Table of Contents

A Overview

In the appendix, we first provide a statement on LLM usage (Appendix B). We then present additional benchmark statistics (Appendix C) and the modality ablation experiments for VideoLLaMA2 (Appendix E). Appendix F describes further evaluation details, while Appendix G introduces the definitions and examples of the 16 tasks in HumanVBench. Next, Appendix H details the implementation of each operator in the proposed *Human-Centric Annotation Pipeline*, with a worked example of the annotation process. Finally, Appendix I provides construction details of all tasks and the contributions of human annotators.

B The Use of Large Language Models

The core research idea, including the conceptualization of HUMANVBENCH and its synthesis framework, originated entirely from the authors. Multimodal Large Language Models (MLLMs) and Large Language Models (LLMs) were then integrally utilized as a methodological component to efficiently automate data annotation and challenging question construction for the benchmark, a key focus of our research. Details of MLLM utilization, including the models, prompts, and annotation pipeline, are provided in the methodology section of the main paper (Section 3) and further elaborated in Appendix H and Appendix I. Additionally, LLMs assisted with language refinement during manuscript preparation. The authors assume full responsibility for all content, including research ideas, methodologies, and findings.

C More Statistics of HumanVBench

HumanVBench focuses on short video understanding, specifically videos with a duration of 30-second or less. It includes a total of 2475 question instances, with the specific number for each task indicated in 1. The total video duration amounts to 5.2 hours and demonstrates a variety of people, scenes, and video shooting styles, as shown in 6.

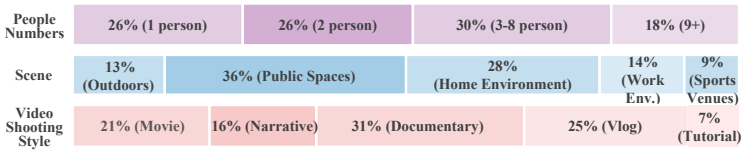


Figure 6: The distribution of the number of people, scenes, and video shooting styles in HumanVBench

D Full Results for 24 Models on 16 Tasks

We meticulously select 22 SOTA open-source video MLLMs. These included both visual-only models such as Qwen-VL series (Bai et al., 2025; Wang et al., 2024), InternVL series (Chen et al., 2024g; 2025), VideoLLaMA3, InternVideo2.5 (Wang et al., 2025a), ViLAMP (Cheng et al., 2025),LLaVA-Video (Zhang et al., 2025c), ShareGPT4Video, CogVLM2-video (Hong et al., 2024), LLaVA-OneVision (Li et al., 2024a), Chat-UniVi (Jin et al., 2024), VILA (Lin et al., 2024b), VideoChat (Li et al., 2023), and audio-visual models capable of analyzing both visual and audio inputs, such as the Qwen2.5-Omni (Xu et al., 2025), MIO (Wang et al., 2025b), Video-LLaMA series (Zhang et al., 2023; Cheng et al., 2024) and generalist MLLMs like ImageBind-LLM (Girdhar et al., 2023), ChatBridge (Zhao et al., 2023), and OneLLM (Han et al., 2024).

E Modality Ablation in VideoLLaMA2

Despite audio-visual MLLMs processing audio data, they perform at random-guess levels on AVSM and ASD tasks, underperforming relative to many vision-only models that rely solely on lip movement analysis. This raises the question: does the poor performance stem from limitations in visual

Table 5: Results on HUMANVBENCH with 15 visual-only MLLMs, 7 audio-visual MLLMs, and 5 proprietary models. "Random" denotes random guessing, and "Human" indicates human-level performance. Task acronyms are defined in Figure 1. For each task, the best overall results are shown in bold, while the best open-source model results are underlined. "-" means the model recognizes its lack of required capabilities for the task and thus refuses to answer. The results for all open-source models are averaged over five runs with different random seeds.

	Emotion Perception					Person Recognition					Behavior Analysis					Speech-Visual Alignment				
Models	**ER**	**ETA**	**AR**	**EIC**	**Avg**	**T2H**	**H2T**	**HC**	**ATD**	**Avg**	**BTA**	**BCA**	**AST**	**TSA**	**Avg**	**AVSM**	**ASD**	**AVAD**	**SCM**	**Avg**
Random	24.6	24.7	25.0	23.1	24.4	27.9	24.6	23.1	25.0	25.2	23.0	23.6	25.0	20.0	22.9	42.8	23.6	33.3	25.0	31.2
ViLA	32.7	24.8	28.7	21.4	26.9	50.4	27.0	40.4	20.2	34.5	33.0	48.6	33.0	51.4	41.5	47.4	23.9	34.3	18.6	31.1
Video-LLaVA	18.3	18.8	26.2	8.0	17.8	27.9	40.6	28.3	31.7	32.1	30.8	32.5	27.0	40.7	32.8	50.0	28.4	34.3	21.2	33.5
Chat-Univi	26.4	15.0	10.9	16.5	17.2	29.1	27.0	17.8	19.8	23.4	27.9	39.4	14.0	6.7	22.0	42.8	20.6	26.3	18.6	27.1
VideoChat2-IT	33.5	29.1	39.6	26.8	32.3	20.1	47.3	11.2	26.7	26.3	45.8	43.7	34.0	24.9	37.1	43.4	27.7	31.4	23.0	31.4
InternVL2	36.1	31.3	40.2	30.4	34.5	70.4	61.2	37.2	20.8	47.4	49.8	52.3	38.0	33.8	43.5	51.7	55.0	33.6	25.5	41.5
Qwen-VL2	38.0	35.1	42.7	37.5	38.3	79.3	72.7	43.4	20.8	54.1	47.8	55.6	32.0	51.4	46.7	50.7	56.1	31.4	23.7	40.5
CogVLM2-Video	38.4	29.9	36.0	25.0	32.3	42.5	51.5	31.1	40.0	41.3	41.9	50.3	34.0	14.1	35.1	59.2	38.7	30.7	17.9	36.6
VideoLLaMA3	34.6	29.9	48.0	46.4	39.7	90.3	67.9	44.9	71.0	68.5	41.5	56.3	56.4	69.0	55.8	64.6	63.1	34.4	17.9	45.0
LLaVAOneVision	36.9	31.3	**62.8**	28.6	39.9	67.0	61.2	49.1	10.0	46.8	45.5	55.6	37.0	47.5	46.4	52.6	51.6	35.0	26.9	41.5
InternVL2.5	37.3	38.1	54.3	37.5	41.8	81.0	73.3	40.6	35.8	57.7	53.0	57.6	41.0	62.1	53.4	65.1	61.3	32.1	15.4	43.5
InternVideo	35.7	42.9	47.6	35.7	40.5	64.2	69.1	50.9	42.5	56.7	56.1	58.3	42.0	55.9	53.1	59.4	59.4	32.8	31.6	41.5
Qwen-VL2.5	43.0	30.6	35.4	**50.0**	39.8	88.8	74.5	50.9	30.8	61.3	51.0	58.3	34.0	50.8	48.5	71.1	61.3	33.6	18.8	46.2
ShareGPT4Video	35.0	39.1	40.9	29.5	36.1	33.0	38.8	24.5	43.3	34.9	32.8	43.7	39.0	16.9	33.1	44.1	31.0	34.3	25.0	33.6
LLaVA-Video	35.4	32.3	59.8	28.6	39.0	74.3	61.8	44.3	26.7	51.8	41.9	57.0	47.0	58.8	51.2	52.0	58.7	32.8	39.3	45.7
ViLAMP	41.4	29.3	48.8	31.2	37.7	59.8	62.4	45.3	20.0	46.9	55.7	49.7	52.0	36.7	48.5	53.3	51.0	32.3	31.6	42.1
VideoLLaMA	30.8	21.6	11.5	20.5	21.1	28.4	23.0	23.9	20.0	23.8	22.9	41.1	23.2	15.4	25.7	40.1	26.6	33.1	26.2	31.5
VideoLLaMA2.1	38.0	30.6	47.0	30.4	36.5	34.6	52.7	41.5	16.7	36.4	53.8	60.3	27.0	33.3	43.6	44.0	31.6	32.1	23.7	32.9
MIO	29.3	20.3	29.3	10.7	22.4	4.5	18.2	10.4	23.3	14.1	22.9	39.7	29.0	19.2	27.7	42.1	31.6	16.1	19.6	27.4
ImageBind-LLM	21.3	22.4	25.0	11.6	20.1	23.5	13.3	23.8	19.5	20.0	15.4	32.4	24.0	23.3	23.8	45.0	25.1	28.9	22.9	30.5
ChatBridge	28.9	18.0	30.2	16.1	23.3	31.4	30.9	23.7	8.7	23.7	24.1	43.7	41.0	16.9	31.4	43.7	25.3	30.4	24.4	31.0
OneLLM	27.0	26.1	34.1	7.1	23.6	29.0	36.4	20.6	27.8	28.5	24.9	49.0	23.0	22.4	29.8	43.4	26.4	29.5	23.2	30.6
Qwen2.5-Omni	42.2	30.1	36.6	33.0	35.5	56.4	64.2	41.5	15.8	44.5	45.8	55.0	28.0	24.3	38.3	71.1	48.4	27.0	71.8	54.6
GPT-4o (20241120)	36.5	43.6	25.6	28.5	33.6	49.2	77.0	47.2	32.5	50.9	62.1	62.9	52.0	71.2	62.1	-	-	-	-	-
GPT-5 (20250807)	43.7	48.9	59.8	34.8	46.8	69.8	84.8	64.2	58.3	69.5	73.1	66.9	64.0	65.0	67.3	-	-	-	-	-
Gemini-1.5-Pro	49.4	51.9	53.0	49.1	50.9	87.1	73.9	52.8	71.7	**71.4**	53.4	60.3	54.0	**75.1**	60.7	90.1	76.8	66.4	84.6	79.5
Gemini-2.5-flash	52.1	**57.1**	59.1	43.8	53.0	92.2	77.6	61.3	71.7	75.7	65.6	68.9	58.0	67.2	64.9	**98.7**	**80.6**	57.7	**99.1**	84.0
Gemini-2.5-Pro	**54.4**	54.1	53.0	**50.0**	**52.9**	**95.0**	**84.8**	**69.8**	**84.2**	**83.5**	**79.0**	**72.2**	**63.0**	68.4	**70.7**	96.7	78.7	**72.3**	98.3	**86.5**
Human	87.6	85.0	87.8	78.0	84.6	98.9	84.1	92.5	78.3	88.5	86.7	84.5	88.6	88.1	87.0	96.0	96.1	87.0	98.3	94.4

Table 6: The performance of VideoLLaMA2's vision-only version (VideoLLaMA2-7B-16F), and the audio-visual version (VideoLLaMA2.1-AV), on HUMANVBENCH, based on different modal inputs (A for Audio, V for Visual).

Models	**Input Modal**	**Speech-Visual Alignment**				
		AVSM	**ASD**	**AVAD**	**SCM**	**Avg**
Random		42.8	23.6	33.3	25.0	31.2
Video-LLaMA2.1-AV	A, V	44.0	31.6	32.1	23.7	32.9
Video-LLaMA2.1-AV	V	43.4	29.0	32.8	18.8	31.0
VideoLLaMA2-7B-16F	V	47.4	38.1	32.1	15.4	33.3

analysis (e.g., lacking lip-reading ability) or from the interference of audio input? To explore this, we conducted ablation experiments using the VideoLLaMA2 model series, chosen for its open-source availability of both vision-only and audio-visual variants.

As shown in the Table 6, VideoLLaMA2-7B-16F (vision-only) exhibits only a slight advantage over Video-LLaMA2.1-AV (audio-visual) on AVSM and ASD tasks, yet still lags far behind vision-only models such as VideoLLaMA3 and InternVL2.5 (Table 5). This indicates that VideoLLaMA2-7B has inherently poor lip-reading capability, which further implies that the audio-visual variant (Video-LLaMA2.1-AV) also suffers from limited visual lip-reading ability. Such limitations constrain its upper-bound performance in speech-visual alignment tasks. On the other hand, Video-LLaMA2.1-AV shows no significant performance advantage when utilizing audio information compared to its vision-only counterpart. This suggests that vocal information is not effectively leveraged, likely due to insufficient speech parsing capability in video MLLMs and inadequate understanding of cross-modal associations between audio and visual content.

F MODEL EVALUATION IMPLEMENTATION

Prompt. In order to facilitate the statistical model to answer the results, following common practices used in MLLM evaluations (Jiao et al., 2025b), we adopt the following prompt to guide the MLLM to

output option letters: " *Select the best answer to the following multiple-choice question based on the video. Respond with only the letter of the correct option. <Question-choices> Only answer best answer's option letter. Your option is:* ". **Evaluation Environments.** All evaluation experiments for open-source models were conducted on a single NVIDIA L20 GPU with an inference batch size of 1.

Baseline Configurations and Runtime Statistics. Table 7 shows the scale, parameter settings, and costs (including memory usage and end-to-end testing time) for each model on HUMANVBENCH. All hyperparameter settings follow the default configurations of these open-source works.

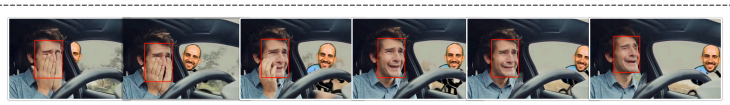
Model	Time (min)	top_p	top_k	num_beams	temp.	frames
Chat-UniVi (7B)	40	1	50	1	0.2	1 f/s
CogVLM2-Video (8B)	37	0.1	1	1	0.2	1 f/s
Video-LLaVA (7B)	49	1	50	1	1	8 f
LLaVA-OneVision (7B)	49	1	50	1	1	8 f
PLLaVA (7B)	41	0.9	50	1	1	16 f
ShareGPT4Video (8B)	50	0.9	50	1	1	16 f
Otter-V (7B)	62	1	50	3	1	16 f
VideoChat2-IT (7B)	53	0.9	50	1	1	16 f
InternVL2 (7B)	44	1	52	1	1.0	8 f
InternVL2.5 (7B)	31	1	52	1	1.0	8 f
Qwen2-VL (7B)	45	0.001	1	1	0.1	2 f/s
Qwen2.5-VL (7B)	35	0.001	1	1	0.1	2 f/s
LLaVA-Video (7B)	182	0.8	20	1	0.7	64 f
Video-LLaMA3 (7B)	90	0.8	20	1	0.7	1 f/s
InternVideo2.5 (7B)	170	1	50	1	1	128f
ViLAMP (7B)	29	0.8	20	1	0.7	1 f/s
Video-LLaMA (7B)	40	1	50	2	1	8 f
Video-LLaMA2.1 (7B)	31	0.9	50	1	0.2	8 f
ImageBind-LLM (7B)	77	1	50	1	1	15 f
ChatBridge (13B)	29	1	50	1	0.2	4 f
OneLLM (7B)	130	0.75	50	1	0.1	15 f
MIO (7B)	88	0.7	0	1	1	FPS/10
Qwen2.5_Omni (7B)	91	1	50	1	1	2 f/s
GPT-4o (20241120)	191	1	-	-	1	FPS/10
Gemini-1.5-Pro	254	1	40	-	0.9	API

Table 7: Model configuration and runtime statistics evaluated on HUMANVBENCH (one pass for all provided test samples).

G DEFINITIONS AND EXAMPLES FOR EACH TASK

G.1 EMOTION PERCEPTION

Emotion Recognition aims to judge the overall emotional state of the person highlighted by a red bounding box in the video. An example is shown in Figure 7.



Question - Please focus on the human in the video highlighted with red bounding box. What complex emotions is the man in the car experiencing that caused such a dramatic change in his behavior?

Options -

A. The man is experiencing a mix of joy and surprise, which led to his emotional distress and crying.

B. The man in the car is experiencing a complex mix of emotions, including sadness, fear, and possibly grief, which led to his dramatic change in behavior.

C. The man in the car is experiencing a range of complex emotions, including happiness, frustration, and possibly even embarrassment.

D. The man in the car is experiencing a range of complex emotions that led to a dramatic change in his behavior, but he is not feeling any sadness.

Figure 7: Example of Emotion Recognition task.

Emotion Temporal Analysis involves analyzing the changes in the emotions of the people highlighted with the red bounding box over time, identifying gradual intensification, diminishment, emotions shifts to test the model's ability to track emotional dynamics. An example is shown in Figure 8.

Question - Please focus on the human in the video highlighted with red bounding box. How does the man's emotional state evolve throughout the video? Please describe the sequence of emotions.

Options -

A. The man starts off feeling curious and surprised, then becomes happy and excited at certain points, and finally to a state of relief.

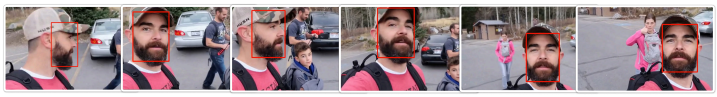
B. The man starts off feeling curious and surprised, then becomes happy and excited at certain points, and finally to a state of relief.

C. The man's emotional state evolves from neutral to angry.

D. The man's emotional state evolves from neutral to surprised, then to shocked, and finally to a mix of shock and confusion.

Figure 8: Example of Emotion Temporal Analysis task.

Attitude Recognition involves inferring a character's attitude towards things, categorized into four fixed options: positive, neutral, negative, and indeterminate. An example is shown in Figure 9.



Question - Please focus on the human in the video highlighted with red bounding box. What is the man in the pink shirt and baseball cap's attitude towards exploring new places? Positive, negative, neutral or indeterminate?

A. Neutral

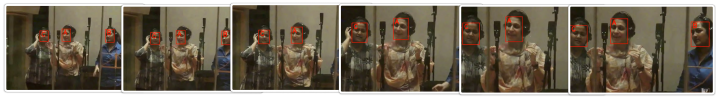
B. Indeterminate

C. Positive

D. Negative

Figure 9: Example of Attitude Recognition task.

Emotion Intensity Comparison requires compares the emotional intensity differences among various individuals in the video to find the most emotional person, assess whether the model can quantify and differentiate emotional intensity. An example is shown in Figure 10.



Question - Please focus on the humans in the video highlighted with red bounding boxes and labeled with letters. Which person in the image, A, B, C, has the strongest emotion? What specific emotion is it?

A. C-happiness

B. B-joy

C. A,happier

D. A-sadness

Figure 10: Example of Emotion Intensity Comparision task.

G.2 Person Recognition

Text-to-Human requires the model to identify the specific person in a multi-person video based on a given text description, to test the model's ability to locate and identify the described person. An example is shown in Figure 11.

Question - Please focus on the human in the video highlighted with red bounding boxes and labeled with letters. Please select the person in the video that best matches the following description:
The person is a man wearing a dark shirt and a blue and red hat, stands on the left, looking straight ahead.

A. A B. B C. C D. D E. E

Figure 11: Example of Text-to-Human task.

Human-to-Text asks the model to choose the most accurate description of the target person in a multi-person video, to ensure that the person is clearly distinguished from others and uniquely identified. This task requires the model to analyze and compare individuals in the video, identifying distinguishing features of the target person, such as appearance, clothing, actions, location, and other characteristics. An example is shown in Figure 12.

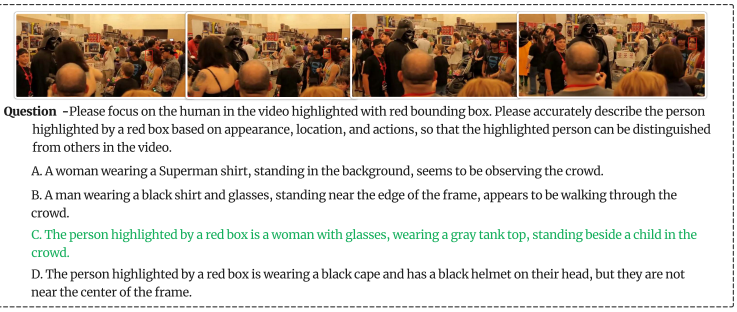


Figure 12: Example of Human-to-Text task.

Human Counting requires the model to determine the total number of distinct individuals in the video, testing its capability to detect, track, and accurately count individuals in complex scenes. An example is shown in Figure 13.

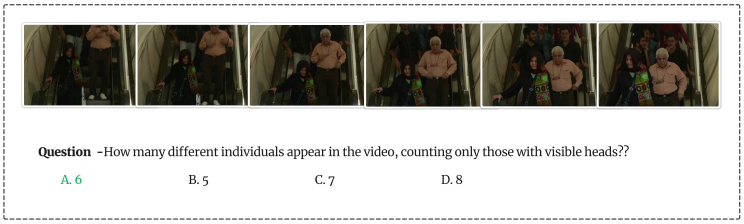


Figure 13: Example of Human Counting task.

Appearance Time Detection requires the model to identify the exact time frames when a specified person appears, demanding the ability to precisely mark the start time, end time, and duration of the individual's presence in the video. An example is shown in Figure 14.

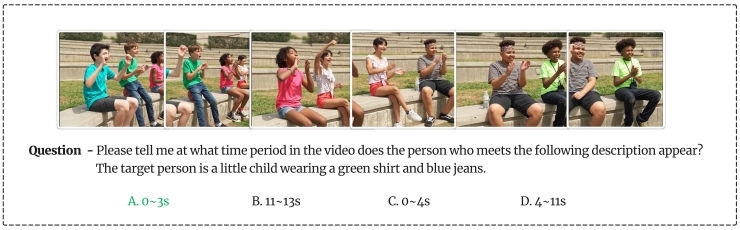


Figure 14: Example of Appearance Time Detection task.

G.3 Human Behavior Analysis

Behavior Temporal Analysis involves analyzing the dynamic changes in a specified person's behavior over time, testing the model's ability to accurately capture and track the temporal characteristics of these changes. An example is shown in Figure 15.

Behavior Causality Analysis aims to investigate the causal relationships underlying a specific behavior, requiring the model to determine whether a person's behavior in the video is triggered by a particular event or leads to subsequent actions. An example is shown in Figure 16.

Question - Please focus on the human in the video highlighted with red bounding box. What sequence of actions does the man in the red shirt perform in the video?

A. The man in the red shirt walks up to a group and hugs them.

B. The man in the red shirt performs a sequence of actions including raising his arms, shaking hands with another person, and then introducing the woman to that person.

C. He raises his legs, walks backward, and then waves at the camera.

D. The man in the red shirt performs a high-five with another person in the video.

Figure 15: Example of Behavoir Temporal Analysis task.

Question - Please focus on the human in the video highlighted with red bounding box. What might cause the man in the yellow and black uniform to kick the soccer ball?

A. The man in the yellow and black uniform might kick the soccer ball as part of a training drill or to pass the ball to a teammate.

B. He may be attempting to score a goal during a practice session.

C. The man in the yellow and black uniform kicks the soccer ball as a result of the referee's whistle.

D. The man in the yellow and black uniform kicks the soccer ball because he is hungry.

Figure 16: Example of Behavior Causualty Analysis task.

Action at Specified Time asks the model to identify a person's behavior or state at a specific time, testing its ability to accurately determine the person's action or state at the given moment. An example is shown in Figure 17.

Question - Please focus on the human in the video highlighted with red bounding box. What special action does the person highlighted by the red bounding box do at 6s of the video?

A. begins to brush the dog

B. begins to pet the dog

C. begins to smile

D. face close to the dog

Figure 17: Example of Action at Specific Time task.

Time of Specific Action focuses on determining the time when a specific behavior occurs, requiring the model to accurately pinpoint the time of a particular action in the video. An example is shown in Figure 18.

Question - Please focus on the human in the video highlighted with red bounding box. The person highlighted by the red bounding box performed a special action in the video: tun around and touch the brim of the hat. At what second of the video did this occur?

A. 7s B. 1s C. 4s D. This is an ongoing action in the video.

Figure 18: Example of Time of Specific Action task.

G.4 Cross-Modal Speech-Visual Alignment

involves analyzing audio cues in multi-person videos to identify the individual whose appearance matches the voice. This task evaluates whether the model can recognize the voice gender and age and compare them with the appearance of the person in the video. An example is shown in Figure

19.

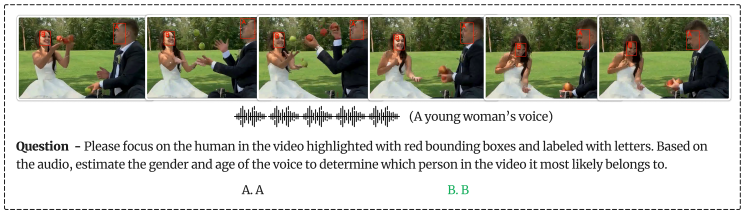


Figure 19: Example of Audio-Visual Speaker Matching task.

Active Speaker Detection asks the model to identify the active speaker in the video, requiring the model to accurately identify who is speaking by combining audio cues with the characters' lip movements. An example is shown in Figure 20.

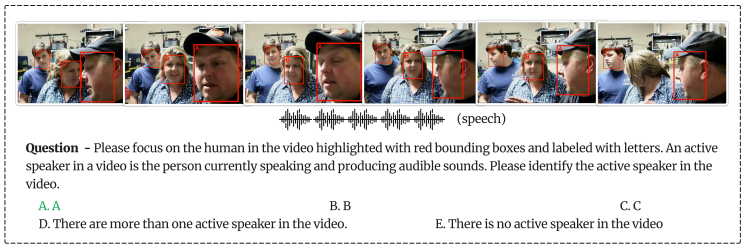


Figure 20: Example of Active Speaker Detection task.

Audio-Visual Alignment Detection requires detecting when the audio and video are synchronized, evaluating the model's ability to synchronize audio and visual content, particularly through analyzing the speaker's lip movements and voice. An example is shown in Figure 21.

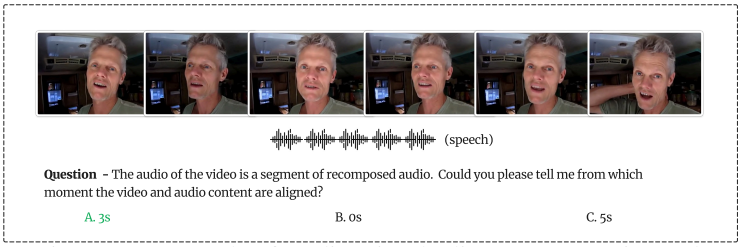


Figure 21: Example of Audio-Visual Alignment Detection task.

Speech Content Matching requires matching the speech content of the video with text, validating the model's ability to transcribe speech or translate lip movements into text. Figure 22 shows an example.

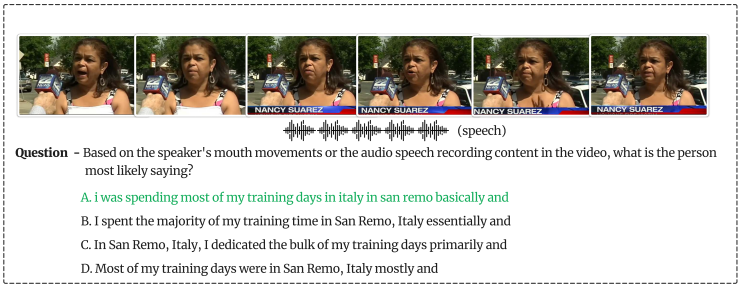


Figure 22: Example of Speech Content Matching task.

H ANNOTATIONS DETAILS AND EXAMPLES IN *Human-Centric Annotation Pipeline*

For the in-the-wild videos collected from Pexels, we first apply splitting and filtering operations. Specifically, we begin by utilizing the `video_resolution_filter`, `video_aesthetics_filter`, and `video_nsfw_filter` operators to select videos that meet the following criteria: a resolution of at least 1280 in width and 480 in height, acceptable aesthetics, and appropriate content. Next, the `video_split_by_scene_mapper` is used to split the videos into scenes. The resulting clips are then filtered using the `video_duration_filter` to exclude clips shorter than 1 second and the `video_motion_score_filter` to remove static videos. These steps utilize existing operators in Data-Juicer (Chen et al., 2024b), with parameters set to their default values except for the `video_motion_score_filter`, where the minimum motion score is set to 1.2. After completing these foundational steps, we apply the `video_face_ratio_filter` with a threshold of 0.65 to retain videos containing people. These videos are then processed using a series of mappers to generate fine-grained, multi-modal, human-related annotations.

We use a video example to demonstrate the annotation process and results, as shown in Figure 23. Below, we detail the models and settings used for each operator.

For the `video_human_tracks_extraction_mapper`, we follow the approach of Light_ASD (Liao et al., 2023), utilizing S3FD (Zhang et al., 2017) as the face detector. A face bounding box is added to a human track if its overlap rate exceeds 50%. After obtaining the face track, we identify the corresponding body bounding box for each face bounding box in the same frame to generate a second bounding box track for the individual, referred to as the body track. The matching criterion selects the candidate bounding box with the smallest horizontal center distance and a smaller area. This process can be expressed by the following formula:

$$\text{closest\_bbox} = \underset{\text{bbox} \in \text{candidate\_bboxes}}{\arg\min} \left(\left(\frac{x_1 + x_2}{2} - \frac{\text{f\_x1} + \text{f\_x2}}{2} \right)^2 + (x_2 - x_1)(y_2 - y_1) \right), \tag{1}$$

where f_x1,f_x2 are the left and right boundaries of the face bounding box, the candidate human bounding boxes are obtained using YOLOv8-human, x_1, x_2, y_1, y_2 are the boundary values of a candidate human bounding box. If no bounding box meets the criteria, the frame is skipped, and detection proceeds with the other frames. Finally, the empty elements in the body track are replaced with the average of the bounding boxes from the surrounding frames.

In the `human_demographics_mapper`, we use DeepFace to perform frame-level detection of facial gender, age, and race. The analysis is conducted on cropped frames obtained directly from the `video_human_tracks_extraction_mapper` results. Finally, for a given face track, the demographics features are determined by taking the mode of the frame-level gender and ethnicity detections, and the median of the age detections.

In the `video_human_description_mapper`, we use the body bounding box track to crop the video, creating a reconstructed video focused on a single individual. This reconstructed video is then processed using ShareGPT4Video (Chen et al., 2024e) for appearance description and simple actions.

In the `video_facial_description_mapper`, we use the face bounding box track to crop the video, creating face-focused reconstructed videos for emotion description using Qwen2.5-VL (Cheng et al., 2024).

The `audio_tagging_mapper` is a built-in operator in Data-Juicer, which we use directly for audio type classification.

The core model for the operator `active_speaker_detection_mapper` is ASD-Light (Liao et al., 2023). Each face track sequence is analyzed together with the corresponding audio segment for the same time period. The model outputs a score sequence of the same length as the face track's frames, where each score evaluates whether the individual is speaking in the current frame. Positive scores indicate active speaking, while negative scores indicate not. To assign a binary "speak or not" label to a human track, we classify an individual as an active speaker if the longest sequence

of consecutive positive scores exceeds 12 frames. Notably, to reduce false positives, we cross-check the voice-based gender and age attributes with the individual's demographic features. If there is a significant mismatch, the positive label is reassigned as negative.

The automatic speech recognition model used in the `ASR_mapper` is SenseVoice (An et al., 2024), which can also be utilized in the `speech_emotion_recognition_mapper`. For the `voice_demographics_mapper`, we use the wav2vec2 (Baevski et al., 2020) model.

The results of the `video_description_mapper` are not directly involved in the construction of multiple-choice questions in this work. However, the environment, atmosphere, and events occurring in the video play a crucial role in understanding the actions and expressions of individuals. Therefore, we have included this mapper in the Human-Centric Annotation Pipeline. The example shown in Figure 23 is generated by ShareGPT4Video.

Notably, in the Human-Centric Video Annotation Pipeline, all the models we use are based on the most advanced open-source models available. As more powerful and specialized models emerge, integrating them into our pipeline can further enhance the quality of annotations.

I Complete Construction Details of All Tasks

We will first explain the details of six descriptive questions generated using the Distractor-Included QA Generation Pipeline, followed by the construction details of the remaining tasks.

I.1 Construction Details of 6 Descriptive Human-Centric Questions

We first present the general instruction templates in the six task generation processes.

The prompt template for the three Video-MLLMs used to refine answers and generate raw distractors is:
Please focus on the people whose heads are highlighted with red bounding boxes in the video and answer my question: ⟨Question⟩; Provide a brief response in one sentence.

The instruction used to compare the answers is:
Based on the video and my question: ⟨Question⟩Tell me which answer is better: (A). ⟨current model's answer. ⟩(B). ⟨previous best answer⟩. Just answer (A) or (B).

The prompt template used in the "LLM for Generating Distractors" in Figure 3 is:
Below is a ready-made question and its multiple-choice options: ⟨Question⟩, Proper Answer: ⟨Answer⟩, Distractors1: ⟨eliminator1⟩, Distractors2: ⟨eliminator2⟩, Distractors3: ⟨eliminator3⟩. This question-option set may have the following issue: The current distractors have no errors; they simply represent alternative answers to the question. This makes the correct answer less distinct compared to the distractors. Therefore, I would like your help to add minor, distinct errors to each distractor so that the correct answer is clearly the only Proper Answer. Here are the minor errors type available for selection: ⟨error type⟩.
Remember that the modified distractors must meet the following requirements: 1. Be modified from the original distractor with only slight changes. You are not allow to creat new ones from scratch. 2. Be distinctly different from the Answer, without being overly semantically similar. Minor errors can be added. 3. Differ from each other. 4. Distractors should have similar length to the correct answer. If it is too short, lengthen the description.

In addition to the questions and options, the differences include the ⟨error types⟩. Next, we describe the construction of each task in detail.

Emotion Recognition: Since *Label-5* is naturally a description based on face-focused cropping videos, it is directly used as the task-oriented caption. Additionally, *Label-4* is included in the task-oriented caption to enhance the detail of the questions. Considering that most in-the-wild videos exhibit positive or neutral emotions, while we aim to ensure a sufficient proportion of negative emotions in the evaluation, videos for question generation are preselected at a ratio of positive:neutral:negative = 1:1:2. This selection is achieved by using an LLM to classify the emotional polarity of the descriptions. The resulting balanced category captions are used for question generation, with the following prompt:

Please generate one question and answer pair based on the person's description: ⟨task-oriented caption⟩. the question should closely related to emotion recognition. Here is an question example: "What emotions might the girl in red dress be experiencing during her practice?"
The video for the question is marked using the face bounding box from the target character's *Label-1*. The type of minor errors (⟨error types⟩) introduced for building distractors is: *Add incorrect emotional descriptors or modify the original emotional descriptors to incorrect ones.*

Emotion Temporal Analysis: We first select videos longer than 7 seconds and then identify described characters with emotional changes based on *Label-5* (using an LLM for binary classification). The videos of these characters are used for question generation. For this task, *Label-5* is directly used as the task-oriented caption, with *Label-4* added to enhance the details of the questions. The question generation prompt is:
Please generate a question-answer pair based on the following video caption. Please note that the questions must be related to the emotional temporal changes. Here are some example: 1. How does the girl in red's emotions change as the video progresses? 2. How does the girl in red's emotions change as she dances in the video?
The video for the question is marked using the face bounding box from the target character's *Label-1*. The type of minor errors introduced for building distractors is: *Add some incorrect emotions to the sequence, remove some correct emotion words, or change the original emotional descriptors to incorrect ones.*

Behavior Temporal Analysis: First, videos longer than 7 seconds are selected for question generation. Then, the target character in the video is highlighted using the face bounding box track from *Label-1*. Based on the marked videos, appearance cues of the target character (i.e., *Label-4*) are added to help to guide the model's attention to the individual. The prompt for obtaining the task-oriented caption is designed as follows:
Please focus on the person highlighted by the red bounding box (⟨Human_Appearance⟩) and tell me if the actions of the person changed over time and what actions does the person take in order? Respond according to the following format: {"Action_Change": True or False, "Action_Sequence": action sequence}.
Based on the task-oriented captions, select characters with changes in actions for LLM question generation. The prompt for question generation is: *Please generate a question-answer pair based on the following human's behavior caption. The generated questions should focus on identifying the action sequence of the highlighted person. The following is a description of a human in the video. ⟨action_sequence⟩. The focused person is ⟨appearance⟩. Here is a question template you can refer to: What actions and behaviors does the girl in the red dress display in the video in order? List them sequentially. Remember do not reveal the answers in your questions and the answer should be brief and just in one sentence.*
The type of minor errors introduced for building distractors is: *Add some nonexistent actions, remove some actions, or replace correct actions with incorrect ones.*

Emotion Intensity Compare: First, count the number of frames corresponding to the track with the longest appearance time in each video. If there are more than three and less than seven tracks in the video that reach this number of frames, keep the video for question generation. This step mainly use the information from *Label-1* . All individuals corresponding to the tracks with the most frames will be used for question generation. The question video is created by utilizing these human tracks to mark the individuals and adding letter labels. For this task, initial question-answer pairs are directly created. The question is, "Which person in the image, ⟨LETTERS⟩, has the strongest emotion? What specific emotion is it? Please respond briefly in the format ⟨letter-emotion⟩.", in which ⟨LETTERS⟩ refers to all the selectable individuals' letter labels. The answer is, "The emotional intensity of the selectable characters in the image is similar, and they are all neutral." The subsequent three models will refine the answer.
The type of minor errors introduced for building distractors is: *If the letters are the same, minor modifications to the emotions can be made to make the options different; if the letters referring to people are different, the emotions can remain unchanged.*

Human-to-Text: First, select videos with 3 to 7 individuals based on *Label-2*, and then choose the person who appears the most frames in the video as the target individual for question generation. Next, highlight the target individual in the video using the face bounding box track from *Label-1*.

Based on the marked video, appearance cues of the target individual (i.e., *Label-4*) are added to help the model focus on the person. The prompt for obtaining the task-oriented caption is designed as follows:
Please accurately describe the person highlighted by a red box(⟨appearance⟩), your answer can be based on appearance, location, and actions, so that the highlighted person can be distinguished from others in the video. Please respond in only one sentence and begin with "The person is ...".
Based on the above description of the target individual, the question-answer pair is directly constructed. The question is fixed as: "Please accurately describe the person highlighted by a red box based on appearance, location, and actions, so that the highlighted person can be distinguished from others in the video." The initial answer is the task-oriented caption.
The type of minor errors introduced for building distractors is:*Based on the items, people, and position information, add small modifications to make the location information incorrect; alternatively, you can also modify the description of the person's appearance to introduce errors.*

Behavioral Causality Analysis: The construction process is similar to the design process of Behavior Temporal Analysis. First, videos longer than 7 seconds are selected for question generation. Then, the target individual in the video is highlighted using the face bounding box track from *Label-1*. Based on the annotated video, appearance cues of the target individual (i.e., *Label-4*) are added to assist the model in identifying the person to focus on. The prompt for obtaining the task-oriented caption is designed as follows:
Please describe the causal events related to the person highlighted by the red bounding box (⟨appearance⟩) in the video: what causes this person to exhibit a certain behavior, or what actions does this person take that led to a certain event. If no causal events exist, respond without causal events. Please answer in the following format: {"causal_events_exist": True or False, "causal_events_description": description}.
Videos and target individuals with causal relationships (i.e. "causal_events_exist" is true) are then selected for question generation. The prompt for question generation is: *Please generate a question-answer pair based on the following video caption. The generated questions should inquire about causal reasoning related to the character's expressions or behaviors. The following is a description of the human in the video: ⟨causal_events_description⟩. The focused person is ⟨appearance⟩. You should either follow the causal analysis question template "Analyze why the girl in the red dress raises her hand." or the result derivation question template "What does the girl in the red dress raising her hand lead to?". Remember do not reveal the answers in your questions and the answer should be brief and just in one sentence.*
The type of minor errors introduced for building distractors is: *Explain the result using incorrect causes, misdescribe the effect of the cause-and-effect relationship, reverse the order of cause and effect, exaggerate or minimize factors.*

I.2 Construction Details of 10 Closed-Ended Human-Centric Questions

Attitude Recognition: This task is constructed based on the first half of the Distractor-Included QA Synthesis Pipeline. The human who appears in the most frames is selected as the target for question generation. The target individual is highlighted in the video using the face bounding box track from *Label-1*. Based on the annotated video, appearance cues of the target individual (i.e., *Label-4*) are added to the prompt to help the model focus on the intended person. The prompt used to obtain the task-specific caption is:
Focus on the person highlighted by the red bounding box (⟨appearance⟩) and tell me: Do the highlighted people display certain attitudes toward specific objects and events? What kind of attitude is it?
The prompt used for question generation is:
Please generate a best question-answer pair based on the following video caption. The generated questions should focus on analyzing the character's attitude, which should be one of positive, negative, or neutral. The following is a description of the human in the video. ⟨task-specific caption⟩The focused person is ⟨appearance⟩. Here are some question templates you can refer to: 1. What is the attitude of the girl in the blue shirt towards taking the bus in the video? positive, negative, or neutral? 2. What is the woman in the beige jacket's attitude? Positive, negative, neutral? Please remember not to reveal the answers in your questions and the answer should be brief and just in one sentence.
The options consist of four choices: Positive, Negative, Neutral, and Indeterminate. The Indetermi-

nate option is included as a supplemental choice to ensure answers optional.

Text-to-Human: The criteria for selecting the videos for questioning are consistent with the Emotion Intensity Compare task selection rules. Then, use the same method as Human-to-Text to obtain task-specific captions and directly use the description of the target person to complete the question template: "Please select the person in the video that best matches the following description: ⟨human description ⟩". The video corresponding to the question is marked with the face bounding boxes of all individuals using *Label-1*, and each individual is distinguished by a capital letter label. The selectable options are the letter labels representing each person.

Human Counting: For an annotated video, the approximate number of people in the video can be estimated directly using *Label-2*. However, due to issues such as blurred crowd background, overlapping between people and objects and other factors, this estimate is often imprecise, especially in crowded scenes. Therefore, *Label-2* is only used to adjust the question distribution (3–5 people: 60, 6–8 people: 60, 9+: 54). The ground truth number is manually annotated, and distractors are constructed based on this value. The distractors construction rule is to randomly select three different numbers within a range of up to 4 from the ground truth number, excluding the ground truth itself.

Appearance Time Detection: First, select videos based on the following criteria: the video duration must exceed 7 seconds, and the target individual's presence should account for between one-third and two-thirds of the total video length (calculated as the ratio of the human track frames to the total frames), primarily using *Label-1*. Then the frame range from *Label-1* is used to determine the target individual's appearance time range (format both ends as integers), which serves as the ground truth for generating questions about this person.

To obtain a detailed and accurate description of the individual, the same method as in the Human-to-Text task is used to generate the task-specific caption for the target. Using the description, questions are constructed in a template-based manner, as shown in Figure 14.

For distractor construction, three random time intervals are generated near the ground truth time interval, ensuring that their overlap with the ground truth interval does not exceed 4 seconds. This ensures the distractors do not cause confusion when selecting the correct answer.

Note that in this task, videos with bounding boxes are only used during the automatic description generation by Video-MLLMs and for manual verification. In the final version of the questions, the videos do not include bounding boxes.

Action at Specified Time and **Time of Specific Action** tasks rely on manual annotation, as attempts with various open-source models revealed their inability to accurately identify the timing of specified actions. For manual annotation, annotators are required to watch the videos and observe whether the highlighted individual performs any distinct short-term actions (quickly completed actions or "the start of an action", but not continuous states). They should record the action and its starting time. The videos and target individuals are consistent with those in Behavior Temporal Analysis task. Based on the specific action–time pairs provided by the annotators, two types of action-time-related questions are constructed.

	Human Emotion Perception				Person Recognition				Human Behavior Analysis				Speech-Visual Alignment			
Labels	**ER**	**ETA**	**AR**	**EIC**	**T2H**	**H2T**	**HC**	**ATD**	**BTA**	**BCA**	**AST**	**TSA**	**AVSM**	**ASD**	**AVAD**	**SCM**
Label-1	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		
Label-2					✓	✓	✓						✓	✓	✓	✓
Label-3													✓			
Label-4	✓	✓	✓		✓	✓		✓	✓	✓	✓					
Label-5	✓	✓														
Label-6													✓	✓	✓	✓
Label-7														✓	✓	✓
Label-8																✓
Label-10													✓			

Table 8: Annotation labels used in the construction process of 16 tasks

For the Action at Specified Time task, the question video consists of the highlighted target individuals with red bounding boxes. Only video samples where short-term actions are present are selected for question generation. The question template is shown in Figure 17. The ground truth is the specific action annotated for the individual. Distractors are generated by LLM from the task-specific captions in Behavior Temporal Analysis, with the following prompt:
Please select and modify 3 actions from the list below to ensure that each action is significantly different from the target action ⟨ground truth action⟩. Here is the original action list: ⟨action_list⟩. Begin with "begin to .." for an action. If the number of actions is less than 3, generate one.,
where the ⟨action_list⟩is the sequence of actions generated by using LLM to summarize the task-oriented caption.

For the Time of Specific Action task, the question video is marked with target individual's bounding boxes. The question template is shown in Figure 18. For question samples with short-term actions, distractors are generated by selecting three numbers that are at least 3 seconds apart from the ground truth action time. For videos where a continuous action state is maintained throughout, the ground truth is set to "This is an ongoing action in the video." The distractors for such cases are fixed at 1s, 4s, 7s, and 10s. Note that to keep the options consistent, each question includes the option "This is an ongoing action in the video."

Audio-Visual Speaker Matching: First, select the appropriate question videos. The constraints mainly include video conditions and character conditions. The video conditions include: the audio label being "Speech", the number of people in the video is between 2 and 4, and the video duration is not less than 4 seconds; the character condition is: the frame coverage of the character must reach more than 67% of the video frame number. Further, the target person is selected as the ground truth according to the correlation between the age and gender attributes of the audio and the appearance of the person. Specifically, if the audio age belongs to "child", the only child is selected from the video as the target person, and the other characters are interference characters; If the audio age is "adult", the only adult with the same gender as the audio is selected from the video as the target person, and the other characters are interference characters. The age information is binary here because the audio age attribute is relatively vague. In addition, the gender characteristics of children's voices are not always distinguishable. Therefore, in order to enhance the optionality of the answer, the character types are divided into only three categories: male, female, and child. The question video uses *Label-1* to mark each optional person and capital letters as the option.

Active Speaker Detection: Suitable question videos are selected based on the criteria of having an audio label of "Speech", 2 to 4 people, and a duration of at least 4 seconds. The video must contain a single active speaker. *Label-1* is used to label all individuals, with the active speaker's label as the ground truth and others as distractors. Since the automated active speaker labels may not always be reliable, two additional options are included for each question to facilitate manual correction later: "There are more than one active speaker in the video." and "There is no active speaker in the video."

Audio-Visual Alignment Detection: Suitable question videos are selected based on the criteria of having fewer than 3 people, a duration of over 8 seconds, an audio type of "speech", and at least one active speaker. The video is then divided into three equal segments, with the left endpoint of each segment (rounded to an integer) used as potential options. One of these options is randomly chosen as the ground truth. The video is then modified by reversing the audio before the selected timestamp to create a "misaligned audio-visual" video.

Speech Content Matching: Videos are selected for question creation based on the following criteria: single-person scenes, duration greater than 5s, audio type "speech", and the person is an active speaker, the speech content being English with its sentence length greater than 35 characters. The ground truth is the automatic speech recognition result corresponding to *Label-8*. Distractors are generated using an LLM, which creates three different sentences with similar meaning and length to the ground truth as distractors.

In Table 8, we illustrate which labels from the Human-Centric Video Annotation Pipeline are used to construct each task.

I.3 Details of Human Efforts for HumanVBench

We employed two professional full-time AI data annotators and invited two graduated-level volunteers to participate in the construction and evaluation of HumanVBench. They collaborate to complete a series of tasks, with two main annotators participating in the full data of each task and two volunteers participating in the sampled data. Inconsistencies will be identified and resolved (for example, through discussion or majority voting to reach a consensus) to ensure high quality. The average annotation time per question is 3 minutes, totaling 10 workdays. Specifically, their tasks include the following four parts.

Human Annotation on Generated QAs: Tasks requiring human annotations to generate questions and options include Human Counting, Action at Specified Time, and Time of Specific Action. The latter two tasks can streamline annotation by annotating a single dataset containing "special short-term action & moment of occurrence". Therefore, in this step, each annotator was assigned to one annotation set. All other tasks were generated automatically, reducing the cost of human annotation.

Manual Verification and Correction: Except for the tasks that are already reliable enough, which include three tasks derived from the aforementioned human annotations, the Audio-Visual Alignment Detection and Speech Content Matching tasks, all other tasks require manual verification to ensure quality, following the process described in Section 3.3. During correction, low-quality samples (e.g., person transitions in human tracking, video freezing midway) are required to be flagged for removal.

Cross-Verification: After completing the above steps, we obtained 16 usable tasks for evaluation. To further ensure the high quality of the questions, we conducted cross-verification on 16 tasks except Emotion Recognition in Conversaton task to reduce the impact of personal biases and errors on the benchmark. Specifically, the tasks were cross-assigned to the two major annotators. For each task, the annotator in this step was ensured to be different from those responsible for the Manual Verification and Correction or Human Annotation. Annotators were first required to answer the multiple-choice questions. For disputed questions where answers were marked "incorrect", the new correct answer or option will be updated for this question, and these disputed questions were reassigned to another annotator for a second review. If errors persisted, both annotators discussed and agreed on a unified answer to serve as the final ground truth.

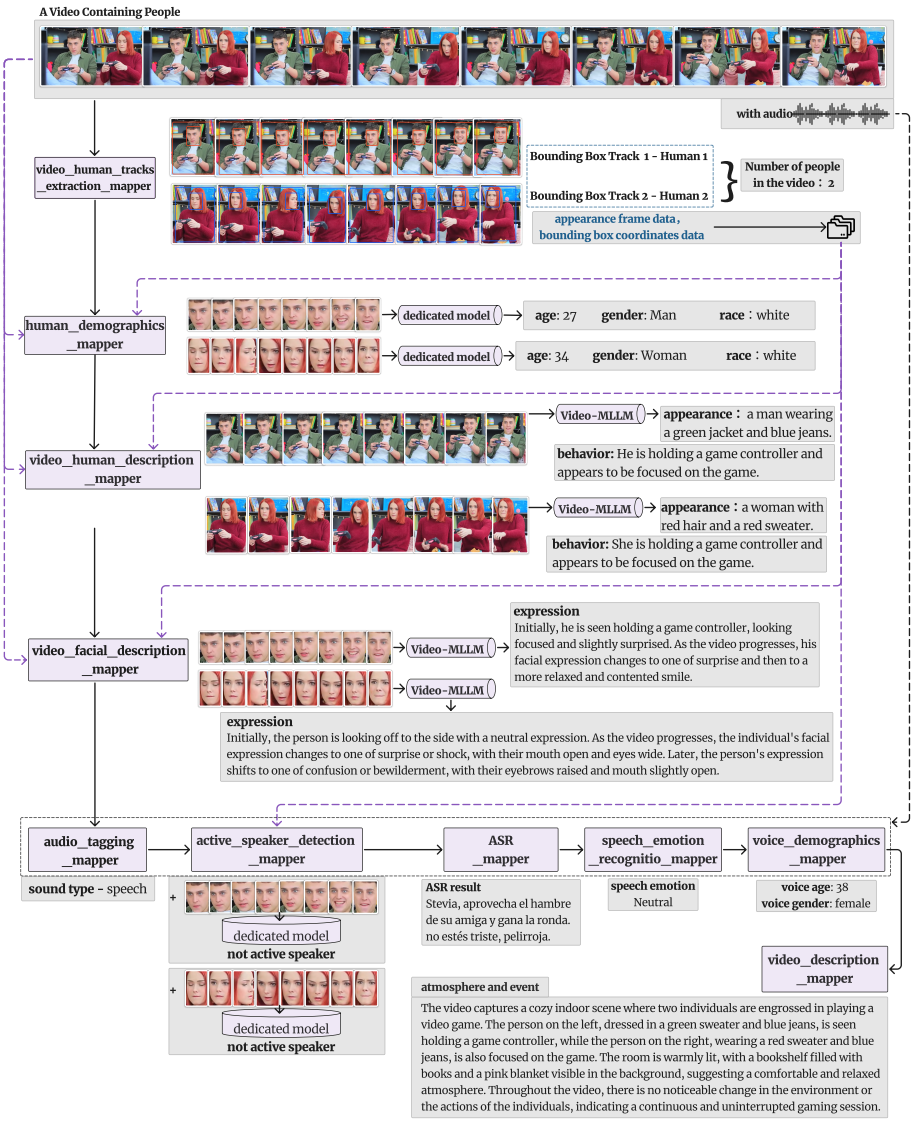


Figure 23: An example of using Human-Centric Annotation Pipeline for annotation.