
RTV-Bench: Benchmarking MLLM Continuous Perception, Understanding and Reasoning through *Real-Time Video*

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Project Page: <https://ljangang.github.io/RTV-Bench>

Abstract

Multimodal Large Language Models (MLLMs) increasingly excel at perception, understanding, and reasoning. However, current benchmarks inadequately evaluate their ability to perform these tasks continuously in dynamic, real-world environments. To bridge this gap, we introduce *RTV-Bench*, a fine-grained benchmark for MLLM real-time video analysis. *RTV-Bench* includes three key principles: (1) **Multi-Timestamp Question Answering (MTQA)**, where answers evolve with scene changes; (2) **Hierarchical Question Structure**, combining basic and advanced queries; and (3) **Multi-dimensional Evaluation**, assessing the ability of continuous perception, understanding, and reasoning. *RTV-Bench* contains 552 diverse videos (167.2 hours) and 4,631 high-quality QA pairs. We evaluated leading MLLMs, including proprietary (GPT-4o, Gemini 2.0), open-source offline (Qwen2.5-VL, VideoLLaMA3), and open-source real-time (VITA-1.5, InternLM-XComposer2.5-OmniLive) models. Experiment results show open-source real-time models largely outperform offline ones but still trail top proprietary models. Our analysis also reveals that larger model size or higher frame sampling rates do not significantly boost *RTV-Bench* performance, sometimes causing slight decreases. This underscores the need for better model architectures optimized for video stream processing and long sequences to advance real-time video analysis with MLLMs.

1 Introduction

The ability to comprehend and respond to complex real-world scenarios in real-time represents a crucial challenge in the pursuit of general artificial intelligence [6, 24, 10]. Drawing inspiration from the remarkable achievements of large language models (LLMs) in a wide range of tasks [25, 11, 2], the potential of multimodal large language models (MLLMs) is increasingly being realized in the domain of visual scene analysis [48, 41, 5]. The research trajectory of Video-LLMs [21, 27, 4, 35, 33] is progressively advancing from the understanding of short, vision-centric videos [15, 13, 22, 19] to

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Figure 1: Specific examples of different tasks in RTV-Bench. 1 and 2 represent the fundamental questions in the question group, and the answers are underlined. 3 is a dynamically answered question, and the correct answer is determined by the time of the query. The correct answer to the query will change at different times, and we have marked the correct answers that should be responded to at different query times.

the integration of omni-modal information—including video, audio, and subtitles [3, 7, 17, 32, 18, 26]—for comprehensive long video analysis.

Recently, VStream [45] was the first to attempt to test this capability, with a focus primarily on extending the duration of videos. In addition, both StreamingBench [39] and OVOBench [20] have made varying degrees of improvements in the types and standards of assessment. However, their evaluation of real-time responsiveness is often inadequate, overlooking the capacity to capture transitions and fleeting details from visual input that arrive sequentially, not instantaneously. This limitation highlights the need for a more focused assessment of continuous analysis abilities.

Based on the above considerations, we introduce *RTV-Bench*, featuring three core innovations designed to benchmark the **continuous analysis capabilities**—specifically perception, understanding, and reasoning—of MLLMs within real-time video contexts. First, the **Multi-Timestamp Q&A** mechanism challenges real-time tracking and state update by posing queries whose answers evolve within a video. Crucially, unlike benchmarks like OVO-Bench [20] that typically introduce different questions at different timestamps, RTV-Bench revisits the same conceptual query, where only the correct answer shifts as the scene unfolds. This approach more rigorously tests the model capacities for continuous analysis in real-time scenarios, surpassing single-query-single-answer and static evaluations. Second, the **Hierarchical Question Structure** enforces reliable, sequential reasoning by employing a basic-to-advanced design where higher-order questions logically depend on grasping foundational perceptions and understanding, thus mitigating cognitive shortcuts. Finally, **Multi-dimensional Evaluation** moves beyond single scores to provide granular diagnostics, assessing performance across eight fine-grained dimensions critical to continuous analysis in dynamic scenarios, offering a more insightful perspective on model capabilities and bottlenecks in handling real-time video information, detailed cases are shown in Figure 1.

Through RTV-Bench’s novel design and the detailed evaluations presented herein, we provide comprehensive insights into the current state of MLLMs for continuous video analysis: Results for all tested models on RTV-Bench reveal significant bottlenecks for existing MLLMs in real-time video analysis, as (1) most models achieve accuracy below 50%. Furthermore, (2) model performance shows minimal correlation with the number of input frames or model size. Notably, (3) models specifically designed for real-time video significantly outperform traditional offline video models, even the lowest-performing real-time model tested (VITA-1.5 [9]) surpasses a traditional offline counterpart (VideoLLaMA2 [4]). Building upon these findings, we further discuss promising research trajectories to enhance MLLM online video processing. We expect that our benchmark, analysis, and outlined future directions will contribute significantly to the development of more robust and capable online video MLLMs.

2 RTV-Bench

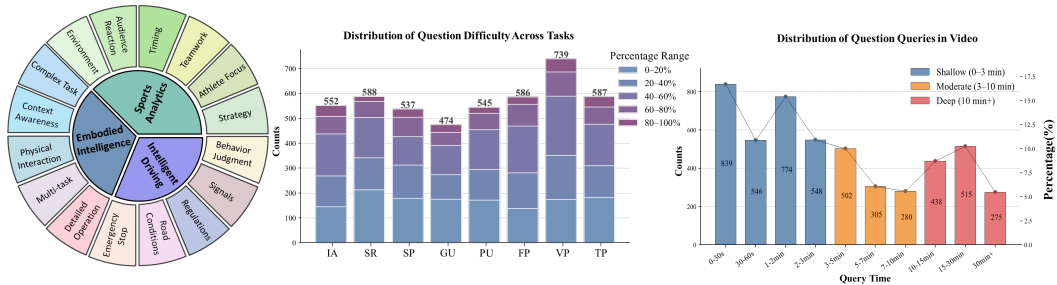


Figure 2: Video Categories and Distribution of Question Difficulty and Query Characteristics. (Left) RTV-Bench over 3 key domains and 16 sub-class video types. (Center) Distribution of question difficulty levels across eight representative task types, measured by percentage-based performance ranges. (Right) Distribution of question queries by video length, categorized into Shallow, Moderate, and Deep levels. The bar heights indicate counts, while the line chart overlays query proportions for each duration bucket.

In this section, we discuss a common challenge in both long video comprehension and real-time video analysis—the continuous analysis capability of MLLMs. To tackle this, we have meticulously curated

a benchmark to assess model performance in real-time and continuous scenarios, and developed new metrics to characterize the performance of multimodal large models in this bench.

2.1 Challenge for Real-Time Video Analysis

Existing benchmarks for long video analysis [8, 38] attempt to gauge the true capacity of MLLMs by extending video duration, enhancing the difficulty of QA tasks, and introducing new sub-tasks. Other works [23] focus on real-time video scenarios, evaluating model responsiveness to queries in real-time contexts. However, current models face the risk of memory loss and attention shift, both in long and real-time video contexts. We categorize these challenges as failures in the continuous analysis capability of MLLMs. In video scenarios, MLLMs are considered to possess strong continuous analysis ability only if they can effectively recall prior visual information to accurately respond to user queries (similar to needle-in-a-haystack tasks in natural language settings) and maintain robust perception of incoming streams of new visual data and queries (akin to multimodal multi-turn dialogues).

2.2 Benchmark Overview

The RTV-Bench is designed to assess a model’s ability to perceive, understand, and reason in long video and real-time streaming contexts. Models should be adept at recognizing correct temporal query patterns. For example, during live sports queries (e.g., goalkeeper actions), models must prioritize current contexts over historical data. However, it should also retrieve relevant information from memory, such as identifying the goalkeeper from earlier footage. This necessitates that models not only possess exceptionally high fundamental scene comprehension capabilities, but also demonstrate effective understanding of all stages within the temporal flow—namely, comprehensive spatiotemporal comprehension encompassing the past, present, and future. To this end, we propose a series of sub-tasks for video continuous analysis, addressing both spatiotemporal elements within the video and the intrinsic capabilities of the model. The intrinsic model capabilities are divided into eight categories: Temporal Perception (TP), Scene Perception (SP), Visual Perception (VP), Future Prediction (FP), Phenomenological Understanding (PU), Intent Analysis (IA), Global Understanding (GU), and Spatiotemporal Reasoning (SR), see Figure 1 for details.

2.3 Benchmark Construction

Terminology The RTV-Bench dataset comprises $N = 552$ videos sourced from the internet. A key characteristic is its question structure designed to directly probe temporal dynamics. For each video, questions are organized into sets. Each question set contains a minimum of three multiple-choice questions.

Crucially, the core design principle revolves around time-varying correct answers (Multi-Timestamp QA): within a set of questions, the same underlying conceptual query (for example, ‘What is person A holding?’, ‘Where is the car heading?’) is effectively evaluated at different points in time within the video. This means that the correct answer option changes depending on the specific timestamp or time interval referenced or implied by the question context or its associated earliest inferable timestamp (Figure 1). This challenges models not just to locate information, but to actively track changes and update their understanding of a situation as it evolves. This design directly targets the assessment of continuous understanding and the model’s sensitivity to temporal changes, see Figure 4 for cases.

The question set features three questions of escalating difficulty. The first two are simpler, while the final question is significantly more complex, demanding integration of broader context or clues. The information and reasoning needed for the final question generally encompass those required for the first two. Successfully answering the complex third question strongly suggests the capability to also answer the simpler ones. This structure evaluates the model’s ability to handle increasing complexity, synthesize comprehensive context, and perform robust analysis.

In addition, we emphasize diversity through the richness of specific sub-scenes and the distribution of video lengths. The RTV-Bench primarily encompasses intelligent driving, sports events, and egocentric videos—categories rich in dynamic information and real-time contextual relevance. Each category includes a variety of sub-categories, as illustrated in Figure 2.

Data Statistic RTV-Bench comprises 552 videos with a total duration of 167.2 hours (average 18.2 minutes per video) and contains 4,631 QA pairs, for detailed information, refer to Figure 2 and Table 1. The benchmark features diverse question scenarios and evenly distributed video durations, thereby establishing a comprehensive framework for video continuous understanding tasks with rich sub-scenarios and structured problem dimensions.

Video Collection and Filtering Our video data sources include EgoSchema [28] and publicly available online videos. Unlike most existing benchmarks, we incorporated manual review during the collection phase. Three data collectors sourced videos from various domains and manually excluded highly similar videos, focusing on long videos with high dynamics and real-time needs. These sources ensure targeted and scientific evaluation of video models’ real-time capabilities.

Manual Annotation Rigorous manual annotation by qualified experts was essential for RTV-Bench’s reliability in assessing continuous video analysis. While an LLM (Deepseek [25]) provided initial question templates, human annotators significantly refined questions to target dynamic scenes and temporal reasoning. They meticulously crafted questions where answers change over time and identified the earliest valid timestamp for each answer option in MTQA. This human-centric, multi-annotator process ensured robustness and created evaluations specifically focused on temporal dynamics in video.

Table 1: Comparison of video QA benchmarks. MT: multi-timestamp questions. Labels: A (automatic), M (manual), A+M (both).

Benchmark	MT	Num. of QA	Avg. Dur. (min)	Total Dur. (h)	Labels
Video-MME [8]	✗	2.7k	17	254.0	M
MSRVTT [40]	✗	73k	0.25	12.5	A
MSVD-QA [1]	✗	13k	0.17	1.4	A
MovieChat-1k [31]	✗	13k	9.4	156.0	M
MVBench [16]	✗	4k	0.25	34.5	A+M
ActivityNet-QA [43]	✗	58k	1.87	25.0	M
Vstream-Q [45]	✗	3.5k	40	21.0	–
StreamBench [37]	✗	1.8k	4.5	25.0	M
OVO-Bench [20]	✗	2.8k	6	66.0	A+M
RTV-Bench (Ours)	✓	4.6k	18	167.2	M

Quality Control To ensure the benchmark’s quality, each video and its corresponding Q&A pairs underwent multiple rounds of review. We manually filtered videos based on length distribution and the presence of sub-scenes examining real-time event changes, resulting in high-quality videos focused on real-time analysis tasks. We conducted manual video-question alignment and precise timestamp checks, utilizing GPT-4 and human review to verify annotation format, translation, and sensitive information.

3 Experiments

3.1 Experiment Setup

Our experiments were conducted across two A800 GPUs to comprehensively evaluate the performance of mainstream MLLMs on our benchmark. The selected models include VideoLLaMA2 [4], VideoLLaMA3 [44], GPT-4O [12], InternLM-XComposer2.5-OmniLive (IXC2.5-OL) [46], VITA1.5 [9], LLaVA-Video [21], LLaVA-OneVision [14], and Qwen2.5-VL [42]. These models were primarily tested with 7B to ensure a fair comparison under similar computational constraints.

Real-Time Video Model vs. Offline Video Model We compare two model categories: traditional offline models (M_{offline}) and novel real-time online models (M_{online}). These categories differ significantly in architecture, training, and data requirements. Architecturally, M_{offline} typically employ sequential vision encoder-decoders, often limited by fixed context windows and incurring higher processing latency. In contrast, M_{online} are designed for continuous, low-latency ingestion of the video stream V . They prioritize maintaining an internal state S_t that summarizes the video information processed up to time t (i.e., $V[0, t]$), enabling real-time responsiveness. Models like IXC2.5-OL [46] implement this using techniques like modular parallelism and dedicated long-term memory. These architectural distinctions lead to different training paradigms and data needs. M_{offline} usually rely on end-to-end fine-tuning using standard annotated video datasets. M_{online} , however, often require specialized training strategies (e.g., VITA-1.5’s staged fusion, IXC2.5-OL’s targeted training for memory and interaction) and benefit most from specialized corpora designed for long-duration, interactive streaming scenarios. The ability of M_{online} to maintain and update state S_t is particularly relevant for RTV-Bench’s Multi-Timestamp QA (MTQA) challenge, where the correct answer $A^*(Q, t_q)$ to a query Q depends on the specific query time t_q . To evaluate both model types on this benchmark, we

adapt the testing procedure. For M_{online} , queries Q are presented at their timestamp t_q , and the models leverage their continuously updated state S_{t_q} to generate the answer $A_{M_{\text{online}}} = M_{\text{online}}(Q, t_q | S_{t_q})$. Since M_{offline} lack this inherent streaming capability, we simulate real-time interaction for them: when a query Q_i is posed at time $t_{q,i}$, we extract and provide only the relevant video segment V_i (corresponding to the query’s context). The offline model’s answer is thus based solely on this isolated segment: $A_{M_{\text{offline}},i} = M_{\text{offline}}(Q_i, V_i)$.

To evaluate the performance of these models, we employed two metrics: **Accuracy** and **Score**.

Accuracy. The accuracy metric measures the proportion of correct answers provided by the model compared to the ground truth.

Score. The score metric evaluates the model’s ability to correctly answer advanced-level questions (type q2), contingent upon its demonstrated mastery of prerequisite basic questions (types q0 and q1) within the same question group, thus emphasizing reliable advanced reasoning built upon a solid foundation. Calculation involves a prerequisite check for each group i : if all basic questions are correct ($B_i = 1$), the group contributes points equal to the number of correctly answered q2 questions ($N_{q2,i}^{\text{correct}}$); otherwise ($B_i = 0$), it contributes zero points. The final score is the ratio of total conditionally awarded points to the total number of q2 questions across all N valid groups (those containing q2). Formula:

$$\text{Score} = \frac{\sum_{i=1}^N B_i \cdot N_{q2,i}^{\text{correct}}}{\sum_{i=1}^N N_{q2,i}^{\text{total}}}$$

where N is the number of valid groups, B_i is the prerequisite indicator (1 if basics are correct, 0 otherwise) for group i , $N_{q2,i}^{\text{correct}}$ is the count of correct q2 answers in group i , and $N_{q2,i}^{\text{total}}$ is the total count of q2 questions in group i . Advantages of this metric include: ensuring foundational accuracy by rewarding advanced correctness only when basics are mastered; reflecting model robustness by penalizing superficial success on complex tasks without fundamental understanding; and aligning with hierarchical learning principles where complex skills build upon simpler ones.

Table 2: Evaluation results on RTV-Bench. **Perception**, **Understanding** and **Reasoning** are different tasks. **FQA** notes that Foundational Video Question & Answering without multi-timestamp answers. **MTQA** notes that Multi-Timestamp Question&Answering with multi-timestamp answers.

Model	#Size	Perception Acc (%) / Score	Understanding Acc (%) / Score	Reasoning Acc (%) / Score	FQA Acc (%)	MTQA Acc (%)	Overall Acc (%) / Score
<i>Open-Source Offline Video Models</i>							
Qwen2.5-VL [42]	7B	33.53/3.53	31.39/3.70	33.65/5.20	31.37	34.37	32.75/4.10
VideoLLaMA2 [4]	7B	40.62/8.67	39.85/7.77	37.49/6.75	45.77	34.95	39.55/7.90
VideoLLaMA3 [44]	7B	37.98/5.83	35.29/5.73	35.78/6.80	38.62	34.91	36.42/6.10
LLaVA-OneVision [14]	7B	35.38/3.97	34.21/4.63	33.57/4.95	35.80	33.58	34.49/4.40
LLaVA-Video [21]	7B	35.83/5.03	33.81/3.77	35.15/5.75	36.28	34.17	34.90/4.80
<i>Open-Source Online Models</i>							
VITA-1.5 [9]	7B	45.66/12.80	44.12/11.83	43.37/10.15	55.06	36.32	44.51/11.80
IXC2.5-OL [46]	7B	<u>47.21/15.87</u>	<u>48.22/15.23</u>	<u>46.18/14.45</u>	59.05	38.21	<u>47.33/15.40</u>
<i>Closed-Source Business Models</i>							
GPT-4o [12]	–	51.61/21.90	49.31/20.76	48.71/23.95	<u>56.53</u>	44.73	50.02/22.10
Gemini 2.0 Flash [34]	–	41.67/11.00	42.71/12.73	41.44/12.05	47.49	<u>38.64</u>	42.00/12.00

3.2 Experiment Results

Online vs. Offline Models. As shown in Table 2, online models optimized for real-time processing—particularly IXC2.5-OL—surpass offline counterparts in overall performance metrics. IXC2.5-OL achieves 47.33% Accuracy and 15.40 Score, significantly outperforming offline models like VideoLLaMA2 (39.55% Accuracy / 7.90 Score). Furthermore, when comparing online models, IXC2.5-OL demonstrates a clear advantage over VITA-1.5 with improvements of 2.82% in Accuracy and 3.6 points in Score. A notable performance gap emerges in temporal analysis tasks: IXC2.5-OL attains 38.21% Accuracy in Multi-Timestamp Question Answering (MTQA), substantially higher than the 33–35% range typical of offline models. This notable discrepancy suggests that current online models may be promising avenues toward continuous analysis capabilities.

Table 3: Detailed evaluation results on the category of **Perception**. Temporal Perception (TP), Visual Perception (VP) and Scene Perception (SP).

Method	#Size	TP Acc (%) / Score	VP Acc (%) / Score	SP Acc (%) / Score	Overall Acc (%) / Score
<i>Open-Source Offline Video Models</i>					
Qwen2.5-VL [42]	7B	32.37 / 2.4	37.48 / 5.8	30.73 / 2.4	33.53 / 3.53
VideoLLaMA2 [4]	7B	39.52 / 7.9	42.49 / 9.4	39.85 / 8.7	40.62 / 8.67
VideoLLaMA3 [44]	7B	37.82 / 6.1	39.24 / 7.6	36.87 / 3.8	37.98 / 5.83
LLaVA-OneVision [14]	7B	35.09 / 3.9	35.86 / 3.8	35.20 / 4.2	35.38 / 3.97
LLaVA-Video [21]	7B	34.07 / 4.8	38.97 / 5.8	34.45 / 4.5	35.83 / 5.03
<i>Open-Source Online Models</i>					
VITA-1.5 [9]	-	46.51 / 12.1	47.09 / 13.2	43.39 / 13.1	45.66 / 12.8
IXC2.5-OL [46]	7B	49.57 / 17.6	49.80 / 16.5	42.27 / 13.5	47.21 / 15.87
<i>Closed-Source Business Models</i>					
GPT-4o [12]	-	48.60 / 18.2	53.59 / 23.4	52.63 / 24.1	51.61 / 21.90
Gemini 2.0 Flash [34]	-	40.49 / 9.5	45.19 / 16.1	39.34 / 7.4	41.67 / 11.00

Open-Source vs. Close-Source Models. While a performance gap persists compared to leading closed-source models like GPT-4o, state-of-the-art online architectures demonstrate remarkable progress. The online model IXC2.5-OL achieves near-top-tier performance with 47.33% Overall Accuracy and 15.40 Score, substantially outperforming mid-range closed-source systems like Gemini 2.0 Flash. Notably, IXC2.5-OL closes the accuracy gap with GPT-4o to 4.4% in perception tasks (Tables 3) and 1.1% in video understanding, demonstrating competitive performance in multimodal domains. However, limitations emerge in complex reasoning where GPT-4o maintains decisive advantages, especially on complex tasks like **Understanding** and **Reasoning** (Tables 4 and 5). This pattern highlights that while modern online models have approached entry-level commercial systems and even challenged premium models in specific competencies, structural innovations remain critical to bridge gaps in advanced cognitive tasks like multi-step reasoning and temporal analysis.

Impact of Model Scales. To investigate the effect of model scale, we evaluated Qwen2.5-VL across 3B-72B parameters. Figure 3 reveals non-monotonic scaling: medium-sized models (7B-34B) outperform both smaller and larger variants. All metrics fluctuate within a 5% range, with no configuration exceeding 34B’s maximums. This scale saturation implies current model architectures may lack the representational efficiency required for effective real-time processing, emphasizing the need for structural innovations rather than pure parameter growth.

Impact of Frame Numbers. Figure 3 presents another counter-intuitive finding. While more input frames typically yield better performance in offline evaluations, our real-time setting shows no performance improvement with increased frames. In fact, IXC2.5-OL exhibits significant degradation. This suggests potential limitations in the model’s processing capacity or a breakdown mechanism, such as attention dilution. A potential limitation is that the current frame numbers may not adequately capture all critical moments or key information within long videos. Even with increased sampling density, crucial details might still be missed.

4 Related Work

4.1 Advanced MLLMs towards Real-time Video Analysis

Video-oriented large-scale models represent a highly promising domain with significant real-world potential, giving rise to numerous valuable applications [27, 8]. Video-LLMs have rapidly advanced, moving from analyzing short videos [15, 21] to longer ones [30, 35, 47] using various techniques. However, most research targets offline video analysis. Real-world applications necessitate real-time,

Table 4: Detailed evaluation results on the category of **Understanding**. Phenomenological Understanding (PU), Global Understanding (GU) and Intent Analysis (IA).

Method	#Size	GU	PU	IA	Overall
		Acc (%) / Score	Acc (%) / Score	Acc (%) / Score	Acc (%) / Score
Open-Source Offline Video Models					
Qwen2.5-VL [42]	7B	29.11 / 2.2	35.69 / 6.9	29.36 / 2.0	31.39 / 3.70
VideoLLaMA2 [4]	7B	37.34 / 7.6	42.21 / 9.5	40.92 / 6.2	39.85 / 7.77
VideoLLaMA3 [44]	7B	33.54 / 5.8	39.13 / 5.9	33.39 / 4.3	35.35 / 5.33
LLaVA-OneVision [14]	7B	32.07 / 4.3	33.51 / 3.0	37.06 / 6.6	34.21 / 4.63
LLaVA-Video [21]	7B	29.42 / 2.5	35.69 / 3.9	36.33 / 4.9	33.81 / 3.77
Open-Source Online Models					
VITA-1.5 [9]	7B	40.30 / 7.2	46.01 / 15.1	46.06 / 13.2	44.12 / 11.83
IXC2.5-OL [46]	7B	43.88 / 11.9	52.17 / 18.7	48.62 / 15.1	48.22 / 15.23
Closed-Source Business Models					
GPT-4o [12]	-	45.02 / 15.7	54.32 / 25.8	48.58 / 20.8	49.31 / 20.76
Gemini 2.0 Flash [34]	-	35.70 / 10.6	45.65 / 11.3	46.78 / 16.3	42.71 / 12.73

Table 5: Detailed evaluation results on the category of **Reasoning**. Future Prediction (FP) and Spatiotemporal Reasoning (SR).

Method	#Size	FP	SR	Overall
		Acc (%) / Score	Acc (%) / Score	Acc (%) / Score
Open-Source Offline Video Models				
Qwen2.5-VL [42]	7B	35.33 / 4.4	33.67 / 4.5	34.50 / 4.45
VideoLLaMA2 [4]	7B	41.47 / 7.5	33.50 / 6.0	37.49 / 6.75
VideoLLaMA3 [44]	7B	38.05 / 6.9	33.84 / 3.9	35.95 / 5.40
LLaVA-OneVision [14]	7B	38.23 / 7.2	28.91 / 2.7	33.57 / 4.95
LLaVA-Video [21]	7B	39.08 / 9.1	31.22 / 2.4	35.15 / 5.75
Open-Source Online Models				
VITA-1.5 [9]	7B	47.95 / 12.2	38.78 / 8.1	43.37 / 10.15
IXC2.5-OL [46]	7B	<u>51.88</u> / <u>18.1</u>	<u>40.48</u> / <u>10.8</u>	<u>46.18</u> / <u>14.45</u>
Closed-Source Business Models				
GPT-4o [12]	–	54.67 / 27.1	42.75 / 20.8	48.71 / 23.95
Gemini [34] 2.0 Flash	–	44.42 / 13.6	38.46 / 10.5	41.44 / 12.05

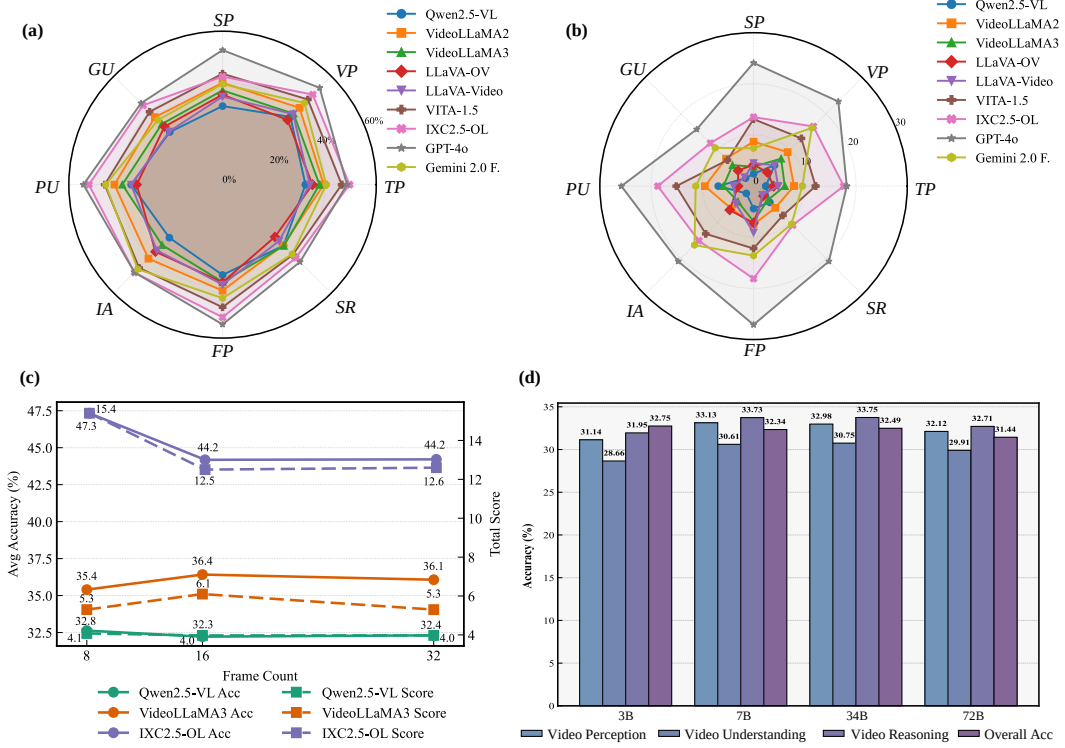


Figure 3: Performance visualization and analysis on RTV-Bench: (a) Visualization of overall **Accuracy** results; (b) Visualization of overall **Score** results; (c) Performance impact of varying input frame counts; (d) Performance comparison across different Qwen2.5-VL model scales.

continuous perception and reasoning on unfolding video streams. While models like InternLM-XComposer2.5-OmniLive [46], VITA-1.5 [9], and Dispider [29] are exploring real-time capabilities, rigorously evaluating their ability to continuously track and understand dynamic events remains a critical challenge.

4.2 Existing Video Benchmarks

Existing benchmarks primarily focus on offline evaluation using offline videos [8, 36, 38]. These are less suited for assessing how MLLMs track dynamically changing states, as they often use static question-answer pairs. Newer benchmarks tackle real-time and streaming aspects [23, 20], evaluating responsiveness and contextual understanding in online settings. However, RTV-Bench specifically addresses the gap in evaluating continuous perception, understanding, and reasoning. Its key distinction is the use of dynamic question answering, where the correct answer evolves with the video stream, directly probing the MLLM’s ability to maintain and update its understanding of complex, unfolding events over time, complemented by a multi-dimensional evaluation structure.

5 Limitations and Future Work

Our benchmark reveals counter-intuitive findings, such as the limited impact of model scale and input frame count on performance, suggesting that MLLM mechanisms for processing continuous video are poorly understood and effective analysis tools are lacking. Furthermore, the current evaluation is primarily limited to the visual modality. Future work will focus on investigating the underlying causes of these phenomena and developing more adapted analytical methods. Concurrently, a key direction involves incorporating important modalities like audio into RTV-Bench to enable a

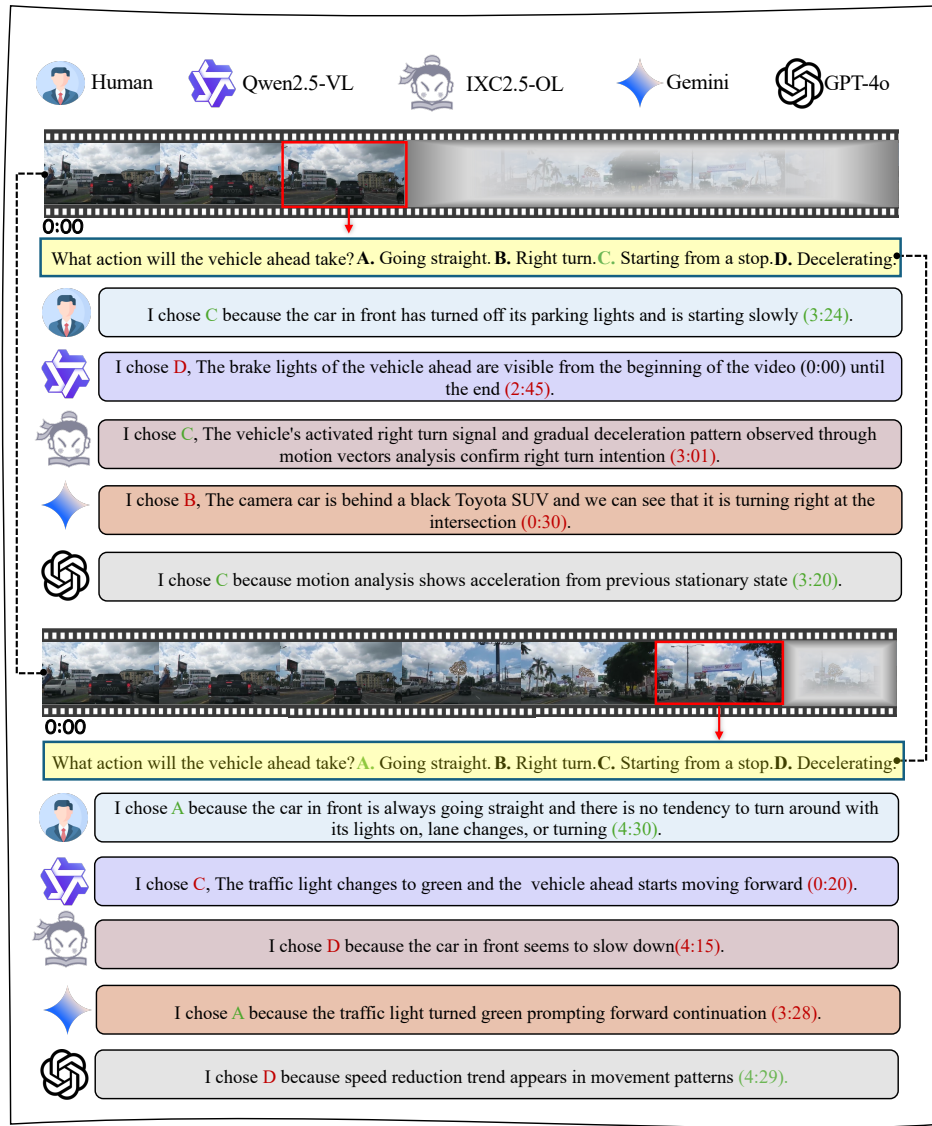


Figure 4: Comparison of response from different models for the same question on the same video. Green indicates correct answers or timestamps; red indicates incorrect answers or timestamps. This case demonstrates that even current high-performance models struggle to provide high-quality responses (where both the answer and the corresponding timestamp are accurate).

more comprehensive evaluation of continuous perception, understanding, and reasoning in realistic multimodal scenarios.

6 Conclusion

In this work, we introduce RTV-Bench, a Benchmark focuses on evaluating the video continuous analysis capabilities of MLLMs. We proposed relevant evaluation tasks and constructed RTV-Bench, which comprises 552 videos and 4,631 QA pairs. Extensive experiments conducted on diverse models reveal that: Models specifically designed for online video processing exhibit superior video continuous understanding capabilities, whereas simply increasing the number of uniformly sampled frames during training or inference stages currently shows limited effectiveness in enhancing performance on video continuous tasks.

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Appendix

The appendix includes the following sections:

- **Section A: Experimental Analysis Supplement.**
- **Section B: Framework Design and Application Extensions.**
- **Section C: Case.**

A Experimental Analysis Supplement

This section supplements the materials on Score Design and OAE Design, including related content and partial experimental data.

Score VS Accuracy In Section 3.1, to comprehensively evaluate the performance of these models, we design two metrics: **Accuracy** for task-specific correctness and **Score** for dynamic reasoning consistency. The Score metric is crucial for revealing reliable, hierarchical reasoning beyond simple Accuracy. While GPT-4o’s Accuracy gain over IXC2.5-OL is moderate (50.02% vs. 47.33%), its substantially higher Score (22.10 vs. 15.40) indicates a more robust reasoning process, reliably building upon foundational understanding to address complex queries. Conversely, lower Scores relative to Accuracy, common among open-source models, suggest instability in multi-step reasoning. Thus, as shown in Figure 3, the Score metric effectively quantifies the deeper, more reliable comprehension capabilities demonstrated by models like GPT-4o on RTV-Bench’s challenging tasks and it can distinguish model performance more clearly.

With the aim of validating the discriminative power of the Score metric, we conducted statistical analysis on 1,527 multi-timespan QA-triples, as shown in A.1. The result revealed a significantly positive correlation between foundational reasoning(Q1-Q2) and subsequent complex reasoning performance(Q3). This demonstrates that models achieving higher accuracy on elementary visual perception tasks exhibit proportionally stronger performance on advanced temporal reasoning tasks.

Such alignment shows our core design philosophy for RTV-Bench: **hierarchical reasoning capabilities** depend on robust foundational perception, mirroring human cognitive processes in real-time video understanding. Furthermore, it also illustrates the rationality of **Score** as a real-time video metric, which addresses critical limitations of conventional single-answer accuracy metrics in assessing continuous reasoning dynamics.

Table A.1: Accuracy Distribution of Question 3 Conditioned on Preceding Question Performance: Q3 Accuracy when at least one of the preceding questions (Q1 or Q2) was answered correctly, versus Q3 accuracy when both preceding questions (Q1 and Q2) were answered incorrectly.

Model	#Size	Q3 Q1/Q2≥1	Q3 Q1&Q2=0
GPT-4o [12]	–	297	64
IXC2.5-OL [46]	7B	499	81
LLaVA-OneVision [14]	7B	309	182
LLaVA-Video [21]	7B	308	195

OAE Design Overview During evaluation, we also incorporated the Object-Action-Event framework(Table B.1) as part of our analytical scope, designed to assess video comprehension from multiple agent-centric perspectives. For example, in live sports scenarios, we evaluate three perspectives: objects (e.g., players appearing or disappearing during an offensive play), actions (e.g., dynamic maneuvers by offensive players), and events (e.g., real-time offensive strategies deployed in the midfield).

Table A.2: Detailed evaluation results on the category of **OAE**. Object, Action and Event.

Method	#Size	Object	Action	Event
		Acc (%) / Score	Acc (%) / Score	Acc (%) / Score
Open-Source Offline Video Models				
Qwen2.5-VL [42]	7B	31.38 / 2.8	34.75 / 4.9	32.63 / 4.5
VideoLLaMA2 [4]	7B	40.39 / 8.2	40.25 / 8.6	38.69 / 6.8
VideoLLaMA3 [44]	7B	34.31 / 4.5	37.77 / 7.4	34.21 / 3.9
LLaVA-OneVision [14]	7B	34.31 / 5.0	35.82 / 4.9	33.42 / 3.4
LLaVA-Video [21]	7B	36.10 / 6.1	35.40 / 4.7	33.88 / 3.8
Open-Source Online Models				
VITA-1.5 [9]	7B	47.39 / 13.7	44.09 / 11.6	42.85 / 10.3
IXC2.5-OL [46]	7B	49.89 / 17.2	46.34 / 14.6	46.61 / 15.4
Closed-Source Business Models				
GPT-4o [12]	–	50.63 / 23	50.97 / 22.3	49.01 / 20.9
Gemini [34] 2.0 Flash	–	42.66 / 12.2	43.34 / 11.5	40.24 / 12.4

Table A.3: Analytical Object Taxonomy: RTV-Bench systematically formulates an object-action-event framework, with explicit definitions of core characteristics and discriminative criteria for each category.

Category	Dimensions
Spatiotemporal Elements	Objects: Physical entities appearing in video frames. Actions: Dynamic behaviors performed by objects. Events: Complex occurrences combining objects and actions.

OAE Accuracy and Score Analysis In Table B.1, GPT-4o maintains the leading positions in all three dimensions of the OAE , and all online models demonstrate significantly higher accuracy and scores compared to offline models, particularly in the Object dimension, this highlights that the perspective design of OAE requires exceptionally strong capabilities in continuous analysis tasks. Overall, the models show no significant gaps in accuracy and scores across the three dimensions. Most offline models achieve their best performance in the Action aspect, while online models excel particularly in Object. Notably, nearly all models exhibit the lowest accuracy and scores in the Event dimension, indicating that continuous analysis tasks with higher complexity remain a formidable challenge for current systems.

B Framework Design and Application Extensions

This section supplements the materials on the rationale for and necessity of evaluation dimension design, while providing an extended analysis on the broader utility of the dataset.

Methodological Foundations for Assessing Continuous Analysis Capabilities To further elaborate on video continuous analysis capabilities introduced In Section 2.2, we formalize the foundational definitions and evaluation protocols for this capacity. Primarily, models are required to possess perception, understanding, and reasoning abilities comparable to state-of-the-art offline video models before addressing real-time streaming contexts. This requirement motivates our two-stage QA design, as elementary offline video analysis capabilities intuitively form the prerequisite for advanced temporal reasoning.

Furthermore, models must demonstrate proficiency in recognizing correct temporal query patterns due to three critical demands inherent to real-time applications: enhanced perception capabilities in highly dynamic scenarios requiring rapid and precise visual processing, deepened understanding of ongoing events under temporal continuity constraints, and effective reasoning about future trajectories based on evolving contextual cues.

Why evaluate across perception, understanding, and reasoning dimensions? To elucidate the necessity of three-dimensional categorization, we subsequently analyze perception, understanding, and reasoning respectively. In egocentric driving environments with high-dynamic scenarios, the video continuous analysis capability fundamentally addresses two aspects of persistent navigation: 1) holistic operational state awareness (e.g., current traffic condition assessment, historical route context) through the integration of offline and online video processing capabilities, and 2) perception speed, comprehension, and analytical capabilities for sudden real-time events.

Regarding perception design, this corresponds to detecting abrupt environmental changes during navigation, such as traffic light transitions, emergent vehicles, and pedestrians - scenarios where conventional video models exhibit critical deficiencies in temporal responsiveness. As visualized in Figure 4, existing architectures struggle to adapt to real-time variations in high-dynamic settings. We systematically decompose this capability into three sub-dimensions: Temporal Perception, Scene Perception and Visual Perception.

Regarding understanding design, it addresses the interpretative capacity for sudden operational changes during driving. For the understanding design, it pertains to scenarios involving the comprehension of abrupt changes during driving, such as interpreting traffic signal indications, road sign semantics, and the rationale behind preceding vehicles’ maneuvering strategies. Previous models have been shown to fall short of fundamental requirements in both processing speed and interpre-

Table B.1: Core Evaluation Dimensions: RTV-Bench systematically defines eight essential evaluation dimensions for continuous video understanding systems, accompanied by formal characterizations and discriminative criteria for each dimension.

Category	Dimensions
Model Capabilities	Temporal Perception (TP): Recognizing temporal sequence and duration. Scene Perception (SP): Understanding holistic environment and layout. Visual Perception (VP): Detecting fine-grained visual features. Future Prediction (FP): Anticipating future developments. Phenomenological Understanding (PU): Interpreting surface phenomena. Intent Analysis (IA): Inferring actor motivations. Global Understanding (GU): Grasping video context. Spatiotemporal Reasoning (SR): Logical deduction from observations.

tative depth. For instance, during traffic signal transitions or lane-changing events, current models struggle to detect such changes within reasonable timeframes. In complex real-time traffic scenarios, beyond insufficient processing speed, existing systems also largely fail to meet advanced comprehension requirements for situational awareness. Through systematic categorization and abstraction of diverse scenarios, we decompose this dimension into three sub-components: Intent Analysis, Phenomenological Understanding and Global Understanding.

Regarding reasoning design, it encompasses scenarios requiring continuous temporal analysis, such as traffic signal duration estimation, and anticipating preceding vehicles' strategies, these demand sophisticated continuous analysis capabilities. Based on the dual requirements of historical context integration and prospective forecasting, we architect this dimension into two sub-dimensions: Spatiotemporal Reasoning and Future Prediction.

Why cross-apply the OAE design with eight evaluation dimensions? We observe notable limitations in the dimensional design frameworks of current mainstream benchmarks, suggesting areas that warrant systematic refinement. Current evaluation taxonomies frequently include components such as Object Recognition and Action Reasoning, yet conspicuously omit complementary dimensions like Object Reasoning and Action Recognition. This prevalent pattern reveals significant arbitrariness in dimension partitioning, resulting in evaluation frameworks whose systematic rigor and scientific credibility remain fundamentally compromised. To address these limitations, we propose a novel taxonomy that first independently categorizes analytical subjects and evaluation dimensions, subsequently implementing cross-categorization to establish a structured and systematic grid framework for dimensional organization.

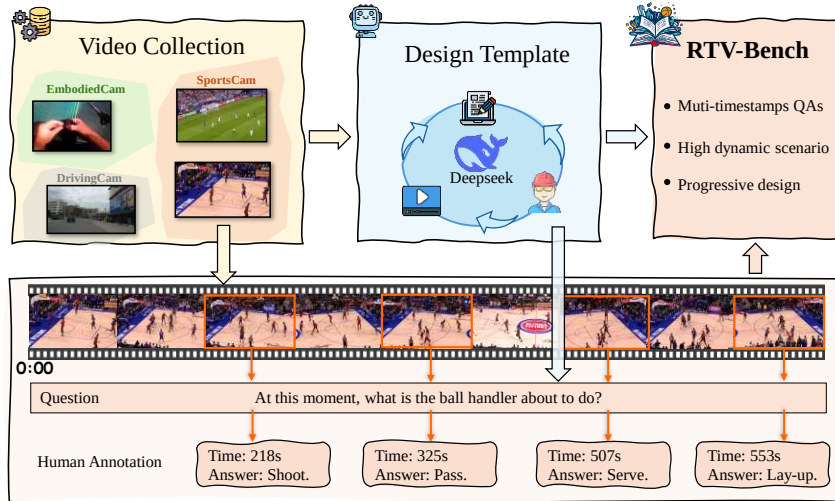


Figure B.1: Our dataset construction pipeline. We develop a dataset generation pipeline consisting of three stages to create RTV-Bench: Video Collection, Templates Design and Human Annotation.

Supplementary Analysis of Dataset Value This work introduces the Real-time Video Understanding Benchmark (RTV-Bench), which holds significant potential to advance video comprehension research and its applications. By defining core capabilities required for real-time video processing through high-dynamic video evaluation, RTV-Bench establishes continuous analysis capabilities as critical developmental objectives. The benchmark demonstrates a novel paradigm for online video capability assessment, potentially accelerating the enhancement of core functionalities in online video understanding models and expediting their deployment in real-time scenarios such as embodied AI, autonomous driving, and live sports commentary.

Experimental analyses using RTV-Bench reveal substantial deficiencies in existing video models’ continuous analysis capabilities while illuminating potential improvement pathways. Our results indicate that increasing model scale or video sampling frequency yields diminishing returns. The substantial performance gap between online and offline models in continuous analysis capabilities not only validates RTV-Bench’s design efficacy but also suggests architectural innovation as a viable development direction.

The RTV-Bench framework is constructed upon three foundational principles: 1) Balanced Taxonomy Design: Prioritizing structural rationality in evaluation dimensions while implementing novel task formulations. 2) QA Integrity Assurance: Maintaining high-quality question-answer pairs while mitigating validity threats from oversimplified QA designs, particularly accuracy inflation through correct guessing in multiple-choice formats. 3) Capability Anchoring: Conducting specialized evaluations for real-time video processing while systematically monitoring potential degradation in foundational video understanding competencies. Furthermore, the rigorous RTV-Bench generation pipeline B.1 also ensures high-quality QA pair production B.2.

Broader Impact By focusing on real-time video comprehension, RTV-Bench rigorously evaluates models’ continuous temporal modeling and dynamic scenario comprehension capabilities. This benchmarking framework directly addresses critical gaps in deploying video understanding systems for latency-sensitive applications, including embodied AI navigation requiring sub-second environmental feedback, autonomous driving systems dependent on frame-by-frame hazard anticipation, and live sports commentary generation demanding real-time event contextualization.

Regarding potential negative societal impact, while RTV-Bench can better facilitate the development and application of real-time video tasks, these technologies may concurrently promote the creation of more sophisticated real-time surveillance systems, which inherently raises privacy concerns. Therefore, the advancement of related technologies must be conducted under the supervision of robust privacy protection measures and ethical standards.

C Case

We present additional examples from RTV-Bench, covering eight evaluation dimensions and three analytical perspectives, to demonstrate the holistic and systematic framework for assessing continuous analysis capabilities.



Figure B.2: This figure presents a word cloud visualization derived from QA question corpora, explicitly highlighting the most frequently occurring terms through typographic prominence.

Temporal Perception

OBJECT

What was the color of the vehicle overtaken by the video car?
A. BLACK B. RED C. YELLOW D. WHITE



Timestamps: 68s

Correct answer: B

Timestamps: 1048s

Correct answer: D

ACTION

What is the pose of the character's hands in the current scene?
A. Left hand open, right hand clenched
B. Right hand open, left hand clenched
C. Both hands open D. Both hands clenched



Timestamps: 90s

Correct answer: A

Timestamps: 114s

Correct answer: C

Timestamps: 131s

Correct answer: B

Timestamps: 167s

Correct answer: D

EVENT

Which part of the target person's body is the character drawing?
A. Mouth B. Nose C. Eyes D. Ears



Timestamps: 59s

Correct answer: A

Timestamps: 87s

Correct answer: C

Timestamps: 111s

Correct answer: D

Timestamps: 125s

Correct answer: B

Scene Perception

OBJECT

Where is the ruler located in relation to the object in the current scene?
A. Bottom B. Top C. Left D. Right



Timestamps: 6s

Correct answer: A

Timestamps: 21s

Correct answer: B

Timestamps: 34s

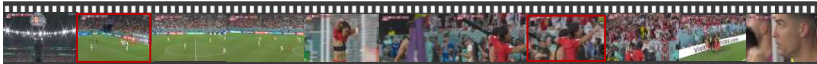
Correct answer: C

Timestamps: 129s

Correct answer: D

ACTION

What did player number 9 do in the past few seconds?
A. Hug the teammates who are welcoming him
B. High-five the celebrating people
C. Jump onto the celebrating people's bodies
D. I can't answer this question



Timestamps: 3s

Correct answer: D

Timestamps: 31s

Correct answer: A

EVENT

Where is the dough being transferred from and to?
A. from the countertop to the machine
B. from the machine to the table
C. from the table to the steamer
D. from the sink to the countertop



Timestamps: 12s

Correct answer: A

Timestamps: 39s

Correct answer: B

Timestamps: 70s

Correct answer: C

Visual Perception

OBJECT

How many things does the man in black have in his hand at this moment?

A. 0 B. 1 C. 2 D. 3



Timestamps: 36s Correct answer: A

Timestamps: 111s Correct answer: B

Timestamps: 177s Correct answer: D

ACTION

Which team scored in the current scene?

A. Cangzhou Mighty Lions
B. Shandong Taishan
C. Cangzhou Mighty Lions



Timestamps: 29s Correct answer: A

Timestamps: 191s Correct answer: C

Timestamps: 332s Correct answer: B

EVENT

How much time has passed since the last shot?

A. 3s B. 5s C. 10s D. 20s



Timestamps: 106s Correct answer: C

Timestamps: 164s Correct answer: D

Timestamps: 185s Correct answer: B

Timestamps: 187s Correct answer: A

Spatiotemporal Reasoning

OBJECT

How many mud bricks did the person make in total during the video?

A. 1 B. 7 C. 3 D. 9



Timestamps: 30s Correct answer: A

Timestamps: 60s Correct answer: C

Timestamps: 133s Correct answer: B

Timestamps: 172s Correct answer: D

ACTION

In which lane from the left to the right are you currently driving?

A. 7 B. 1 C. 2 D. 9



Timestamps: 12s Correct answer: C

Timestamps: 39s Correct answer: B

EVENT

How many vehicles have passed in the opposite direction?

A. 1 B. 2 C. 4 D. 3



Timestamps: 2s Correct answer: B

Timestamps: 6s Correct answer: D

Timestamps: 10s Correct answer: C

Global Understanding

OBJECT

How many hands can be seen in the picture at this moment?

A.1 B.2 C.3 D.4



Timestamps: 33s
Correct answer: B

Timestamps: 50s
Correct answer: C

Timestamps: 56s
Correct answer: A

Timestamps: 79s
Correct answer: D

ACTION

How many cars have passed the intersection in the current scene?

A.1 B.2 C.4 D.9



Timestamps: 1931s
Correct answer: C

Timestamps: 1945s
Correct answer: A

Timestamps: 1967s
Correct answer: B

Timestamps: 1996s
Correct answer: D

EVENT

How many players are currently celebrating?

A.3 B.4 C.5 D.6



Timestamps: 118s
Correct answer: D

Timestamps: 334s
Correct answer: B

Timestamps: 341s
Correct answer: A

Timestamps: 422s
Correct answer: C

Intent Analysis

OBJECT

What is the purpose of the front vehicle's headlights in the current scene?

A. Stop B. Left turn C. Decelerate D. Right turn



Timestamps: 35s
Correct answer: A

Timestamps: 146s
Correct answer: C

ACTION

What is the purpose of removing the screw?

A. Install subsequent components
B. Disassemble the entire object
C. Need to replace the screw
D. Fix components



Timestamps: 7s
Correct answer: A

Timestamps: 142s
Correct answer: D

EVENT

Why does the video car slow down?

A. Slow down when turning
B. Avoiding other cars
C. Passing a speed bump
D. Passing a bumpy road section



Timestamps: 644s
Correct answer: A

Timestamps: 844s
Correct answer: C

Timestamps: 1095s
Correct answer: B

Timestamps: 1279s
Correct answer: D

Phenomenological Understanding

OBJECT



What is the part being repaired by the person in the video?

A. Tire B. Brake mechanism C. Brake disc D. Axle

Timestamps: 3s

Correct answer: C

Timestamps: 101s

Correct answer: B

ACTION



What is the emotional state of the players in this scene?

A. Frustration after conceding a goal
B. Dissatisfaction with the referee's decision
C. Joy after scoring a goal

Timestamps: 57s

Correct answer: C

Timestamps: 240s

Correct answer: A

Timestamps: 274

Correct answer: B

EVENT



At this moment, which team is Argentina playing against?

A. Saudi Arabia B. France
C. Netherlands D. Croatia

Timestamps: 166s

Correct answer: B

Timestamps: 549s

Correct answer: A

Timestamps: 781s

Correct answer: C

Timestamps: 948s

Correct answer: D

Future Prediction

OBJECT



What item is the person about to acquire in the current scene?

A. Vegetables B. Fruits
C. Cutting tools D. Cleaning supplies

Timestamps: 2s

Correct answer: C

Timestamps: 94s

Correct answer: A

ACTION



What does the ball handler want to do at this moment?

A. Shoot B. Pass C. Drive D. Unknown

Timestamps: 15s

Correct answer: C

Timestamps: 17s

Correct answer: B

Timestamps: 321s

Correct answer: A

EVENT



What action will the vehicle ahead take?

A. Going straight B. Turn Right
C. Starting from a stop D. Reversing

Timestamps: 17s

Correct answer: B

Timestamps: 204s

Correct answer: C

Timestamps: 270s

Correct answer: A

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