-2-8B	27.0	51.0	30.8	48.6	63.0	22.1	43.7	34.5	46.9	11.3	35.7	35.8	11.9	35.6

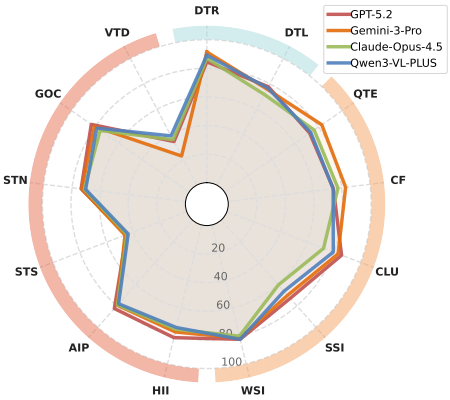

Figure 4: Capability Boundaries of Mainstream MLLMs.

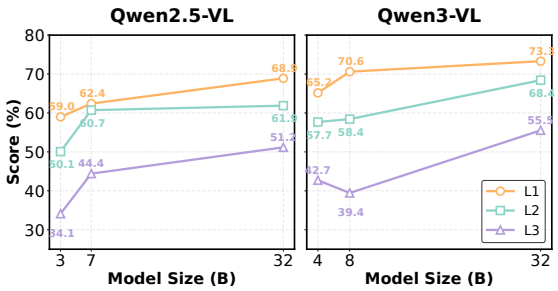

Figure 5: Performance across model sizes and task levels. Across both Qwen2.5-VL and Qwen3-VL families, L1 remains easier than L2, and L3 is consistently the most challenging, indicating that the three-level hierarchy preserves a clear difficulty separation across scales.

raises overall data quality and removes the L2 degradation introduced by direct LLM synthesis.

4.2 Key Findings

We conduct extensive experiments to thoroughly analyze the challenges presented by WearerText. Our analysis centers on the following questions: **Q1: How do tasks differ in difficulty?** As shown in Figure 5, across both Qwen2.5-VL and Qwen3-VL families, task difficulty increases from L1 to L3. L1 perception scores highest, L2 understanding trails behind, and L3 reasoning remains most challenging. This clear separation ($L1 > L2 > L3$) confirms that task complexity grows with each level. Notably, the substantial performance gap between L1 and L3 (up to 20 points) suggests that current MLLMs struggle to move from reading unstable text to wearer-view alignment and goal-oriented text evidence selection.

Q2: Why do current models fail? To move beyond aggregate scores, we manually categorize GPT-5.2's incorrect predictions on the held-out test set. As shown in Figure 6(d), the dominant failure type is goal-oriented text evidence reasoning (57.4%), followed by unstable text recognition (26.6%) and wearer-view alignment (16.0%). These results suggest that the key bottleneck is not only OCR, but the ability to select and reason over the right textual evidence under the wearer's view. Figure 6 illustrates these failure modes. In (a), the

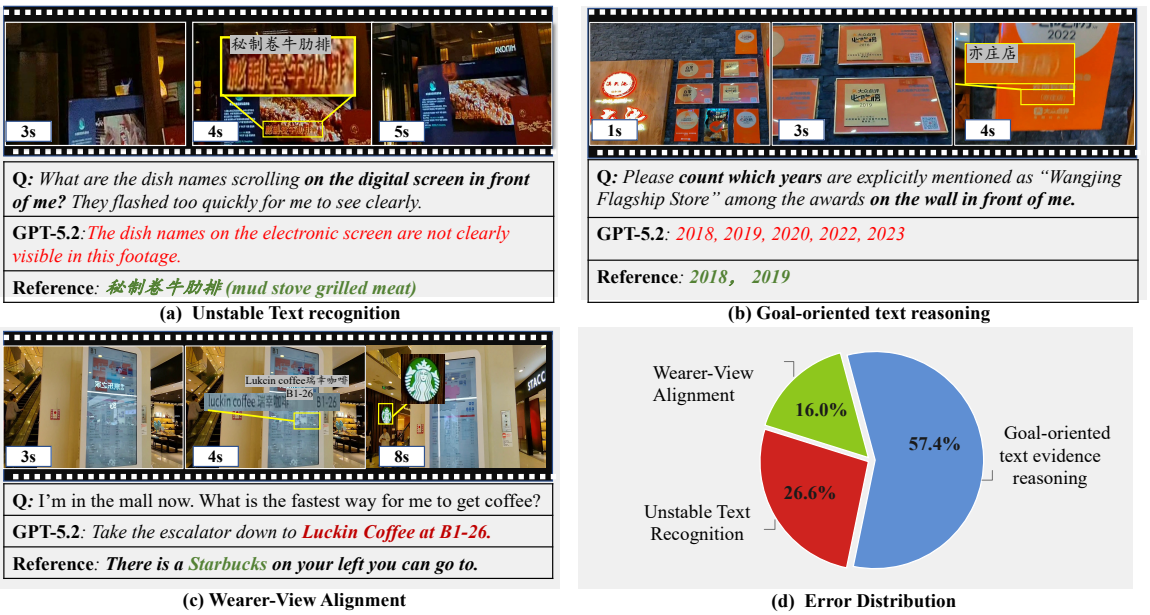

Figure 6: Representative failure cases and Error distribution on WearerText. Red text denotes model predictions, while green text denotes reference answers.

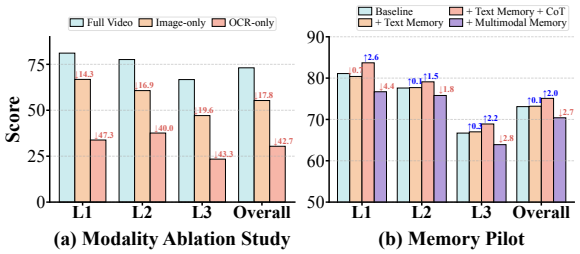

Figure 7: Diagnostic bar comparisons for GPT-5.2. (a) Modality ablation: full video, sampled keyframes, layout-aware OCR text. (b) Memory strategies: no memory, OCR text memory, structured text memory with reasoning, and raw multimodal memory. Arrows indicate changes relative to the full-video baseline.

model fails to recognize briefly visible scrolling text on a digital screen, showing the difficulty of unstable text reading under blur and short exposure. In (b), the model incorrectly includes years from visually similar awards, indicating weak temporal evidence accumulation and fine-grained text selection. In (c), the model gives an incorrect navigation suggestion because it fails to align visible shop signs with the wearer's spatial context. Overall, these cases show that AI-glasses text understanding requires the joint ability to read unstable text, ground it from the wearer's viewpoint, and accumulate goal-relevant evidence over time.

Q3: Does the benchmark require full AI-glasses video? We compare GPT-5.2 with full video, sampled keyframes, and layout-aware OCR text. As shown in Figure 7(a), full video consistently outperforms reduced inputs across L1–L3 and overall. The gap is modest for image-only input but much larger for OCR-only input, especially at L3, indicating that higher-level tasks require visual context and temporally ordered wearer-view signals beyond extracted text.

Table 4: Effectiveness of Scalable Verified Data Generation. **Bold** indicates the best performance; underline indicates the second best. ↑ and ↓ denote improvement or decline relative to the v0 baseline.

Metric	v0 Zero-shot	v1 Unverified LLM	v2 MAH-V
L1	62.4	65.0 ↑2.6	**66.1** ↑3.7
L2	60.7	59.5 ↓1.2	**62.5** ↑1.8
L3	56.5	**59.0** ↑2.5	57.0 ↑0.5
Overall	59.5	60.3 ↑0.9	**61.4** ↑1.9

Q4: Does memory help AI-glasses text understanding? We compare four memory strategies on GPT-5.2 in Figure 7(b): no memory, unstructured multimodal memory with raw past frames, OCR-derived text memory with concatenated OCR tokens, and structured text memory with distilled per-frame text indexed by the wearer's viewpoint trajectory and paired with a reasoning prompt. Three task-specific patterns emerge. (i) **Memory helps when evidence is temporal.** Gains concentrate on L3 *Wearer-Grounded Reasoning* (e.g., L3.1 HII and L3.5 GOC), while frame-local L1 perception is largely unaffected. This suggests that the L3 deficit in Q1 partly reflects a memory-architecture limita-

tion rather than model capacity alone. (ii) **Structure beats raw recall.** OCR-only memory brings little gain, whereas trajectory-indexed distilled text with a reasoning prompt improves overall performance by $+2.0$. It is also the only configuration that helps L3.4 STN and L3.6 VTD, both of which explicitly query the wearer's movement. (iii) **Raw multimodal memory hurts.** Stale frames degrade accuracy below the no-memory baseline, suggesting that re-perception competes with current-frame perception and amplifies the unstable-text errors. *Design implication:* future systems should maintain a low-bandwidth episodic record of distilled text indexed by the viewpoint trajectory rather than a verbatim multimodal buffer.

5 Conclusion

We introduce WearerText, a benchmark for evaluating AI-glasses text understanding in real-world wearable scenarios. Through our three-level task hierarchy, we assess 20 recent MLLMs on real-world public text-use challenges. Our findings have shown that current models remain limited on wearer-centered scene text understanding and reasoning, especially when answers require selecting relevant text evidence from partial observations according to the wearer's goal. These results suggest that progress in this setting requires stronger wearer-view alignment, structured memory over observed text, and intent-aware reasoning.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (NSFC) under Grant No. 62476275.

Limitations

WearerText is collected from real wearable-glasses videos, but its coverage is still bounded by the recording locations, participant behaviors, device characteristics, and public-space scenarios included in our study. Although the benchmark contains multilingual and mixed-language text, its distribution is not intended to represent all languages, regions, signage conventions, or accessibility needs. Future extensions should include broader geographic coverage, more diverse users, and additional low-resource languages.

Our task design focuses on offline question answering over short egocentric clips. Thus, "goal-oriented text evidence selection" refers to selecting relevant textual evidence within 5–10 second interaction primitives according to the wearer's current goal, rather than long-horizon memory over minutes or hours. This setting enables controlled comparison across models, but it does not fully capture interactive use cases in which a wearable assistant can ask clarification questions, adapt its guidance, or operate under real-time latency and energy constraints.

WearerText is wearer-centered in the sense that questions are grounded in the camera-view trajectory of the person wearing the device. However, our RayNeo recordings do not include eye-tracking signals, so camera view should not be interpreted as true gaze. Future versions with synchronized gaze sensing could separate head direction, eye fixation, and user intention more precisely.

Ethical Considerations

This work advances AI-glasses text understanding by providing a comprehensive and rigorous benchmark. All data contributors provided informed consent. To ensure privacy, we implemented rigorous anonymization (facial blurring) for all third-party individuals. Our pipeline prioritizes transparency and bias mitigation throughout the collection and annotation process.

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A Dataset Statistics

We summarize the statistics of **WearerText** in Table 5. The dataset consists of 1,101 real-world egocentric videos collected in three text-rich scenarios—shopping centers, transportation hubs, and tourist destinations—and contains 15,336 question–answer pairs spanning diverse perceptual, contextual, and reasoning-oriented tasks. Figure 8 presents representative qualitative examples across all 13 WearerText tasks. The examples illustrate the progression from dynamic text perception (L1), through contextual understanding (L2), to wearer-grounded reasoning over goals, history, and viewpoint trajectories (L3).

The collection spans sub-domains such as restaurants, supermarkets, menus, subway and railway stations, airports, street scenes, parks, and museums. Common wearable-video conditions related to the challenges discussed in the main paper are intentionally preserved: 72.0% of videos contain viewpoint changes, 33.7% contain briefly visible text, and 4.8% contain visible motion blur. These conditions are not mutually exclusive, since a single video may contain multiple challenges. We view this coverage as diagnostic rather than exhaustive; broader geographic and linguistic expansion remains future work.

The benchmark primarily covers Chinese and English language settings. Most QA pairs are in Chinese (67.59%), while English and mixed Chinese-English QA pairs account for 16.40% and 15.19%, respectively. At the video level, 29.22% of the visible scene text is Chinese-only, while 69.15% contains mixed Chinese-English text, reflecting the multilingual nature of everyday embodied text environments.

We reserve 1,391 QA pairs as the held-out test split used for the complete 13-task zero-shot leaderboard and human-alignment analysis in the main paper. The remaining 13,945 QA pairs form a separate training pool and are never used to tune the zero-shot leaderboard models. The controlled Qwen2.5-VL-7B SFT comparison in Table 4 evaluates v0, v1, and v2 on the same 11-task subset (L1.1–L3.4), excluding L3.5 and L3.6; its absolute scores are therefore not directly comparable to the complete 13-task results in Table 3.

B Multi-Faceted Per-Task Evaluation

To complement VerEval, we also report two surface-similarity metrics so that readers can compare WearerText models under traditional VQA scoring conventions: (1) **ANLS** (Average Normalized Levenshtein Similarity) measures exact string accuracy via normalized Levenshtein similarity (edit distance divided by the longer string length), shown in Table 6. (2) **SAS** (Semantic Answer Similarity) measures the semantic similarity between the predicted answer and the ground truth answer, so paraphrased but equivalent answers still score highly, shown in Table 7.

Table 5: Statistics of **WearerText**. Wearable-video condition percentages are non-exclusive: one video may contain multiple conditions.

Statistic	**Value**
Total Videos	1,101
Total Questions	15,336
By Scenario	
Shopping Centers	378 videos
Transportation Hubs	412 videos
Tourist Destinations	311 videos
Wearable-Video Conditions (non-exclusive)	
Viewpoint Changes	72.0% videos
Briefly Visible Text	33.7% videos
Visible Motion Blur	4.8% videos
QA Language	
Chinese	67.59%
English	16.40%
Mixed Chinese-English	15.19%
Other	0.82%
Video Text Language	
Chinese	29.22%
Mixed Chinese-English	69.15%
Verification Split	
Test Set	1,391 QAs / 107 videos
Train Set	13,945 QAs / 994 videos

C Implementation Details

C.1 Data Construction Pipeline

The OCR tool used in this paper is PaddleOCR (Cui et al., 2025), and the layout-aware transformation, which reorganizes OCR tokens into reading-order reference text T_{ref} conditioned on detected bounding boxes, is performed by o4-mini (OpenAI, 2025); this is a separate stage from scoring and does not interact with the judge. The Fact and Consistency Agents return continuous scores in $[0, 1]$; QA pairs whose Fact score falls below the acceptance threshold $\tau = 0.7$ or whose Consistency Agent emits a conflict report are routed to the Refinement Agent, which is allowed up to 2 revision passes before any still-failing pair is dropped. The retained pairs then proceed to the

Figure 8: Per-task qualitative examples from WearerText. The examples cover all 13 tasks in the three-level hierarchy and pair representative frames from AI-glasses videos with the corresponding bilingual wearer-centered queries.

human-verification stage.

C.2 VerEval Judge Setup

The VerEval judge operates in two modes. In the *evidence-based mode*, it receives the prediction, question, and verified ground truth, but not the video frames, and evaluates consistency with this verified evidence record. In the *video-aware mode*, the original video is additionally provided, allowing the judge to re-examine the visual evidence directly. In this paper, all main-table results are obtained in the evidence-based mode using a fixed, locally deployed Qwen3-VL-32B judge (Bai et al., 2025a). We adopt this setting for the 20-model leaderboard because it avoids additional input tokens per video and isolates the evaluated model's perception from a second judge-perception pass. The three scorers each make one call per answer. Decoding uses temperature 0, a 1,024-token cap, and a deterministic seed.

C.3 VerEval Scoring Prompts

We employ three prompts for model evaluation in the VerEval framework. The Fact Scoring Prompt generates a structured factual assessment $S_{fact} = (s_{fact}, \mathcal{R}_{fact})$ by detecting discrepancies in key information (e.g., numbers, timestamps, and entities) against video content and ground truth; it reports both a diagnostic score s_{fact} and suggested corrections $\mathcal{R}_{fact}$. The Logic Scoring Prompt assesses the structural integrity of the reasoning process and its alignment with spatio-temporal constraints, outputting the Logic Score (S_{logic}). The Consistency Scoring Prompt jointly reviews the fact judgment, logic judgment, their rationales, and the model answer, producing the Consistency Score ($S_{consist}$). In the final VerEval score, $S_{consist}$ refers specifically to the output of the consistency-scoring prompt in Figure 9c. It is not a renamed version of the Fact Agent's structured assessment S_{fact}. We treat its scalar component s_{fact} as an intermediate diagnostic because the consistency scorer already checks factual evidence while also assessing whether the fact and logic judgments are mutually coherent. Empirically, raw fact scoring showed weaker separation from human judgments than the consistency and logic scores. Therefore, s_{fact} is excluded from the aggregate, and $S_{overall}$ is computed only from $S_{consist}$ and S_{logic}. The full scoring prompt templates are shown in Figure 9.

Fact Scoring
You are a rigorous expert in fact scoring. Please evaluate the accuracy of the answer to be assessed based on the ground truth and video.

QA to be Scored
Question: *{question}*
Ground Truth: *{ground_truth}*
Answer to be Evaluated: *{answer}*

Scoring Task Requirements
1. Fact Assessment (Core: Hallucination Detection)
Verify every word/number in the answer to check for:
- Information that contradicts the ground truth
- Information inconsistent with the video, especially significant text recognition errors
- Fabricated non-existent content
- Errors in key information such as numbers, names, times, locations

2. Completeness Assessment
Check for omissions of key information in the ground truth and important content in the video

Scoring Criteria
- Total score = 1.0, minimum 0
- **Critical Error**: Factual contradiction with the ground truth or video in key information -> Deduct 0.4-0.8 points
- **Minor Error**: No critical errors, but secondary errors or minor deviations in supplementary statements -> Deduct 0.1-0.3 points
- **Incomplete Information**: Answers the question without factual contradictions but does not fully cover the ground truth and video -> Deduct 0.05-0.15 points
- **Perfect Match**: Fully consistent with the ground truth and video -> 1.0 points

Output Format
Strictly output in the following JSON format: ```{ "score": "xxx", "reason": "xxx" } ```
Where "score" is a two-decimal-place score, and "reason" explains the factual errors or inconsistencies with the video in the answer to be evaluated. Please rigorously verify every specific piece of text and validate it with the video information!

(a) Fact scoring prompt.

Logic Scoring
You are a logic scoring expert specializing in evaluating the logical rigor of question design and answers, and verifying them in conjunction with video.

QA to be Scored
Question: *{question}*
Ground Truth: *{ground_truth}*
Answer to be Evaluated: *{answer}*

Scoring Task Requirements
1. Evaluation of Logical Rigor in Answers
Quality of logical reasoning in the answer:
- Whether the reasoning process is reasonable and the conclusion is natural
- Whether the logical chain is complete and rigorous
- Whether there are logical leaps or contradictions

2. Accuracy of Question Understanding
Assess whether the core requirements of the question are accurately understood

3. Logical Consistency with video
Check whether the answer's logic aligns with the video:
- Whether the understanding of the video scenes is correct
- Whether the reasoning based on the video is reasonable
- Whether there are logical judgments that contradict the video

Scoring Criteria
- Total score = 1.0, minimum 0
- **Logical Confusion**: The reasoning process contains serious logical errors or contradictions with the video -> Deduct 0.4-0.8 points
- **Misunderstanding**: Misinterpretation of the question, leading to an incorrect answer direction -> Deduct 0.4-0.8 points
- **Logical Laxity**: The reasoning process is mostly correct but lacks rigor or is poorly integrated with the video -> Deduct 0.1-0.3 points
- **Logical Rigor**: The reasoning process is reasonable, the conclusion is natural, and fully consistent with the video -> 1.0 points

Output Format
Strictly adhere to the following JSON format for output: ```{ "score": "xxx", "reason": "xxx" }```
Where "score" is a two-decimal-place score, and "reason" is the justification for the score, explaining the logical errors in the answer to be evaluated and any inconsistencies with the video. Please strictly follow the logical standards for evaluation and verify them in conjunction with the video information!

(b) Logic scoring prompt.

Consistency Scoring
You are a comprehensive judgment expert, providing final judgments based on factual and logical scoring results.

QA Information
Question: *{question}*
Ground Truth: *{ground_truth}*
Answer to be Evaluated: *{answer}*

Factual Scoring Results
- **Fact Score**: *{fact_score}*
- **Fact Scoring Reason**: *{fact_reason}*

Logical Scoring Results
- **Logic Score**: *{logic_score}*
- **Logic Scoring Reason**: *{logic_reason}*

Scoring Criteria
- Total Score = 1.0, minimum 0

Evaluation Task
Based on the above factual and logical scoring results and video, provide a final consistency judgment:
- Balance factual accuracy and logical rigor, considering both dimensions
- Evaluate the overall consistency between the answer and the video
- Assess the overall quality and consistency level of the answer
- Consider primary and secondary issues
- Provide a final comprehensive score

Output Format
Strictly adhere to the following JSON format for output: ```{"score": "xxx","reason": "xxx"}```
Where "score" is a two-decimal-place score, and "reason" is a detailed scoring rationale, explained in conjunction with the video. Please provide a strict and fair judgment!

(c) Consistency scoring prompt.

Figure 9: Scoring prompt templates used in VerEval.

Table 6: ANLS Performance. **Bold** indicates the best, Underline indicates the second best. Task abbreviations: DTR (Dynamic Text Recognition), DTL (Dynamic Text Localization), QTE (Query-Guided Text Extraction), CF (Confirmation), CLU (Cross-Lingual Understanding), SSI (Situated Semantic Interpretation), WSI (Wearer-Centered Situational Inference), HII (History-Conditioned Intent Inference), AIP (Action-Trajectory Intent Prediction), STS (Structured Text Synthesis), STN (Spatio-Temporal Navigation Reasoning), GOC (Goal-Oriented Comparison), VTD (Viewpoint Trajectory Description).

Model	L1: Perception		L2: Understanding					L3: Wearer-Grounded Reasoning						Overall
	L1.1 DTR	L1.2 DTL	L2.1 QTE	L2.2 CF	L2.3 CLU	L2.4 SSI	L2.5 WSI	L3.1 HII	L3.2 AIP	L3.3 STS	L3.4 STN	L3.5 GOC	L3.6 VTD	AVG
Closed-source Models														
GPT-5.2	**62.4**	**19.7**	20.3	8.6	**16.4**	**23.0**	15.9	0.5	0.0	0.6	0.0	0.0	0.0	12.9
Gemini-3-Pro	59.0	18.7	**29.9**	**21.0**	19.1	30.3	**20.0**	**3.2**	**0.0**	**1.5**	**0.0**	**1.6**	6.6	**16.2**
Claude-Opus-4.5	68.8	20.6	27.9	9.8	6.5	18.3	19.6	0.0	0.0	0.0	0.0	0.5	0.0	13.2
Qwen3-VL-PLUS	73.1	20.0	29.9	13.9	10.5	21.4	18.2	0.5	0.0	0.5	0.0	0.0	0.0	14.5
Seed-1.6	72.4	17.5	32.9	10.7	7.5	19.7	20.7	1.9	0.0	0.0	0.0	0.0	**5.1**	14.5
Open-source Models														
InternVL3.5-8B	34.6	2.7	6.6	3.4	3.7	3.9	1.1	0.0	0.0	0.0	0.0	0.0	1.2	4.4
InternVL3.5-38B	51.2	16.9	10.5	1.6	2.7	7.7	7.2	0.0	0.0	0.0	0.0	0.0	14.9	8.7
Qwen2.5-VL-3B	43.9	7.0	7.8	5.4	3.4	6.1	6.4	0.7	0.0	0.5	0.0	0.0	22.9	8.0
Qwen2.5-VL-7B	50.4	3.8	13.3	5.9	9.3	10.8	5.0	0.6	0.0	0.0	0.0	0.0	20.0	9.1
Qwen2.5-VL-32B	61.1	12.2	15.0	4.6	8.4	9.6	11.6	0.5	0.0	0.0	0.0	0.0	12.7	10.4
Qwen3-VL-4B	55.3	20.7	13.0	4.0	9.8	11.0	8.5	0.6	0.0	0.5	0.0	0.0	9.9	10.3
Qwen3-VL-8B	61.1	16.4	20.2	2.8	8.9	14.1	11.2	0.0	0.0	0.0	0.0	0.0	0.0	10.4
Qwen3-VL-32B	59.7	15.1	16.0	4.4	9.2	11.6	12.7	0.0	0.0	0.0	0.0	0.0	2.4	10.1
GLM-4.6V-Flash-9B	51.4	15.7	19.9	1.6	7.8	10.7	8.9	0.0	0.0	0.0	0.0	0.0	0.0	8.9
GLM-4.6V-106B-A12B	62.1	22.1	21.8	8.3	9.7	17.8	10.7	0.5	0.0	0.0	0.0	0.0	12.1	12.7
MINICPM-V-4.5	51.3	14.7	23.1	11.2	3.8	9.6	6.8	0.0	0.0	0.0	0.0	0.0	0.0	9.3
Open-source Video Models														
VideoLLaMA3-7B	16.7	5.2	1.9	2.2	1.8	2.7	2.6	0.0	0.0	0.0	0.0	0.0	0.0	2.5
LLaVA-NeXT-Video	0.0	0.5	0.5	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
VideoR1-7B	1.5	1.2	2.4	0.0	1.1	1.7	0.5	0.0	0.0	0.0	0.0	0.0	0.8	0.7
MOLMO-2-8B	15.7	14.0	8.3	0.8	4.8	2.4	3.7	0.0	0.0	0.0	0.0	0.0	0.0	3.8

D Additional Analyses

D.1 MAH-V Quality Control Ablation

We perform an ablation analysis over the three quality control agents to validate their effectiveness, as shown in Table 8. For each ablation, we sampled 1,391 QA pairs and calculated the average human acceptance over three trained annotators. Removing any quality control module decreases human acceptance: removing the Fact Checker causes the largest drop (-9.0 percentage points, to 86.5%), followed by the Consistency Agent (-7.1 points) and the Logic Checker (-2.8 points). Removing all agents further degrades acceptance to 84.1%.

D.2 Layout-Aware OCR Ablation

To isolate the contribution of spatial layout information, we compare layout-aware OCR with OCR tokens without layout-based reordering in Table 9. Removing layout-aware reordering reduces the overall score by 1.7 points, demonstrating that preserving spatial structure is particularly important.

D.3 VerEval Weighting Ablation

We select the final VerEval aggregation weight by maximizing alignment with human judgments on held-out annotated samples. Since $S_{consist}$ is produced by the consistency prompt and subsumes factual conflicts as well as fact–logic coherence, it serves as the primary term; S_{logic} provides a secondary penalty for flawed reasoning chains. We report AUC (area under the ROC curve), which measures how well a metric ranks human-labeled *Correct* answers above *Wrong* answers; higher values indicate stronger agreement with human judgments. Table 10 shows that the $0.9/0.1$ consistency–logic weighting achieves the highest average AUC across annotator sets. The variance across configurations is below 0.002, indicating that VerEval is robust to the exact weighting choice rather than sensitive to parameter tuning.

D.4 Model-Size Scaling

Figure 5 shows scaling effects for Qwen2.5-VL and Qwen3-VL. Qwen2.5-VL shows steady gains across all levels, with L1 rising by 9.9 points and L3 by 17.1 points. Conversely, Qwen3-VL displays non-monotonic patterns: while L1 and L2

Table 7: SAS Performance. **Bold** indicates the best, Underline indicates the second best. Task abbreviations: DTR (Dynamic Text Recognition), DTL (Dynamic Text Localization), QTE (Query-Guided Text Extraction), CF (Confirmation), CLU (Cross-Lingual Understanding), SSI (Situated Semantic Interpretation), WSI (Wearer-Centered Situational Inference), HII (History-Conditioned Intent Inference), AIP (Action-Trajectory Intent Prediction), STS (Structured Text Synthesis), STN (Spatio-Temporal Navigation Reasoning), GOC (Goal-Oriented Comparison), VTD (Viewpoint Trajectory Description).

Model	L1: Perception		L2: Understanding					L3: Wearer-Grounded Reasoning						Overall
	L1.1 DTR	L1.2 DTL	L2.1 QTE	L2.2 CF	L2.3 CLU	L2.4 SSI	L2.5 WSI	L3.1 HII	L3.2 AIP	L3.3 STS	L3.4 STN	L3.5 GOC	L3.6 VTD	AVG
Closed-source Models														
GPT-5.2	84.4	**74.4**	69.5	**77.3**	**76.5**	**76.6**	**56.1**	**71.8**	**70.2**	**74.1**	**71.5**	**71.8**	**70.4**	72.6
Gemini-3-Pro	84.1	75.2	**77.0**	81.7	77.8	78.7	64.7	76.4	71.4	76.9	76.4	76.7	72.4	**76.1**
Claude-Opus-4.5	86.8	73.1	76.1	81.5	72.5	73.4	63.6	74.0	72.8	75.3	76.6	74.4	74.3	75.0
Qwen3-VL-PLUS	**89.1**	72.1	73.1	77.0	74.0	72.2	65.8	71.0	69.7	74.3	73.5	73.2	70.4	73.5
Seed-1.6	87.9	70.0	73.1	76.5	67.7	72.3	65.9	67.3	63.9	70.2	67.3	67.0	66.3	70.4
Open-source Models														
InternVL3.5-8B	66.6	59.6	54.4	62.9	54.9	54.5	26.5	60.7	50.1	61.6	60.9	58.7	55.3	55.9
InternVL3.5-38B	79.2	68.7	54.9	55.5	58.4	54.6	36.9	51.2	51.9	54.6	51.1	52.8	59.3	56.1
Qwen2.5-VL-3B	75.0	67.7	64.8	73.6	62.0	59.7	34.7	62.0	64.5	61.2	62.1	61.0	54.9	61.8
Qwen2.5-VL-7B	79.8	65.0	65.4	74.7	69.5	65.3	30.0	68.0	69.4	68.6	68.3	65.7	82.4	67.1
Qwen2.5-VL-32B	83.2	69.2	64.1	76.7	70.0	65.3	51.7	64.2	66.5	67.2	65.9	65.2	64.5	67.2
Qwen3-VL-4B	80.4	72.1	65.1	73.2	71.3	65.6	48.6	67.6	66.0	68.3	64.3	64.5	58.3	66.6
Qwen3-VL-8B	82.4	67.7	65.1	60.8	70.6	64.5	56.9	56.1	62.8	57.1	55.6	53.1	64.7	62.9
Qwen3-VL-32B	83.1	70.4	66.4	76.3	71.7	69.3	57.1	65.3	68.7	69.1	69.8	66.0	69.2	69.4
GLM-4.6V-Flash-9B	80.3	63.4	60.3	44.0	57.1	57.8	42.7	46.1	51.5	47.1	47.0	46.5	44.7	53.0
GLM-4.6V-106B-A12B	83.8	73.2	64.1	73.7	71.7	66.7	51.0	60.4	62.0	64.8	61.5	59.4	62.5	65.8
MINICPM-V-4.5	78.0	64.0	64.6	74.6	52.9	61.9	45.9	61.6	59.2	61.9	60.5	57.7	42.3	60.4
Open-source Video Models														
VideoLLaMA3-7B	58.4	59.9	61.3	67.9	61.1	55.5	35.6	60.9	61.8	65.3	64.3	62.1	42.5	58.2
LLaVA-NeXT-Video	39.6	56.4	46.5	60.7	56.0	48.1	26.5	54.6	58.3	57.3	60.3	57.6	22.7	49.6
VideoR1-7B	56.8	61.0	54.8	64.4	61.4	63.9	44.1	55.2	56.1	54.4	55.9	52.7	67.9	57.6
MOLMO-2-8B	56.7	65.2	54.8	60.2	63.3	53.9	34.4	54.7	56.6	55.3	53.9	52.0	37.5	53.7

Table 8: Ablation study evaluating the impact of each quality control agent on the acceptability of the synthesized tasks.

Fact Checker	Logical Checker	Consistency Agent	Human Acceptance
✗	✗	✗	84.1%
✗	✓	✓	86.5%
✓	✗	✓	92.7%
✓	✓	✗	88.4%
✓	✓	✓	95.5%

Table 9: OCR layout ablation. Scores are reported by task level and overall average.

Input	L1	L2	L3	Overall
OCR+Layout	**33.8**	**37.6**	23.4	**30.4**
OCR-NoLayout	27.2	35.6	**23.6**	28.7

Table 10: VerEval weighting ablation measured by AUC against human annotations.

Weight	Ann-1	Ann-2	Ann-3	Avg.
0.5 / 0.5	0.827	0.827	0.837	0.830
0.7 / 0.3	0.827	0.826	0.840	0.831
0.8 / 0.2	**0.828**	**0.827**	**0.840**	0.831
0.9 / 0.1	**0.828**	**0.827**	**0.840**	**0.832**

scale upward, L3 performance regresses at 8B (42.7 → 39.4) before recovering at 32B. These results indicate that perception scales predictably, whereas understanding and reasoning exhibit instability at scales.

D.5 Video-Pretrained Models

Video-native models show mixed results, with most underperforming image-based counterparts. LLaVA-NeXT-Video exhibits catastrophic failure (15.1 overall), while VideoLLaMA3-7B (40.9) and MOLMO-2-8B (35.6) trail behind similarly-sized image models like Qwen3-VL-4B (51.9). VideoR1-7B achieves competitive performance (50.4) with notable strength in L3.2 (62.4), but still struggles with Structured Text Synthesis (L3.3: 24.2) and Viewpoint Trajectory Description (L3.6: 24.6). These results suggest that conventional video pre-training on third-person, motion-centric datasets does not directly transfer to first-person, text-dense wearable scenarios where frame-level text clarity, wearer-view alignment, and semantic consistency matter more than generic motion modeling.

Table 11: Available language-stratified VerEval check for Qwen2.5-VL-7B.

Question language	VerEval
Chinese-only	54.5
Chinese–English mixed	53.9

D.6 Language-Stratified Analysis

Table 5 provides the complete dataset breakdown by QA and scene-text language. As an additional language-stratified model check reported during rebuttal, Qwen2.5-VL-7B obtains similar VerEval scores on Chinese-only and Chinese–English mixed questions (54.5 vs. 53.9; scores are multiplied by 100). This two-group result suggests no large gap between these strata for this model.

E Data Collection and Ethics

Participants and Consent. Eight volunteers, all members of the research team, recorded the first-person videos. There was no external recruitment, paid crowdsourcing, or participant payment. Before recording, every participant received the collection and privacy protocol and provided informed consent with full information about the research purpose, data processing, and planned distribution. All collection procedures followed institutional ethical and privacy guidelines.

Intent-Driven Collection Protocol. Recording was restricted to permitted public settings in shopping, transportation, and tourism scenarios. Participants received instructions covering safety, privacy, and desired coverage of text-rich activities, but were not given scripted actions or questions. Instead, they selected genuine activities they intended to perform, such as reading a sign, confirming a location, comparing displayed options, or navigating with public text. Candidate QAs were grounded in each recorder's video evidence, after which the original recorder checked their intent alignment.

Expert Validation. Following MAH-V, three domain experts independently validated each candidate QA pair against the original video, verified reference text, and task definition. Annotators could correct or reject a problematic question or answer rather than merely assign an acceptability label. Final retention required unanimous approval or a 2/3 majority. This correction-and-majority procedure provides a correctness-oriented check, while the separately reported inter-annotator agreement of $\kappa = 0.89$ measures the reliability of the validation decisions.

Face Anonymization. All third-party faces in videos and global images were automatically detected and blurred while preserving the non-face scene context needed for the tasks. Human reviewers subsequently performed frame-level inspection of the processed data. Any incomplete anonymization was reprocessed and checked again before release.

Data Usage and Distribution. The anonymized dataset is intended exclusively for academic, non-commercial research. Its usage agreement prohibits attempts to reverse anonymization or identify individuals and requires appropriate attribution and responsible handling. Rejected or insufficiently anonymized material is excluded from the release.