MMHU: A LARGE-SCALE MULTIMODAL BENCHMARK FOR HUMAN BEHAVIOR UNDERSTANDING IN AUTONOMOUS DRIVING

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Figure 1: We propose **MMHU**, a large-scale dataset for human behavior understanding. We collected 57k human instances with diverse behaviors such as playing with a mobile phone, holding objects, or using mobility devices, from diverse scenes such as in the city, school, park, and alley. We provide rich annotations, including motion and trajectory, text descriptions for human motions, and the labels for behaviors that are critical to driving safety.

ABSTRACT

Humans are integral components of the transportation ecosystem, and understanding their behaviors is crucial to facilitating the development of safe driving systems. Although recent progress has explored various aspects of human behavior—such as motion, trajectories, and intention—a comprehensive benchmark for evaluating human behavior understanding in autonomous driving remains unavailable. In this work, we propose **MMHU**, a large-scale benchmark for human behavior analysis featuring rich annotations, such as human motion and trajectories, text description for human motions, human intention, and critical behavior labels relevant to driving safety. Our dataset encompasses 57k human motion clips and 1.73M frames gathered from diverse sources, including established driving datasets such as Waymo, in-the-wild videos from YouTube, and self-collected data. A human-in-the-loop annotation pipeline is developed to generate rich behavior captions. We provide a thorough dataset analysis and benchmark multiple tasks—ranging from motion prediction to motion generation and human behavior question answering—thereby offering a broad evaluation suite. Our dataset will be released to promote further human-centric research in this vital area of autonomous driving.

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1 INTRODUCTION

Humans play an essential role in transportation systems, making the comprehensive understanding of human behaviors—such as motion (Xu et al., 2023), intention (Osman et al., 2023; Xie et al., 2024; Yang et al., 2022), and trajectory (Zhang et al., 2024c; Fang et al., 2024)—critical for developing safe autonomous driving systems. To effectively interact with humans, autonomous vehicles must answer human-centric questions, such as "What is the person doing?", "Is the person going to cross the street?", and "Where does the person intend to go?" Failing to accurately comprehend these behaviors could lead to misinterpretations of human intent, potentially resulting in fatal accidents.

While significant efforts have been devoted to understanding individual aspects of human behaviors by investigating human motion, intention, and trajectory, the absence of a unified dataset limits the comprehensive evaluation of algorithms for human behavior understanding, especially in autonomous driving scenarios that mainly account for human safety. Existing driving datasets are typically designed for general driving tasks, such as depth estimation, 2D or 3D object detection, odometry, and semantic segmentation (Sun et al., 2020; Caesar et al., 2020; Geiger et al., 2013), or narrowly designed human-related tasks, such as intention prediction (Rasouli et al., 2019; Bhattacharyya et al., 2021; Rasouli et al., 2017b), motion and trajectory prediction (Von Marcard et al., 2018), or motion reconstruction (Wang et al.; Kim et al., 2024; Liu et al., 2024c). Moreover, with the emergence of driving-oriented vision-language models (VLMs) (Touvron et al., 2023; Lin et al., 2023a; Chen et al., 2024c; Liu et al., 2024b; 2023b; 2024a; 2023a; Zhang et al., 2024b; Bai et al., 2023) , human behavior understanding tasks can now be approached in a more integrated and flexible manner through images and text queries. However, existing training data for these VLMs are not specifically tailored to human behavior, limiting their effectiveness in capturing critical human-centric details essential for safe driving.

In this work, we aim to answer three core questions regarding human behavior understanding tasks in autonomous driving scenarios: ❶ What aspects of human behavior are critical to autonomous driving? ❷ How effectively do current approaches model human behaviors in autonomous driving contexts? ❸ How can a comprehensive benchmark advance the development of human behavior understanding algorithms? To this end, we propose **MMHU**, a large-scale unified benchmark explicitly designed for comprehensively understanding various human behaviors in driving scenarios. MMHU includes rich annotations generated by a human-in-the-loop annotation pipeline, enabling scalable and precise labeling from diverse data sources using only monocular video inputs. Specifically, we have collected 1.73M frames featuring 57K human instances from source videos obtained from Waymo (Sun et al., 2020), YouTube, and self-collected data. As shown in Fig. 1, the dataset provides detailed annotations covering: **(1)** human motion and trajectory; **(2)** text descriptions of human motions generated using templates and VLMs; **(3)** critical human behaviors extracted via VLMs, along with question-answer (QA) pairs designed to benchmark driving-oriented and generalist VLMs.

Our contributions can be summarized as follows:

- We introduce **MMHU**, a unified, human-centric dataset that provides a comprehensive understanding of humans' behaviors in driving scenarios that can be used as a benchmark for a range of human-centric understanding tasks.
- We develop a scalable, human-in-the-loop annotation pipeline employing multi-source fitting strategies to produce accurate labeling across diverse video sources, ranging from driving videos and general YouTube videos to self-collected streams.
- We evaluated baseline methods of human behavior understanding and analyze their performance, we further demonstrated that our dataset helps these methods achieve better performance.

2 RELATED WORKS

2.1 HUMAN MOTION

Human motion is essential to autonomous driving. We categorize human motion representations into 2D and 3D representations. 2D human motion (Jiang et al., 2024b; Belagiannis & Zisserman, 2017; Luo et al., 2021; Li et al., 2021; Jin et al., 2020) leverages keypoints or heatmaps to mark the local body motion on the image. For 3D representations, the SMPL series (Loper et al., 2015; Romero et al., 2017; Pavlakos et al., 2019) provide compact and expressive representation via learned

parameters. While most human motion datasets focus on general human motions (Ionescu et al., 2013; Von Marcard et al., 2018; Xu et al., 2024; Mahmood et al., 2019; Lin et al., 2023b), there are several datasets are specially designed for driving scenarios (Wang et al.; Liu et al., 2024c; Kim et al., 2024). However, these datasets mainly focus on the human movements and their text description, the behaviors of humans remain unavailable. Based on the representation and datasets, several efforts have been put into human motion reconstructions from temporally aligned multi-view cameras (Huang et al., 2021), unaligned multi-view cameras (Dong et al., 2020), and monocular cameras (Luvizon et al., 2023; Li et al., 2022; Ye et al., 2023; Yuan et al., 2022). Other works have explored human motion generation from action labels (Cervantes et al., 2022) or text (Tevet et al., 2022; Zhang et al., 2024a). However, due to the lack of high-quality data, there is little work that specifically generates human motion in driving scenarios.

2.2 Human Behavior Understanding

Understanding human behavior in driving situations is essential for driving safety. Although there are some datasets and methods to understand human behavior and actions (Zhang et al., 2024c; Rai et al., 2021; Punnakkal et al., 2021; Wang et al., 2012; Li et al., 2010; Soomro et al., 2012; Niebles et al., 2010; Kay et al., 2017; Marszalek et al., 2009), they mainly focus on recognizing human actions in general or sports scenes. While sharing some common behavior that concerns driving safety, they mainly focus on general actions like shaking hands, dancing, or running. The behaviors specifically concerning driving safety remain unexplored. In autonomous driving, besides motion reconstruction, there are some approaches and datasets for understanding several aspect of human behaviors such as (1) human trajectory prediction (Zhang et al., 2024c; Goncalves & Busso, 2022; Medina et al., 2024; Wang et al., 2024c; Guo et al., 2023; Mao et al., 2020), where models are required to predict the future trajectory from previous ones, or (2) human intention prediction (Zhang et al., 2023; Osman et al., 2023; Sharma et al., 2023; Rasouli et al., 2019; Kotseruba et al., 2021; Rasouli et al., 2017a), where pedestrians are simply classified into two states - crossing the street and not crossing the street. Besides the binary classification of crossing the street, there are several datasets Kwak et al. (2017); Quintero et al. (2015); Schneider & Gavrila (2013); Rasouli et al. (2017b) that provide more detailed behavior labels such as stopping, glancing, or running. However, these works still focus on specified aspects of human behavior, such as the posture and action when a pedestrian is crossing the street. Recently, the development of vision language models (VLMs) (Touvron et al., 2023; Lin et al., 2023a; Chen et al., 2024c; Liu et al., 2024b; 2023b; 2024a; 2023a; Zhang et al., 2024b; Bai et al., 2023) enables question-answering based on images or videos, making human behavior understanding more flexible. There have been many specialists driving VLMs (Ma et al., 2024; Sima et al., 2024; Chen et al., 2023a; Shao et al., 2024; Wang et al., 2024b; Yuan et al., 2024; Chen et al., 2024a) and autonomous driving QA datasets (Marcu et al., 2024; Arai et al., 2024; Nie et al., 2024; Chen et al., 2024a; Inoue et al., 2024; Qian et al., 2023). However, these models and the datasets are designed for general VQA tasks for autonomous driving. The comprehensive understanding of human behaviors remains unexplored. We show a comparison of related datasets in Tab. 1.

2.3 Autonomous Driving Datasets

Autonomous driving has been one of the most popular research topics in recent years. There are several datasets that are specially created for developing and evaluating autonomous driving algorithms (Geiger et al., 2013; Sun et al., 2020; Caesar et al., 2020; Maddern et al., 2017). These datasets are typically collected from a vehicle mounted with multiple sensors, such as multi-view cameras, LiDARs, RaDARs, IMU, etc., supporting autonomous driving tasks such as 2D and 3D object detection, semantic segmentation, depth estimation, and planning. Further, some works such as BDD-X (Kim et al., 2018) and Rank2Tell (Sachdeva et al., 2024) have put significant efforts into improving the explainability of decisions made by the automatically driven vehicles. WOMD-Reasoning (Li et al., 2024) leveraged commercial VLM to generate large-scale interaction reasoning data in driving. However, it is built for general autonomous driving, lacking structured labeling of human behaviors. In addition, the dataset is totally labeled by VLMs without human involvement. The labeling quality will be highly restricted by the VLM's ability and is inflexible to further incorporate human knowledge. Recently, several works have focused on some specific scenes in autonomous driving, such as the accident (Fang et al., 2021), snowy scenes (Chen et al., 2023b), and foggy scenes (Sakaridis et al., 2018). Some datasets have provided the labeling of several aspects of human behaviors in driving scenarios, such as human motion and trajectory (Kim et al., 2024; Wang et al.;

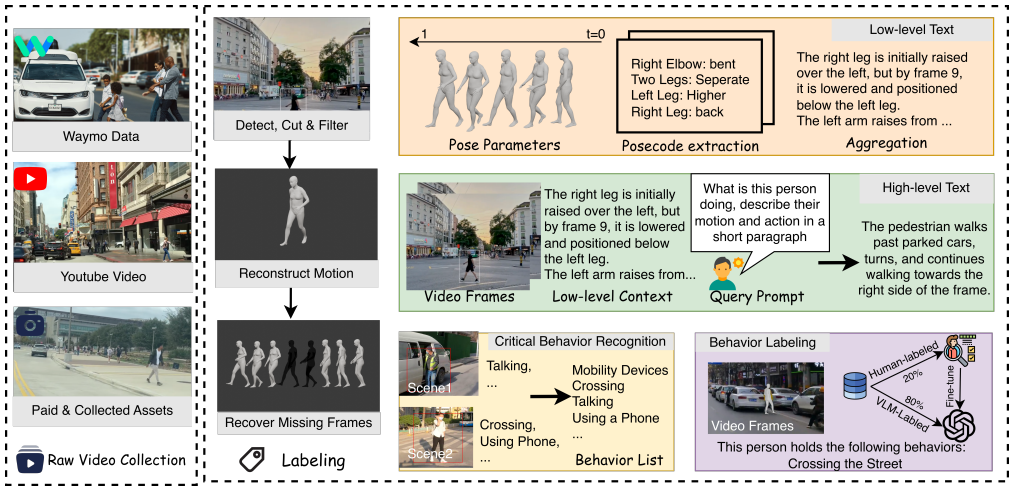


Figure 2: **Data Collection and Annotation.** (Left) We collect data from three sources: the Waymo dataset, the YouTube videos, and the self-collected or paid driving videos. (Right) We demonstrate the annotation pipeline; we first filter and cut the raw videos based on the rough human detection results. Then we reconstruct the SMPL motion for each detected frame. The missing frames are further recovered by an interpolation procedure. For the labeling of text descriptions, we leverage low-level text as a bridge between the SMPL parameters and the semantic label. Then we generate the high-level text from the low-level ones and the video. We recognize the critical behavior lists by leveraging a VLM to go through the Waymo (Sun et al., 2020) data, based on the visual and text information. For behavior labeling, we first employ human annotators to label a small portion of the data, then a VLM is fine-tuned on the human-labeled data and used to label the rest of the instances.

Liu et al., 2024c; Taketsugu et al., 2025; Saadatnejad et al.), intention of crossing the street (Rasouli et al., 2017b; Bhattacharyya et al., 2021; Rasouli et al., 2019), or in the form of general VQA (Arai et al., 2024; Qian et al., 2023; Inoue et al., 2024; Sima et al., 2024). However, these datasets only investigate some specific human behaviors, and the comprehensive understanding of human behavior remains unexplored.

3 The MMHU Dataset

Overview. We propose **MMHU**, a comprehensive human-centric benchmark with rich annotations, emphasizing the criticalness of human behavior understanding in autonomous driving. We built our dataset using high-quality videos from various sources, as shown in Fig. 2. Then we applied a scalable annotation pipeline that only involves minor human effort to get the rich annotations from the collected videos. The annotation for each video clip includes the 3D motion with trajectory, intention, high- and low-level text description, and critical behavior labels concerning driving safety. We will present our data collection details in Sec. 3.1. We then introduce the annotation pipelines and data analysis of human motion and trajectory (Sec. 3.2), text description (Sec. 3.3), and intention and critical behaviors (Sec. 3.4). We show the statistics of the dataset in Sec. 3.5. We show some visualization of the data sampled from MMHU in Fig. 4.

3.1 Data Collection

Video Acquisition. We collected raw videos of 1.73M frames in total from three kinds of data sources as follows: Autonomous Driving Data contains multi-modality sensor information and rich annotation for generic autonomous driving tasks such as object detection, depth estimation, etc. We collected 1.7 hours videos from Waymo (Sun et al., 2020), which consist of 73K frames. In-the-wild Data includes first-person driving videos that are publicly available on the Internet. We collected 10 hours of YouTube videos, each with a CC license, consisting of 318.25K frames with a resolution ranging from 1080p to 2k. Self-collected Data is driving recordings collected by ourselves or from paid sources. We collected 66.5 hours of videos, consisting of 2393.96 k frames and the resolution varies from 1080p to 4k.

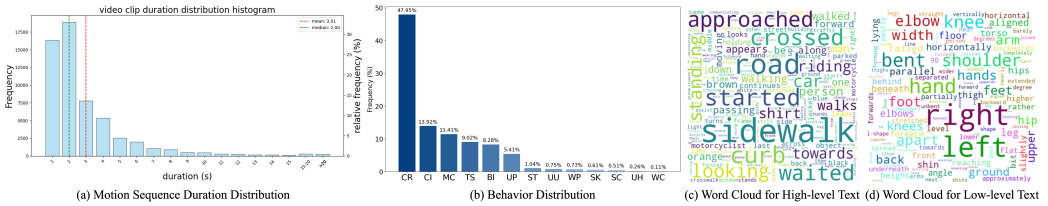
Table 1: **Comparison of Related Datasets.** We compare our dataset with related datasets. From left to right, the columns are the dataset name, total frame count or time duration, human count, providing labels of motion, trajectory, VQA pairs, and text descriptions, and the number of behavior classes. ‡ represents datasets for general purposes. Datasets labeled with * in the "Instance" column capture the motion from real participants. † means upper-bound; § means only consisting the rough direction of the trajectory; ¶ means estimated number. Datasets labeled with "Unstructured" in the last column do not provide explicit human behavior labels but involve them in the QA pairs or captions. Our dataset supports all four tasks and provides the most behavior classes among the driving datasets.

Dataset	Frames / Duration (s)	Instances	Motion	Trajectory	VQA	Text	Behaviors
PIE (Rasouli et al., 2019)	293k / -	1.3k	✗	✗	✗	✗	1
Euro-PVI (Bhattacharyya et al., 2021)	83k / -	7.7k	✗	✗	✗	✗	1
PMR (Wang et al.)	225k / -	54*	✓	✓	✗	✗	✗
CityWalker (Liu et al., 2024c)	- / 110k	120k	✓	✓	✗	✓	✗
BlindWays (Kim et al., 2024)	300k / 10k	11*	✓	✓	✗	✓	Unstructured
3DPW‡ (von Marcard et al., 2018)	51k / 1.7k	7*	✓	✓	✗	✗	✗
Human3.6M‡ (Ionescu et al., 2013)	3.6M / -	11*	✓	✓	✗	✗	15‡
JAAD (Rasouli et al., 2017b)	82k / 33k†	2.2k	✗	✗	✗	✗	11
Drama (Malla et al., 2023)	- / 36k	-	✗	✗	General Driving	✓	Unstructured
CoVLA (Arai et al., 2024)	6M / -	-	✗	✗	General Driving	✓	Unstructured
DriveLM-nuScenes (Sima et al., 2024)	4.8k / -	-	✗	✗	General Driving	✓	Unstructured
nuScenes-QA (Qian et al., 2023)	340k / -	-	✗	✗	General Driving	✓	✗
BDD-X (Kim et al., 2018)	8.4M / 277k	-	✗	✗	General Driving	✓	Unstructured
Rank2Tell (Sachdeva et al., 2024)	23k¶ / 2.3k¶	-	✗	✓§	General Driving	✓	12
MMHU (Ours)	1.73M / 173K	57K	✓	✓	Human-Centric	✓	13

Video Cutting and Filtering. Directly applying the annotation pipeline to the entire video can be expensive. We first roughly detect the human presence and filter out the frames that lack human presence. Specifically, we employ Yolo-V8 (Varghese & Sambath, 2024; Jocher et al., 2023) as a human detector to detect the human presence on the raw video at 1 FPS. Then cut the raw video into fragments separated by frames without human presence. We then drop the fragments that are less than two seconds, which are of high probability to produce very short human motion sequences.

3.2 Motion and Trajectory

Extraction. Human motion provides rich information about human actions and behaviors. We employed the widely-used SMPL (Loper et al., 2015) to represent the human motion and trajectory. The details of SMPL representation is described in the appendix. After obtaining the roughly filtered fragments as described in Sec. 3.1, we further extract the video clip of each human instance in each fragment. The details are described in the appendix. Then, given a video clip $V = \{I_0, ..., I_T\}$ for a human instance, we extract a SMPL (Loper et al., 2015) parameter sequence $\mathcal{S} = \{S_t = (\Theta_t, \boldsymbol{r}_t, \boldsymbol{\pi}_t) | t \in \{1, ..., T\}\}$ following (Shin et al., 2024), where S_t is the SMPL parameters for the tth frame, $\Theta_t \in \mathbb{R}^{n\times 3}$ the human motion, $\boldsymbol{r}_t \in \mathbb{R}^3$ the human orientation and $\boldsymbol{\pi}_t \in \mathbb{R}^3$ the location. We put the orientation and location of the human together to represent the human trajectory, denoted as $\Gamma_t = (\boldsymbol{r}_t, \boldsymbol{\pi}_t)$.



(a) Motion Sequence Duration Distribution (b) Behavior Distribution (c) Word Cloud for High-level Text (d) Word Cloud for Low-level Text

Figure 3: **Statistics of MMHU.** The average duration of motion sequences is 3s. The most common behavior is crossing the street, while the rarest behavior is using a wheelchair. For behavior definition, please refer to Sec. 3.4.

Completion. The SMPL sequence of a person can lack a few frames in the middle due to occlusion. To make the motion sequence consistent, we employed a missing motion prediction procedure to complete the missing frames. The human motions Θ_t of the missing frames are completed using angle-based interpolation from the nearest previous and following frames. The missing trajectory

parameters τ_t, π_t are completed using linear interpolation. Please refer to Sec. C.3 in the appendix for more details.

3.3 HIERARCHICAL TEXT ANNOTATION

In addition to the parameterized SMPL motion, the semantic understanding of human behaviors is also critical. We use text as a semantic-level description of the human motion. To narrow the domain gap between the semantic text description and the SMPL parameter, we employ a hierarchical text annotation approach. We first convert the SMPL parameters to an element-level text description for each part of the body at each frame in a rule-based schema. Then we utilize large language models to aggregate the low-level descriptions of each joint over time. Based on the detailed low-level motion description, combined with the video clip, we abstract the high-level descriptions for each motion sequence. The details of hierarchical text annotation are introduced in the supplementary materials. Low-level Text Annotation: As shown in Fig. 2, the low-level text describes the movement of each body part in detail. Following (Delmas et al., 2022), we generate the low-level text description for the SMPL motion S_t at each frame t by calculating the angle, distance, position relation, etc. of different body parts. We then aggregate the movement of each body part over time to get the low-level description of human motion. High-level Text Annotation: High-level captions provide a semantic-level description of human action and motion. We generate one high-level description for the motion sequence of each person, leveraging large vision language models. We provide the VLM with the low-level descriptions and several frames uniformly sampled from the corresponding video clip. The VLM is then prompted to summarize a high-level text description for the video clip.

3.4 CRITICAL BEHAVIORS

Understanding human behaviors — for example, crossing the street — is critical for autonomous driving algorithms. We model the critical behaviors as binary attributes, indicating whether a person is subject to the corresponding behavior.

Table 2: **Motion Generation Evaluation.** Given the high FID distance, the generic text-to-motion models cannot properly generate motions in driving scenes.

Model	FID ↓	Multi Modality
Real	0.002	-
MotionDiffuse (Zhang et al., 2024a)	39.275	2.36
MotionGPT (Jiang et al., 2023)	27.059	5.42

Critical Behavior Recognition. Before we can assign the values to each attribute, we should first answer the question: what behaviors are critical to autonomous driving? One of them might be whether a person is going to cross the street, which is known as the intention prediction task in autonomous driving. As illustrated in Fig. 2, we recognize the critical behaviors by leveraging VLMs. Specifically, we sample n video clips from the dataset. For each video clip, we ask the VLM to recognize the critical behaviors in the scene. Lastly, the answers are collected, and a VLM is instructed to summarize the critical behaviors for autonomous driving. We recognize 13 behaviors, namely walking pets (WP), talking (TS), using a phone (UP), using an umbrella (UU), using headphones (UH), carrying items in hand (CI), crossing the street (CR), using wheelchair (WC), using stroller (ST), riding bike (BI), riding scooter (SC), using skateboard (SK), and riding motorcycle (MC).

Critical Behavior Labling. Given the recognized behavior set $\mathcal{B} = \{\boldsymbol{b}_k | k \in \{1, ..., m\}\}$, the label of critical behaviors for a person h is defined as the subset $\mathcal{B}_h \subseteq \mathcal{B}$ in which the behaviors hold for the person. For each instance, we enumerate each element in the behavior set $b_k \in \mathcal{B}$ and construct a corresponding question q_k. Then we provide the corresponding frames to a VLM and ask it about the question q_k. Based on the answer, we append b_k to the behavior set $\mathcal{B}_h$ for the person. Directly applying pre-trained VLMs can suffer from noisy labeling results. To alleviate this, we perform a human-in-the-loop labeling strategy. We randomly selected a small portion of the dataset and employed human annotators to label whether the given person has certain behaviors. Then we use the human-labeled data to fine-tune the annotation VLM, which will further be applied to the rest of the unlabeled data. The details of the human annotation are described in the supplementary materials.

3.5 STATISTICS

As shown in Fig. 3 (a) and Tab. 1, our dataset provides 48 hours human motion sequences and corresponding video clips in total. The frame rate of both the motion sequence and video clip is 10 Hz, thus the total frames sum up to 1.73M. The durations of motion sequences range from 1 to 12 seconds. The mean and median durations are 3.01 and 2 seconds. The average length of low- and

Table 3: **Evaluation of Human Behavior Visual QA.** We construct closed-ended questions where the model is asked to select whether the person is subject to certain behaviors. We report the F1 score for each behavior, and then an instance-averaged F1 score is used to evaluate the overall performance. For behavior definition, please refer to Sec. 3.4.

Baseline	WP	TS	UP	UU	UH	CI	CR	WC	ST	BI	SC	SK	MC	Micro-F1
Phi-4-multimodal	42.9	35.6	24.6	90.9	15.4	39.4	26.1	100.0	31.2	56.3	66.7	33.3	77.1	45.5
MiniCPM-o-2_6	75.0	27.4	58.6	100.0	44.4	33.4	26.4	85.7	77.8	88.9	80.0	50.0	73.6	52.2
Dolphins	42.9	2.3	1.0	22.2	40.0	0.3	16.9	40.0	6.5	1.7	40.0	57.1	1.3	3.1
Qwen2-VL-7B	66.7	2.8	63.3	100.0	25.0	30.7	66.7	100.0	76.9	69.3	80.0	66.7	80.7	52.1
Qwen2.5-VL-7B	42.9	16.4	36.4	76.9	15.4	40.6	32.4	85.7	34.3	47.9	66.7	25.0	73.9	44.7
InternVL2-8B	33.3	1.5	17.2	100.0	15.4	11.2	6.3	85.7	25.0	54.7	66.7	28.6	68.8	27.7
InternVL2.5-8B	75.0	14.5	32.6	100.0	15.4	27.3	24.4	100.0	76.9	72.5	80.0	50.0	75.5	42.2
Mantis-8B-SigLIP	80.0	28.1	68.6	100.0	28.6	52.5	22.6	100.0	93.3	91.0	80.0	50.0	87.0	58.4
Aya-Vision-8B	46.2	23.8	43.3	100.0	40.0	40.4	21.3	100.0	75.0	77.6	80.0	50.0	29.1	38.6
Idefics3-8B-Llama3	42.9	18.5	19.7	90.9	15.4	23.5	24.4	85.7	33.3	64.1	80.0	28.6	84.6	40.1
Pixtral-12b	36.4	22.9	18.4	90.9	18.2	25.6	21.7	100.0	37.0	58.5	66.7	33.3	78.7	41.1
Gemma-3-12B-it	53.3	36.6	32.2	90.9	25.0	51.6	12.1	100.0	41.0	63.3	66.7	40.0	87.1	52.9
Deepseek-vl2-small	42.9	19.9	54.1	76.9	15.4	30.6	37.6	85.7	34.3	37.5	66.7	28.6	44.0	34.9
Kimi-VL-A3B	46.2	21.2	39.4	76.9	20.0	35.8	23.0	85.7	46.7	66.7	66.7	33.3	85.7	47.7
GPT4o-mini	85.7	67.7	62.5	100.0	40.0	55.0	58.4	100.0	66.7	90.1	80.0	50.0	65.36	64.8

Table 4: **Evaluation of Motion Prediction Baselines.** We evaluate the motion prediction baselines on MMHU-T. All of the baselines generate plausible trajectory predictions. Among of them, PhysMoP achieves the best performance.

	MPJPE↓							
frame_id	1	3	7	9	13	17	21	24
PhysMoP (Zhang et al., 2024c)	0.4	1.7	9.0	14.4	26.3	36.2	45.3	54.3
AuxFormer (Xu et al., 2023)	17.0	32.7	47.8	60.0	71.1	79.0	84.3	86.1
CIST-GCN (Medina et al., 2024)	18.5	25.3	37.2	40.8	46.2	46.6	46.8	47.4

Table 5: **Benefiting Behavior VQA.** By finetuning on MMHU, the baseline model shows a significant improvement on accuracy and F1-score.

Model	Accuracy↑	F1-Score ↑
Baseline	35.31	44.72
Finetuned	67.77	68.54

high-level descriptions is 390 and 34 words, respectively. The word clouds for the two kinds of text are illustrated in Fig. 3 (c) and (d). We also show the frequency of different behaviors in Fig. 3 (b).

4 TASKS

MMHU supports multiple human-centric tasks. In this section, we will present the definition of tasks and corresponding evaluation metrics in our experiments.

4.1 MOTION PREDICTION

Understanding the historical motion and predicting future ones is essential for the safety of autonomous driving. Following PhysMoP (Zhang et al., 2024c), we leverage the sequence of human motion keypoints as the representation. Specifically, human motion involves n frames $M_1, ...M_n$, each of which represents the global location of human joints at frame I_i. Each motion frame M_i consists the location of m key joint point on human body, i.e. $M_i = \{p_k \in \| k \in \{1, ..., m\}\}$. The human motion prediction task is about predicting future motion frames from historical ones, i.e., predicting $M_{t1+1}, ...M_{t_1+t2}$ from $M_0, ..M_{t1}$. We employed two widely used metrics to evaluate the baseline methods: (1) Mean Per Joint Position Error (MPJPE), which measures the mean 3D Euclidean distance between the predicted and ground truth joint positions after aligning the root joint; (2) and the ACCL metric, measuring the acceleration error averaged over time to measure the physical plausibility of the predicted motion.

4.2 MOTION GENERATION

Though motion is an informative and compact representation of human actions, collecting them in the real driving scene is expensive and even dangerous for some behaviors. Motion-from-text generation can be a very efficient and effective way to augment motion data. Specifically, given a text description of motion, the algorithm is supposed to generate motion sequences that are subject to the text description. We thus test the capacity of existing current text-to-motion approaches to generate human motions in a driving scene. We follow MotionDiffuse (Zhang et al., 2024a) to model motion sequences by converting from the SMPL parameters. We leverage the high-level description as the

text prompt to generate the motions. We employ FID (Heusel et al., 2017) and multi-modality as evaluation criteria. The former evaluates the distributional distance between the generated motions and the ground-truth motions, while the latter measures joint position differences among 32 motion sequences generated from the same text description.

4.3 Behavior VQA

Humans in the street can have multiple characteristics and behaviors. Unlike previous related tasks, such as intention prediction, where the behavior is simply classified into binary labels — crossing the street or not crossing the street, we propose a new behavior set that provides more comprehensive aspects of human behaviors. To make the tasks flexible and easy to extend, we formulate the task as a visual question-answering (VQA) task. We label humans with 13 behaviors, which are all binary labels, as mentioned in Sec. 3.4. We construct closed-ended questions for all labeled behaviors using a template. An example is "Is the person in the video riding a bike? (A) Yes (B) No." We then evaluated the accuracy of the baseline methods. We employed the accuracy and F1-score as evaluation metrics.

5 Experiments

In this section, we evaluate recent methods for human behavior understanding in our dataset. Specifically, we evaluated methods related to human motion prediction, text-to-motion generation, and human behavior VQAs. We analyze their performance on their corresponding tasks.

5.1 Dataset Splitting

MMHU is split into three subsets, namely MMHU-V, MMHU-H, and MMHU-T, each consisting of 47k, 9.5k, and 840 human instances, representing the VLM-labeled, human-labeled, and testing data. We sample the human-labeling subset (which is MMHU-H + MMHU-T) equally from three strategies. (1) in-video-clip sampling: For some video clips, we randomly sample some individuals from each of them as human-labeling data and the rest as MMHU-V data. (2) in-video sampling: we sample some video clips from each raw video and use all the individuals as human-labeling data, and the rest video clips serve as MMHU-V data. (3) out-of-video sampling: we randomly choose some raw videos, and the entire videos serve as the human-labeling dataset. Similarly, we split the MMHU-H and MMHU-T subsets from the human-labeling data. In the experiments, without specifically mentioning, we use both MMHU-V and MMHU-H as training data, denoted as MMHU. We illustrate the three sampling strategy in Fig. 5.

5.2 Baselines

Motion Prediction: For motion prediction, we employ PhysMoP (Zhang et al., 2024c), CIST-GCN (Medina et al., 2024), and AuxFormer (Goncalves & Busso, 2022) as the baselines. Following the settings in (Zhang et al., 2024c), we randomly select 50 continuous frames from each motion sequence, using the first 25 frames as the input for the baselines and comparing their output with the remaining 25 frames. Motion Generation: We choose MotionDiffuse (Zhang et al., 2024a) and motionGPT (Jiang et al., 2023) as our baseline. For both methods, we provided the high-level descriptions from our dataset as the text prompt. Following motionGPT (Jiang et al., 2023), we only use motion sequences that are within 20 to 196 frames. Behavior VQA: For the 13 critical behaviors, there is no specialist model that is trained to predict all of them. Thus, we employed generalist vision-language models as our baselines. We provided the vision language models 4 to 6 frames sampled from the corresponding video and a closed-ended question constructed from the behavior labels as input, and evaluated whether the VLMs can accurately recognize these essential behaviors and answer the provided question. We employ multi-image querying VLMs, including Phi-4-multimodal (Abouelenin et al., 2025), MiniCPM (Yao et al., 2024), Qwen (Wang et al., 2024a; Bai et al., 2025), InternVL (Chen et al., 2024d), Mantis (Jiang et al., 2024a), Idefics3 (Laurençon et al., 2024), Pixtral (Agrawal et al., 2024), Gemma3 (Team et al., 2025a), Deepseek-VL2 (Wu et al., 2024), Kimi-VL (Team et al., 2025b).

5.3 Baseline Evaluation

Motion Generation. As shown in Tab. 2 and Fig. 8 (upper row), motion generation models pre-trained on generic human motion datasets are not capable of generating plausible motions in driving scenes, due to the domain gap between the general motions and motions in the street.

Table 6: **Benefiting Motion Prediction.** After adding MMHU to traning set, the baseline model PhysMoP (Zhang et al., 2024c) shows significant performance gain when evaluated on 3DPW (von Marcard et al., 2018).

Train Set	MPJPE-avg↓	ACCL↓
3DPW	47.67	3.8
3DPW+MMHU	38.18	2.7

Table 7: **Benefiting Intention Prediction.** Adding MMHU to the training set of the baseline model TrEP (Zhang et al., 2023), the model achieved more percise intention prediction on the JAAD dataset (Kotseruba et al., 2016).

Train Set	Accuracy ↑	F1-score↑	AuROC↑
JAAD	84.49	84.45	92.98
JAAD+MMHU	91.89	91.89	97.72

Table 8: **Benefiting Motion Generation.** Models fine-tuned on MMHU (labeled with *) can generate better human motions in the driving scene.

Model	FID↓	Multi Modality
Baseline	39.27	2.36
Finetuned*	1.86	2.31

Behavior VQA. We evaluated the ability of mainstream vision-language models to recognize human behaviors in driving scenes. We constructed closed-ended questions based on the behaviors and provided 4 to 6 frames to the VLMs. We evaluated the VLMs based on their correctness in answering these behavior-related questions, results shown in Tab. 3.

Motion Prediction. We evaluated the pre-trained baselines on MMHU-T, to unify the time argument used in computing the MPJPE metric, we use the frame id to replace it. All baselines are evaluated on the same frames. The results are shown in Tab. 4. All of the approaches generate plausible results, even though they are not specially trained for driving scenes. Among them, PhysMoP (Zhang et al., 2024c) achieves the best performance in our dataset.

5.4 Improving Human Behavior Understanding

In this section, we show that MMHU can facilitate versatile tasks of human behavior understanding. By finetuning different baseline models on our dataset, we observe significant performance gains.

Behavior VQA. We employed QWen2.5-VL (Bai et al., 2023) as our baseline. We fine-tuned the baseline model on our dataset and evaluated both models using the average accuracy and the F1 score on MMHU-T. As shown in Tab. 5, the fine-tuned model achieves a significant performance gain of 32.46% and 23.82% with respect to the average precision and F-1 score.

Motion Prediction. We trained PhysMoP (Zhang et al., 2024c) on the mixed data of 3DPW (von Marcard et al., 2018) and MMHU, and compared it with that trained on 3DPW only. We then evaluated both variants on the original 3DPW dataset, following the original settings of PhysMoP. As shown in Tab. 6, the model training with our MMHU data generalizes to 3DPW and significantly outperforms the baseline model by 9.49 average MPJPE and 1.1 ACCL.

Intention Prediction. Intention prediction answers the question of whether or not a person is going to cross the street, which is a special aspect of behavior QA. We select TrEP (Zhang et al., 2023) as the baseline. We train the baseline model on the JAAD (Kotseruba et al., 2016) dataset, which is a widely used dataset for intention prediction. We then compared the baseline model to that trained on the mixture of JAAD (Kotseruba et al., 2016) and MMHU. From Tab. 7 we observe MMHU significantly contribution to a performance gain of the baseline model. All evaluations are conducted on the JAAD (Jiang et al., 2024a) test set following the original settings of TrEP (Zhang et al., 2023).

Motion Generation. We show that MMHU can narrow the domain gap between generic text-to-motion generation and motions in driving scenes. We fine-tuned MotionDiffuse (Zhang et al., 2024a) on MMHU, and we observe a significant improvement in FID, as shown in Tab. 8. Please find more qualitative results in Fig. 8 and Sec. D.4 in the appendix.

6 Conclusion

In this work, we present **MMHU**, a large-scale dataset for human behavior understanding. The MMHU dataset consists of 57k human instances, each of them are richly annotated with 3D motion sequences, text descriptions, and labeling of 13 critical behaviors. We collected driving videos from various sources and developed a human-in-the-loop annotation pipeline to get high-quality annotations. We evaluated and analyzed the baseline models on the proposed dataset regarding the task of motion prediction, text-to-motion generation, and human behavior VQA. We also conduct experiments to show how MMHU can benefit these tasks.

7 AI USE, ETHICS AND REPRODUCIBILITY STATEMENT

AI Use Statement. In this work, we used generative AI tools to polish the writing and generate synthetic data. The rest of the required disclosure tasks are not applicable to this work. We wrote the initial manuscript ourselves and verified that all LLM-assisted revisions preserved the original meaning. We take responsibility for the final content of this work, including text, claims or artifacts produced with the aid of generative AI.

Ethics Statement. We follow the previous YouTube dataset (Abu-El-Haija et al., 2016; Xu et al., 2018; Liu et al., 2024c) to protect the privacy of web-sourced videos. All the YouTube videos are with the CC license and are compiled with YouTube's privacy policy and terms of service[1]. We also added mosaics on the copyrighted objects, such as the logo and channel owner information. In addition, we will not provide the video clips directly; instead, we will only provide reference links to the original YouTube videos, which come with all the labels and the bounding boxes to refer to the corresponding individual in the original video. We will provide the processing script to get the corresponding video clips from the video link. For self-collected data, we have removed the identity information by applying mosaics to the faces or license plates, following the approach described in (Grauman et al., 2022). For the VLM-labeled subset, we leveraged the open-source Qwen/Qwen2.5-VL-3B-Instruct model (Bai et al., 2025) for the annotation pipeline. The foundation model is fine-tuned on the human-labeled MMHU-H subset before being used to label the MMHU-V subset. We have followed the Qwen RESEARCH LICENSE AGREEMENT[2] in the data processing. MMHU will be under the CC BY-NC-SA 4.0 license. Additionally, we will implement protective measures on our dataset webpage, including detailed user agreements, encryption protocols for personal data, enforced access restrictions, and monitoring systems to detect misuse or unauthorized access.

Reproducibility Statement. We have provided the details of the dataset in Sec. 3 and Sec. C. The details of the experiments are described in Sec. 4, Sec. 5, and Sec. D. We will release the dataset, with detailed documentation and develop tool kits, upon the acceptence of this paper.

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A Appendix Overview

We introduce some background and preliminaries in Sec. B. Then we describe the details of the dataset and its construction in Sec. C. In the last, we describe the details of the experiments we conduct in Sec. D.

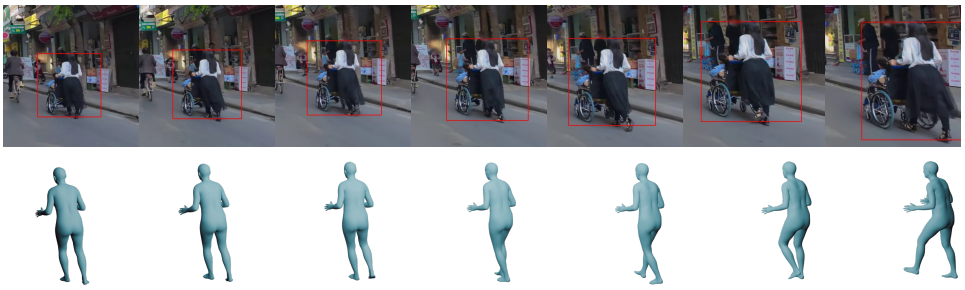
B Background and Preliminaries



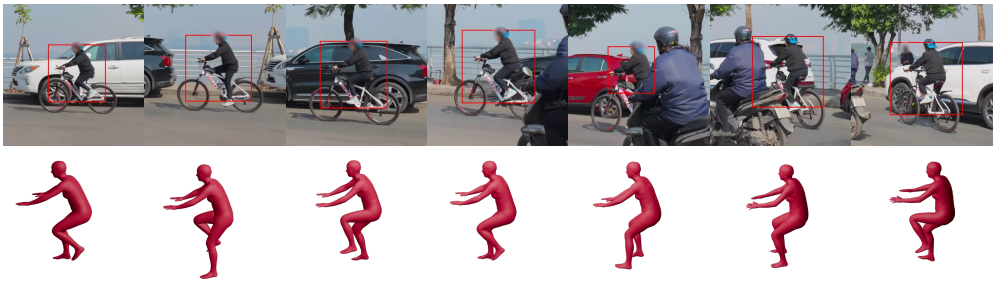
The pedestrian continues running, maintaining a steady pace with arms swinging and legs alternating in a rhythmic motion.



The pedestrian walks across the street, maintaining a steady pace with arms slightly raised and hands close together. They continue to walk past a police vehicle and a taxi, eventually stopping near a traffic light. [Crossing the Street, Carrying Items By hand]



The pedestrian continues pushing the wheelchair forward, maintaining a steady pace and consistent posture. [Wheelchair, Carrying Items by Hand]



The cyclist maintains a steady pace, with hands gripping the handlebars and knees bent, navigating through traffic. [Bicycle]

Figure 4: **Visualization of the MMHU dataset.** For each human instance, the first line shows the video frames that are sampled from the video clips. The human instance is highlighted using a red bounding box. We crop and zoom in on the human instance for a clearer view. Under each of the frames shows the corresponding mesh-rendered human motion, followed by the text description for the human motion and the behavior labels.

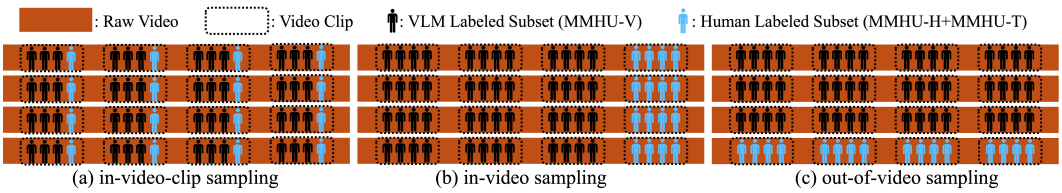


Figure 5: **Example of the Sampling Strategies:** We show an example of the three sampling strategies mentioned in Sec. 5.1. In the example, the ratio of VLM-labeled data to the Human-labeled data is assumed to be 3:1.

B.1 The Skinned Multi-Person Linear (SMPL) Representation.

The SMPL model (Loper et al., 2015) is a parametric human body representation. It represents the human body as a triangulated surface and uses linear blend skinning (LBS) to control both pose and body shape. A template mesh in a canonical rest pose is defined as $\mathcal{M}_h = (\mathcal{V}, \mathcal{F})$, where $\mathcal{V} \in \mathbb{R}^{n_v \times 3}$ is the set of n_v vertex positions and $\mathcal{F}$ the set of faces. Given shape parameters β and pose parameters θ, SMPL first produces a shaped mesh by adding learned offsets to the template vertices: $\mathcal{V}_s = \mathcal{V} + B_S(\beta) + B_P(\theta)$, where $B_S(\beta) \in \mathbb{R}^{n_v \times 3}$ are the shape-dependent displacements and $B_P(\theta) \in \mathbb{R}^{n_v \times 3}$ are the pose-dependent displacements, both defined in xyz space. The vertices $\mathcal{V}_s$ describe the body in the shaped space. To obtain the final posed mesh corresponding to a target pose θ', SMPL applies LBS to $\mathcal{V}_s$. It uses fixed skinning weights $W \in \mathbb{R}^{n_k \times n_v}$ and a set of joint transformations $G = \{G_k\}_{k=1}^{n_k}$. Each vertex v_i is transformed according to $v_i' = \left(\sum_{k=1}^{n_k} W_{k,i} G_k\right) v_i$, where n_k is the number of skeletal joints. The transformations G_k are functions of the source pose θ, the target pose θ', and the shape parameters β. The pose vector is usually split into a body pose term $\theta_b \in \mathbb{R}^{23 \times 3 \times 3}$ and a global orientation term $\theta_g \in \mathbb{R}^{3 \times 3}$. The official SMPL repository[3] extends SMPL with global orientation and translation, represented by $\Gamma_t = \{\boldsymbol{r}_t, \boldsymbol{\pi}_t\}$, where $r_t \in \mathbb{R}^3$ and $\pi_t \in \mathbb{R}^3$ denote the root orientation and translation with respect to the camera.

B.2 The Closed- and Open- Ended Questions.

In the VQA task, the term "closed-ended" question generally means the questions with limited possible answers. In contrast, the "open-ended" question refers to a question that allows the respondent to generate any free-form answer. For example, multiple-choice questions are closed-ended questions. And the question asking "What do you think are the paper's strengths and weaknesses?" is an open-ended question. The further explanation of the two terms can be found in (Baburajan et al., 2022).

C Dataset Details

C.1 Visualization

In Fig. 4, We provide the visualization of some examples from our dataset. In each example, we show the sampled video frames in the first row, the human instance is highlighted using a red bounding box. The corresponding poses are visualized under each frame in the second row, followed by the text description and the behavior labels. In Fig. 5, we provide an illustration of the three dataset splitting strategies described in Sec. 5.1.

C.2 Data Collection

For the YouTube source, we filtered and downloaded videos with the *Creative Commons Attribution license (reuse allowed)* license using yt-dlp[4]. We also filtered the videos by checking whether they contain the keywords "drive" or "driving" in their title. We collect video clips that sum to over 11 hours, consisting of 10k human instances. We list the details of the used YouTube channels in Tab. 9.

[3] https://github.com/vchoutas/smplx
[4] https://github.com/yt-dlp/yt-dlp

Table 9: **Collected YouTube Raw Data**

Channel Name	License	Collected Minutes	Human Instances
TravelRelaxListen	Creative Commons Attribution	179	2028
planetearthtraveler	Creative Commons Attribution	92	3122
RoamingBrit	Creative Commons Attribution	65	497
Evan-Explores	Creative Commons Attribution	147	62
VietnamSilentRoutes	Creative Commons Attribution	187	4812

C.3 Motion Completion for Missing Frames

Given reconstructed SMPL parameter sequence $\mathcal{S} = \{S_1, S_2, ..., S_{k-1}, ..., S_{k+m+1}, S_{k+m+2}, ..., S_n\}$ with m missing frames $\{S_k, S_{k+1}, ..., S_{k+m}\}$, the predicted SMPL parameter $S_{k+j} = \{\Theta_{k+j}, \Gamma_{k+j}\}$ at frame $k+j$ is interpolated as follows:

$$\hat{\Theta}_{k+j} = \frac{\sin((1-\frac{j}{m})\theta)}{\sin(\theta)}\hat{\Theta}_{k-1} + \frac{\sin(\frac{j}{m}\theta)}{\sin(\theta)}\hat{\Theta}_{k+m+1} \tag{1}$$

$$\theta = \arccos\langle\Theta_{k-1}, \Theta_{k+m+1}\rangle \tag{2}$$

$$\Gamma_{k+j} = \frac{m+1-j}{m+2}\Gamma_{k-1} + \frac{j+1}{m+2}\Gamma_{k+m+1} \tag{3}$$

C.4 Extracting the Video Clip for Each Human Instance

After roughly cutting the raw video into fragments following Sec. 3.1, the next step is to detect each human instance and extract the corresponding video frames. Following (Shin et al., 2024), we apply the human detector (Varghese & Sambath, 2024; Jocher et al., 2023) on each frame of the video fragment. For each detected human in each frame, we leverage mmpose (Contributors, 2020) for 2D keypoint extraction and tracking. Then we collect the frames to form the video clip of each human instance. The Waymo (Sun et al., 2020) dataset provides human bounding box labels for each frame. In this case, we leverage the ground-truth human bounding box instead of the detected ones to make it more precise. However, these human instances are labeled based on the 3D point cloud, which may be invisible to the current video point of view. Thus, we drop the bounding boxes that do not intersect with any of the detected bounding boxes with at least 0.2 IoU. In the remaining bounding boxes, if any two of them intersect with each other with at least 0.2 IoU, we drop both of them.

C.5 Details of the Human Annotation for the Behavior Labels

We present the details of the human annotators for the MMHU-H and MMHU-T subsets. We employ 12 annotators. Each annotator is provided with 6 frames of the video clip. The target human is cropped and labeled with a bounding box. We asked the annotators to check for each behavior that the human holds. We use label studio (Tkachenko et al., 2020-2025) to build the annotation environment. The English version of the annotation interface is shown in Fig. 6.

C.6 Details of Hierarchical Text Annotation

To bridge the gap between parameterized SMPL motion and semantic-level understanding, we implement a hierarchical text annotation pipeline that translates joint-level motion into structured language descriptions.

We use PoseScript (Delmas et al., 2022) to extract joint-wise behavioral descriptions (the low-level description) from SMPL pose sequences. Unlike the original method, which outputs a single paragraph per frame summarizing the full-body posture, our approach decomposes captions into joint-specific phrases by isolating text segments corresponding to individual joints. We focus on the most salient joint movements and retain only those joints mentioned in at least 50% of the frames within a sequence. To ensure temporal consistency, we align the low-level descriptions of each selected joint across the sequence. These temporally aligned joint descriptions are aggregated using a large language model to produce concise summaries of each joint's motion over time , as shown in Fig. 7.

The low-level descriptions are utilized to support the subsequent aggregation of high-level semantic behavioral descriptions. We show an example of the low-level (joint-wise) descriptions in Box 1. Then, a vision-language model is employed to aggregate the low-level (joint-wise) descriptions with the high-level semantic behavior information from the keyframes. The instructions for this procedure are demonstrated in Box 2.

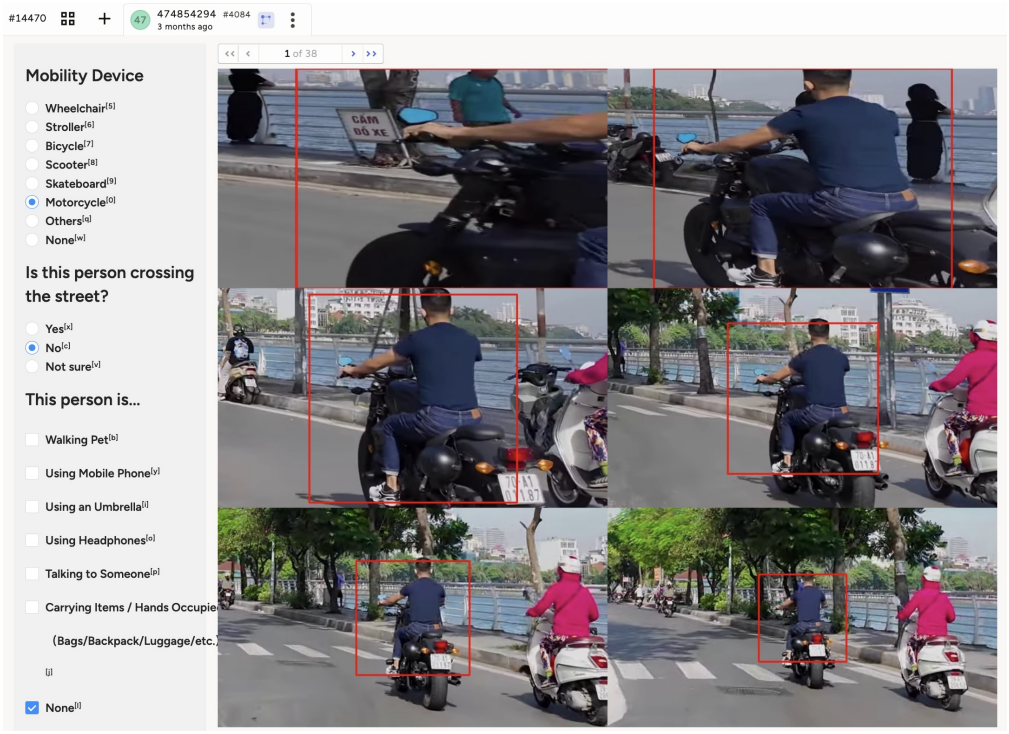


Figure 6: **Example of Annotation Interface.**

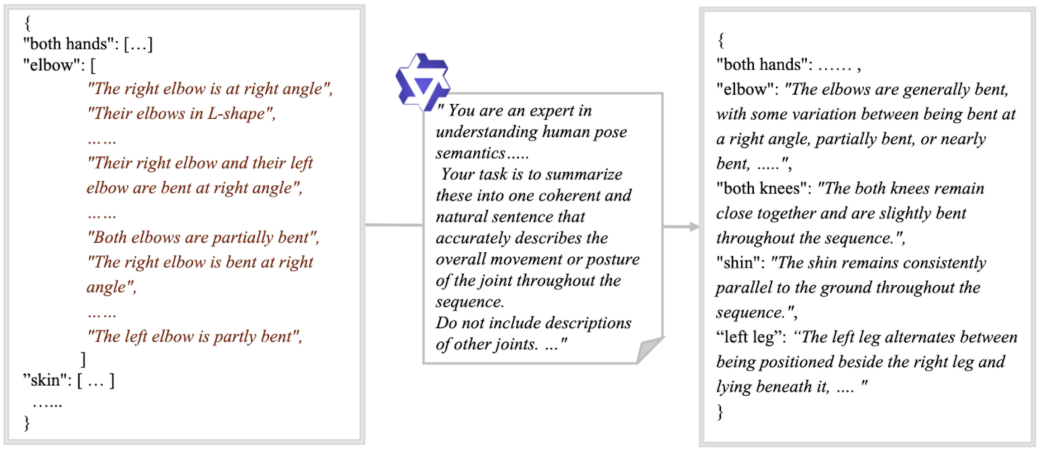


Figure 7: **Example of Low-level Text Aggregation.** Left: per-frame text description for human parts at each frame; Right: aggregated low-level text description.

Box 1. Example of Low-Level Descriptions

Selected Key Frames for Reference:



Low-Level (Joint-wise) Descriptions:

- **Elbow:** The elbows are generally bent throughout the sequence, with some variation in the degree of bending.
- **Forearm:** The forearm remains mostly horizontal with occasional alignment with the thighs and shins, indicating a stable position with some minor adjustments.
- **Knee:** The knees are generally bent with slight variations, occasionally straightening or separating at shoulder width, indicating a dynamic posture.
- **Left Elbow:** The left elbow remains mostly bent throughout the sequence, with occasional variations indicating slight changes in its position.
- ...

Box 2. Instruction Template for Aggregated Text Description

System Prompt: You are an expert in human motion analysis and natural language refinement.
Your task is to reorganize and clarify human pose descriptions derived from SMPL-based 3D models. Ensure all descriptions are structured, concise, and consistent, while strictly preserving the original semantics—do not add, remove, or alter key motion elements.
When provided with low-level pose information (e.g., joint-based summaries or posecodes), use it to enhance the clarity or specificity of the description, especially regarding posture and limb motion. However, maintain overall cohesion and naturalness, with a clear focus on the pedestrian's observable behavior in context.

User Prompt: You are given a sequence of images showing a pedestrian in a green bounding box, captured by a front-facing car camera, along with a dictionary of low-level joint-based pose descriptions.
Your task is to:

- Write a concise, one- to two-sentence summary capturing the pedestrian's overall motion and any key changes in action throughout the sequence.
- Emphasize how the pedestrian's behavior evolves over time (e.g., walking, stopping, turning, crouching, changing direction).
- Use the low-level pose descriptions to refine details when relevant, but avoid excessive mechanical phrasing or redundancy.
- Describe only what is clearly supported by the visual and pose data — do not speculate.

Format your final response using the following tags: `<description>` human pose description here. `<description_end>`
Example: `<description>` The pedestrian stepped forward with arms raised, paused briefly, then lowered their body and turned slightly to the left. `<description_end>`

Here is the low-level pose description: {Input Low-Level Description}

Box 3. Example of Human Behavior VQA: Carrying Items

Frames:



System Prompt: You are an expert pedestrian behavior labeler, specializing in analyzing pedestrians' behavior on the road. You will perform visual analysis on multiple sequential images over time.

Question 1: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
Is the pedestrian carrying items?
Please answer y or n, only one letter.

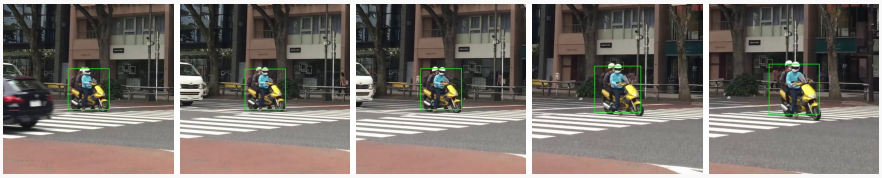
Answer: `y`

Question 2: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
The pedestrian is not carrying items. Is this statement correct?
Please answer y or n, only one letter.

Answer: `n`

Box 4. Example of Human Behavior VQA: Using Scooter

Frames:



System Prompt: You are an expert pedestrian behavior labeler, specializing in analyzing pedestrians' behavior on the road. You will perform visual analysis on multiple sequential images over time.

Question 1: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
Is the pedestrian using a scooter?
Please answer y or n, only one letter.

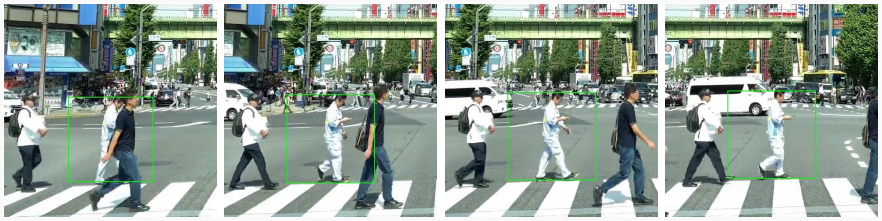
Answer: `y`

Question 2: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
The pedestrian is not using a scooter. Is this statement correct?
Please answer y or n, only one letter.

Answer: `n`

Box 5. Example of Human Behavior VQA: Using a Phone

Frames:



System Prompt: You are an expert pedestrian behavior labeler, specializing in analyzing pedestrians' behavior on the road. You will perform visual analysis on multiple sequential images over time.

Question 1: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
Is the pedestrian using a phone?
Please answer y or n, only one letter.

Answer: `This person is crossing the street.`

[RollBack] Question 1: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
Is the pedestrian using a phone?
Please answer y or n, only one letter.

[RollBack] Answer: `y`

Question 2: The images show a pedestrian in a bounding box with surrounding context. The image is a cropped frame from a car's front camera.
The pedestrian is not using a phone. Is this statement correct?
Please answer y or n, only one letter.

Answer: `n`

D EXPERIMENTS

D.1 HUMAN BEHAVIOR VQA DETAILS.

For each behavior, we construct closed-ended questions based on the template. We provided 4 to 6 frames to the VLMs. The frames are uniformly sampled from the video clips. To reduce randomness, we will ask the VLMs twice, one direct question and one counter question, respectively. The VLM should answer both questions correctly in order to be evaluated as correct for the behavior. We show two examples in Box 3 and Box 4 (both answered correctly). We find that some VLMs have difficulty following the instructions; thus, if the answer has the wrong format, we will roll back at most three times and repeat the same question. An example is shown in Box 5.

D.2 GENERALIZING ON MOTION PREDICTION

We train the PhysMoP (Zhang et al., 2024c) model on MMHUalone, without any training on the original training set. We then evaluate the model on the original test set of 3DPW (von Marcard et al., 2018). The results are listed in Tab. 10, from which we observe that even trained on MMHUalone, the baseline model still produces plausible results, demonstrating the generalizability of MMHU.

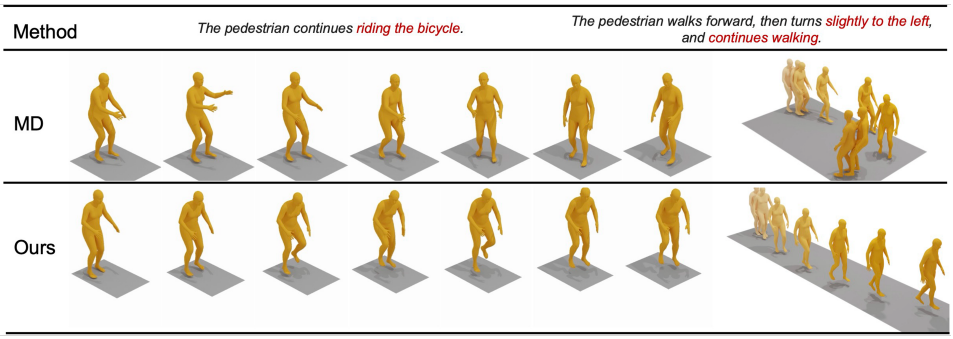


Figure 8: **Qualitative Comparison of Motion Generation.** The baseline model (MotionDiffuse, MD) is not capable of generating proper motions in driving scenes. After fine-tuning on MMHU(second row), the model demonstrates the ability to generate human motions in autonomous driving scenarios.

D.3 Trajectory Recovery

We employed two recent trajectory recovery approaches (Shen et al., 2024; Chen et al., 2024b) and evaluated them on the MMHU-T subset. As shown in Tab. 11, the recent approaches all produce plausible results on MMHU-T, indicating the correctness of the human trajectory in the dataset.

D.4 Additional Results on Motion Generation

Table 10: **Generalizability on Motion Prediction.** The baseline model trained on MMHUonly produces plausible results and generalizes to the 3DPW (von Marcard et al., 2018) testset.

TrainSet	TestSet	MPJPE-avg↓	ACCL
3DPW	3DPW	47.67	3.8
MMHU	3DPW	49.89	2.4

To better show the performance improvement of motion generation tasks after finetuning on MMHU dataset, we provide quantitative comparisons in Fig. 8. In the supplementary material, we further provided rendered videos for three extra cases to show that the fine-tuned model is more capable of generating human motion in the driving scene. The video is named following the pattern of "{casenumber}-{Baseline/Finetune}-{behavior_label}-{Mesh/Skeleton}". The first case shows that the baseline is not capable of generating feasible motion of riding a bike. In the second case, the baseline model only captured the "walking" keyword and ignores the behavior of "talking to someone", while the fine-tuned model can generate a more plausible motion with hand postures. In the Third case, we add a more detailed description of human pose, and the fine-tuned model shows the ability to follow the more detailed instructions.

D.5 Benefiting End-to-End Driving Model

We conduct a case study using LightEmma (Qiao et al., 2025) to show how understanding the human behavior can be beneficial to end-to-end autonomousing driving models. As shown in Fig. 9, explicitly incorporating pedestrian behavior descriptions helps the model to generate a more plausible driving plan that better accounts for the pedestrian's anticipated motion.

D.6 Validation of Labeling

Table 11: **Evaluation of Trajectory Recovery.**

Method	MPJPE(mm)	PA-MPJPE(mm)
Shen et al. (Shen et al., 2024)	24.24	45.44
LEAP-VO (Chen et al., 2024b)	27.86	42.93

Human Motion Labels. We show the correctness of our human motion labels by comparing the SMPL keypoints extracted by our pipeline with the ground-truth human keypoints provided in the official Waymo toolkit[5]. Due to the difference in human keypoint representation between the Waymo (9 points) and the SMPL (24 points), we conduct visual validation on the rendered keypoints. Specifically, we back-project and render the GT keypoints and our SMPL keypoints to the original

[5]https://github.com/waymo-research/waymo-open-dataset/blob/master/tutorial/tutorial_keypoints.ipynb

image frames. As shown in Fig. 10. The SMPL keypoints in MMHU are generally aligned with the GT keypoints and the human body in the image.

Behavior Labels. We employed two more data quality validators to validate random 5K samples sampled from MMHU-H + MMHU-T dataset. The validators are asked to label the data independently without knowing the pre-labeled behaviors. We compared the consistency between the labels from previous annotators and the two validators, resulting in a 97% agreement rate, which verifies the data quality.

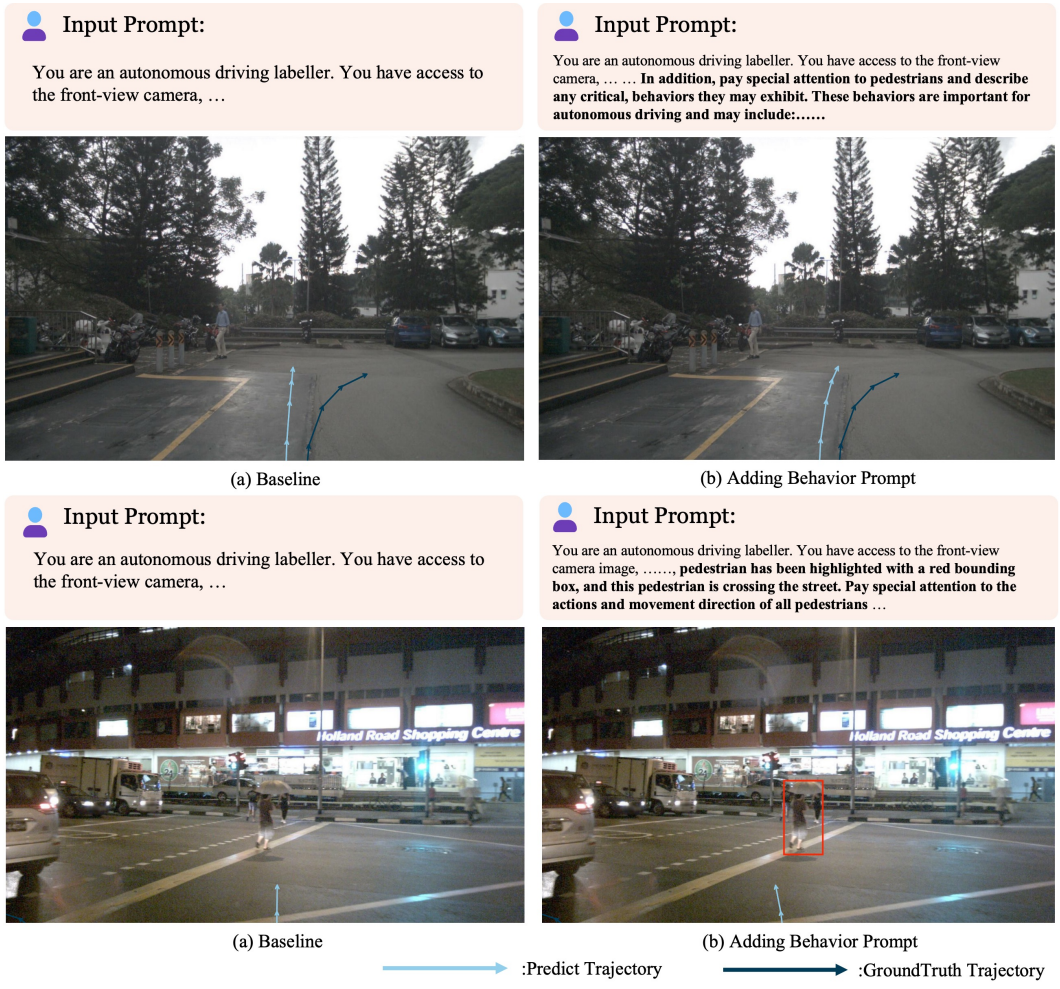


Figure 9: **Benefiting End-to-End Driving Models.** LightEmma (Qiao et al., 2025) generates a more plausible future trajectory when additional human behavior information is added to the text prompt.

D.7 Setting Details in Finetuning Models

We provide the details of the fine-tuning procedure used in Sec. 5.4 of the main paper.

Motion Prediction. The training data consists of the entire 3DPW dataset (training set) (von Marcard et al., 2018) and 30k randomly selected human sequences from MMHU. All training settings follow the default configurations described in these papers. Since the frame rate of 3DPW is 25 FPS, while ours is 10 FPS, we upsample all sequences in our dataset to 50 FPS and then downsample them to 25 FPS. Training is conducted on an NVIDIA RTX 4090 GPU.

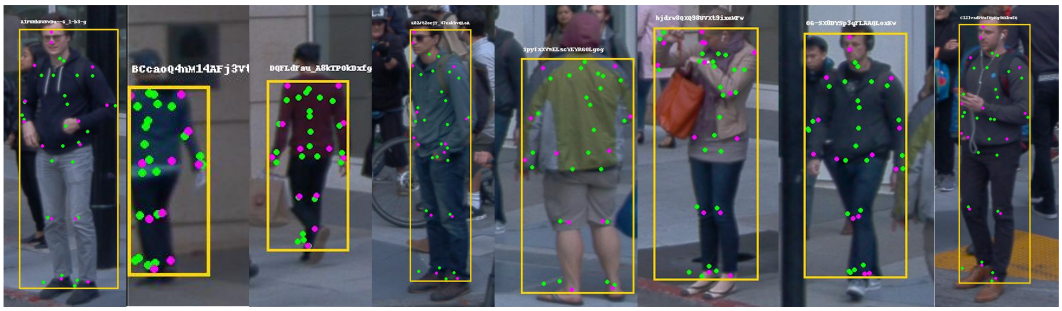


Figure 10: **Validating Motion Labels.** We render the ground-truth keypoints and the SMPL keypoints provided in MMHUtogether with the original human image. The SMPL keypoints are aligned with both the ground-truth keypoints and the human body.

Motion Generation. We select the test set from our MMHU dataset and split it into training, validation, and test subsets with a 7:1:2 ratio for this experiment. The main training settings and model architecture follow the default configurations in MotionDiffuse (Zhang et al., 2024a). We use the Adam optimizer with a learning rate of 0.0002. For fine-tuning, we set the batch size to 192 and train for 20 epochs using a single NVIDIA RTX 6000 Ada GPU.

Human Behavior VQA. We apply LoRA (Hu et al., 2022) fine-tuning to Qwen2.5-3B-Instruct by using LLaMA-Factory Framework (Zheng et al., 2024). The visual branch is frozen, and LoRA is applied to all other MLP layers of the model. Our LoRA settings are: lora_rank = 8 and lora_alpha = 16. The model is trained for one epoch on a subset of the MMHU dataset and evaluated on the MMHU-T dataset. Due to class imbalance, we employed resampling to ensure the same training data from each behavior class. The training is conducted on 4 NVIDIA RTX 6000 Ada GPUs with a total batch size of 128. The learning rate is set to 1e-4, with a warmup ratio of 0.1, and the learning rate scheduler is CosineAnnealingLR. All input images are cropped to 256×256 around the bounding box, or resized to 256×256 if the bounding box is larger than 256×256.

Intention Prediction. The training data consists of the JAAD dataset and MMHU training set. All training settings primarily follow the default configurations in Trep (Zhang et al., 2023) on the JAAD dataset. All models are implemented using the Adam optimizer with a learning rate of 0.005. We adopt an early stopping strategy with a patience of 5, and experiments are conducted on a single NVIDIA RTX 6000 Ada GPU.