egoEMOTION: Egocentric Vision and Physiological Signals for Emotion and Personality Recognition in Real-World Tasks

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https://siplab.org/projects/egoEMOTION

Abstract

Understanding affect is central to anticipating human behavior, yet current egocentric vision benchmarks largely ignore the person's emotional states that shape their decisions and actions. Existing tasks in egocentric perception focus on physical activities, hand-object interactions, and attention modeling—assuming neutral affect and uniform personality. This limits the ability of vision systems to capture key internal drivers of behavior. In this paper, we present *egoEMOTION*, the first dataset that couples egocentric visual and physiological signals with dense self-reports of emotion and personality across controlled and real-world scenarios. Our dataset includes over 50 hours of recordings from 43 participants, captured using Meta's Project Aria glasses. Each session provides synchronized eye-tracking video, head-mounted photoplethysmography, inertial motion data, and physiological baselines for reference. Participants completed emotion-elicitation tasks and naturalistic activities while self-reporting their affective state using the Circumplex Model and Mikels' Wheel as well as their personality via the Big Five model. We define three benchmark tasks: (1) continuous affect classification (valence, arousal, dominance); (2) discrete emotion classification; and (3) trait-level personality inference. We show that a classical learning-based method, as a simple baseline in real-world affect prediction, produces better estimates from signals captured on egocentric vision systems than processing physiological signals. Our dataset establishes emotion and personality as core dimensions in egocentric perception and opens new directions in affect-driven modeling of behavior, intent, and interaction.

1 Introduction

Egocentric vision systems are well positioned to capture the signals for modeling human attention, interaction, and behavior in real-world environments. Benchmarks in this area have driven advances in action recognition [15], object manipulation [31, 48], gaze prediction [25], and interaction understanding [17, 18]. These tasks focus on what people do and attend to, using first-person visual input to model external behavior [17, 18, 38]. Such progress has expanded the scope of perception systems, in domains such as Mixed Reality [23, 40], front-line productivity work [9], and context-aware interaction [5, 19]. However, current benchmarks overlook internal states like emotion and personality that shape these behaviors, implicitly assuming affect-neutral and behaviorally uniform participants [18], ignoring individual differences. This limits how egocentric systems can model behavior that depends on mood, arousal, or personality traits [17]. Tasks involving decisions [45], social interaction [17], and memory [47] require grounding in affect. We argue that without such affective modeling, emerging egocentric platforms cannot fully understand human behavior.

*Equal contribution

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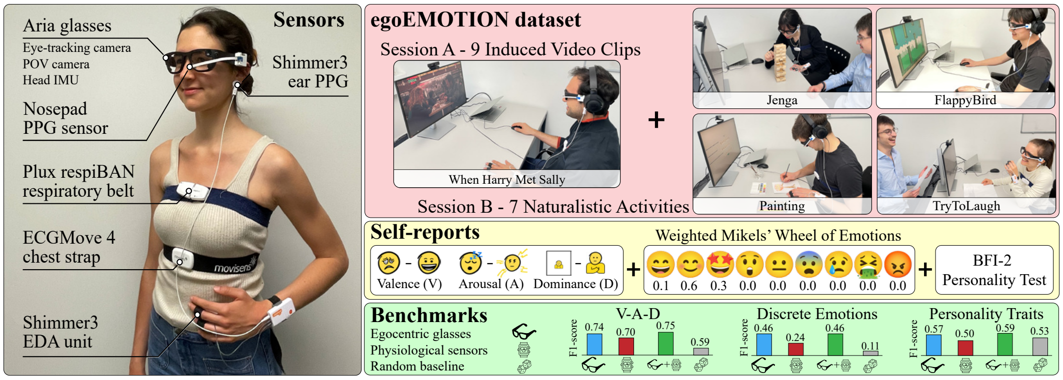

Figure 1: **egoEMOTION is a multimodal emotion and personality recognition dataset that captures participants' facial, eye-tracking, egocentric, and physiological signals during induced video stimuli and naturalistic real-world activities**. Participants reported their emotions via emoti-SAM [20] and a weighted Mikels' Wheel [41], and their personality using the Big Five model [10].

In this paper, we present egoEMOTION, a dataset for affect and personality recognition from egocentric visual and physiological signals. Our dataset thus addresses the current gap in egocentric vision by supplying emotional and trait labels grounded in self-reports. egoEMOTION comprises synchronized multimodal data during both emotion-elicitation protocols and naturalistic tasks, such as watching video clips, painting, playing social and video games. Each session captures a participant's eye-tracking video, inertial motion (IMU), outward point-of-view (POV) camera, and photoplethysmogram (PPG) to gauge cardiac activity from Meta's Project Aria glasses [13], as well as physiological baseline measurements, including electrocardiograms (ECG), respiratory rates (RSP), and electrodermal activity (EDA)—all suitable to extract indicators of a person's affective state [42, 62]. Participants reported their affect using the Circumplex Model [54] and Mikels' Wheel [41] and assessed their personality using the Big Five model [10]. In total, our dataset spans 50 hours of recordings from 43 participants across varied emotional and social contexts.

We then define three prediction benchmarks—continuous affect regression, discrete emotion classification, and personality inference— and provide baselines showing that egocentric signals, particularly eye-tracking features, outperform traditional physiological baselines in real-world emotion prediction. This highlights the promise of affective modeling from egocentric vision systems and establishes egoEMOTION as a foundation for future research in this direction.

Collectively, we contribute:

1. the first multimodal dataset that uses an egocentric vision system for emotion and personality recognition. Our dataset comprises both induced and naturalistic tasks that cover a wide range of elicited emotions, while offering nuanced mixed-emotions self-reporting.
2. three benchmark tasks and associated baseline: valence-arousal-dominance, discrete emotion, and personality recognition. Our results show that using features solely from egocentric vision systems outperforms estimates from physiological signals.
3. an open-source release of our ethics-approved dataset and baseline implementations (23 `ETHICS-008`).

2 Related Work

Emotion elicitation can be either induced, using predefined stimuli like videos or sounds, or naturalistic, arising spontaneously in real-life contexts. The terms *in-the-wild*, *real-world*, or *naturalistic* data have been denoted to describe data collection when the experimenters do not control the emotion elicitation nor constrain the data acquisition [33]. These emotional responses may occur in either static environments, where participants remain still (workplace, car, cinema), or ambulatory environments, where data is collected during everyday activities [33].

Induced. Due to the challenges of collecting physiological data in real-world settings [43, 51, 59], many emotion recognition studies have been conducted in controlled laboratory settings and have

Table 1: **Comparison of public multimodal affective datasets.**

			Elicitation				**Sensing Modalities**										**Annotation**			
Dataset (year)	No. Subjects	Mobile Sensors	Induced	Natural	Individual	Social	BVP	ECG	EDA	EEG	Eye Tracking	Face	IMU (head)	IMU (wrist)	POV camera	RSP	A-V (-D)	Emotion Tags	Weighted Tags	Big-5
egoEMOTION (2025)	43	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
EmoPairCompete [12] (2024)	28	✓		✓		✓	✓		✓					✓				✓	✓	
G-REx [3] (2024)	191	✓		✓		✓	✓		✓								✓			
eSEE-d [58] (2023)	48		✓		✓						✓							✓	✓	
BIRAFFE2 [29] (2022)	102	✓		✓	✓			✓	✓					✓			✓			✓
PPB-Emo [36] (2022)	40			✓	✓			✓		✓		✓					✓	✓		
K-EMOCON [49] (2020)	21	✓		✓		✓	✓	✓	✓	✓		✓		✓			✓	✓		
AMIGOS [42] (2018)	40	✓	✓		✓	✓		✓	✓	✓		✓					✓	✓		✓
ASCERTAIN [62] (2016)	58	✓	✓		✓			✓	✓	✓		✓					✓			✓
DEAP [26] (2012)	32		✓		✓		✓		✓	✓						✓	✓			
MAHNOB-HCI [60] (2012)	27		✓		✓			✓	✓	✓	✓	✓		✓		✓	✓	✓		

Datasets where participants were shown videos are classified as 'induced' elicitation.
A: Arousal, V: Valence, D: Dominance. BVP: Blood Volume Pressure (from PPG sensor).

used pre-selected video clips as emotional stimuli, as shown in Table 1. DEAP [26] collected electroencephalogram (EEG), facial, and physiological data from 32 participants who self-reported their emotions using valence-arousal-dominance (V-A-D) ratings after viewing 40 1-minute-long music videos. MAHNHOB-HCI [60] collected signals similar to those of DEAP with the addition of audio and eye gaze data. Their study gathered 27 participants who, after watching 20 short videos in a first experiment, followed by 28 images and 14 videos in a second experiment, annotated their emotions using V-A-D rating scales and emotional tags. ASCERTAIN [62] extended these studies by using wireless physiological sensors and facial features from 58 participants, while also capturing personality traits through the Big Five model [10]. AMIGOS [42] further advanced the field by introducing group-based video viewing and assessing mood in parallel to emotions and personality.

Naturalistic. While controlled lab settings are useful for isolating variables and evaluating specific emotions, their ecological validity is limited, raising concerns about real-world applicability [33, 57]. The G-REx [3], EmoPairCompete [12], and K-EmoCon [49] datasets naturally induced emotions in participants through group movie sessions, solving puzzles in pairs, and paired debates, respectively. BIRAFFE2 [29] exposed its participants to IAPS [32] visual and IADS [4] audio stimuli, followed by three mini-quest video games. PPB-Emo [36] recorded participants in a driving simulator. While these datasets have advanced emotion recognition in static real-world tasks, they remain limited in the array of sensors used and their range of emotionally-diverse activities. To vary naturalistic emotions recorded, emotion recognition has been investigated in ambulatory real-world settings, using mobile phones to self-report emotions [27, 56, 57, 64] and personality [28]. However, these in-the-wild studies face key limitations: self-reports are often infrequent and intrusive, the lack of known stimuli hinders interpretation of physiological responses, and signal quality is affected by motion artifacts and inconsistent sensor use.

Egocentric. The rise of mobile egocentric systems has enabled large-scale [21], in-the-wild datasets such as EPIC-KITCHENS [11], Ego4D [17], Ego-Exo4D [18], and Nymeria [38], supporting tasks like activity recognition and social behavior modeling. However, these datasets assume neutral affect and lack emotional context, limiting their use for modeling user intent or emotion-driven behaviors. Integrating emotion recognition could enable more affect-aware activity analysis and adaptive human-AI interaction. In this context, the eye-tracking videos recorded with our glasses offer a valuable modality for capturing users' intrinsic emotional states during diverse real-world tasks. MAHNOB-HCI [60] was one of the first datasets to introduce eye-tracking as a modality. While emotion recognition using *mobile* eye-tracking systems has been explored [30, 46, 63], their datasets were not made public and gathered few participants. To date, eSEE-d [58] is the only public dataset

Table 2: **Summary of emotional elicitation tasks**: induced (`1-9`) and naturalistic (`10-16`).

Activity	ID	Description	Duration
*Video Clips**	`1-9`	AnimalCruelty, AuroraBorealis, BearGrylls, CollegeAcceptance, HarrySally, JoJoRabbit, LoveActually, MovingShapes, Psycho	9×48 s
Flappy Bird	`10`	Click to keep a bird flying through pipes. Restart upon failure.	4 min
Jelly Bean	`11`	Eat three unpleasant-tasting jelly beans.	2 min
Jenga	`12`	Remove blocks from a tower without collapsing it with experimenter.	5 min
Painting	`13`	Paint with brushes and crayons, listening to *Your Song* (Elton John).	4 min
Sad Letter	`14`	Write a letter to someone lost, listening to *Adagio for Strings*.	4 min
Slenderman	`15`	Find eight pages in dark woods while escaping the Slenderman.	6 min
Try to Laugh	`16`	Take turns with experimenter telling pre-written jokes.	4 min

*A detailed description of the emotion-inducing video clips is presented Table 12 of Appendix A.

for emotion recognition using mobile eye-tracking. However, its limited four-emotion questionnaire, absence of physiological signals, and controlled setup (e.g., chin rest) reduce its validity for real-world applications. While heart rate can be estimated from facial videos [8, 52, 68], other physiological signals, such as EDA, remain challenging to estimate [6, 7] but are significant for judging a person's emotional response [37]. Personality recognition from mobile eye-tracking systems has been explored by Hoppe et al. [22] with participants walking on a university campus and Berkovsky et al. [2], in which participants watched images from the IAPS dataset [32] in laboratory settings. Neither of these studies recorded physiological signals, nor released their dataset.

3 egoEMOTION Dataset

Prior work on emotion and personality recognition using physiological sensors has typically focused on affect, valence, and personality recognition—often in controlled lab settings with specialized equipment. We go further by collecting detailed emotion self-reports alongside affect, valence, and personality, across both induced and naturalistic tasks (see Figure 1). While our setup includes both standard physiological sensors and an egocentric vision system, we show that egocentric video alone is sufficient to enable practical, real-world applicability beyond traditional sensor-based approaches.

3.1 Dataset Design

3.1.1 Experimental Protocol

Upon arrival, we explained the study protocol and self-report questionnaires to the participants, asked them to sign a consent form, and then equipped them with the sensors. The experimental protocol (see Figure 1) consisted of two sessions (A and B) with a total of 16 different tasks. We conducted the experiment in a regular office next to a window, with the experimenter seated behind a curtain to avoid affecting participants' emotional reactions. Before starting session A, each participant performed an eye-tracking calibration. In session A, participants watched nine video clips ($\mu = 48$ s, see Table 2) corresponding to the eight emotions from Mikels' Wheel [41], plus a ninth neutral emotion. All videos were extensively validated by previous work to elicit target emotions [60, 62]. Before each video clip, participants had to watch a 5-second video of a fixation cross to refocus their gaze [42, 62]. In session B, participants conducted seven activities (see Table 2) that we selected to reflect spontaneous everyday activities to further the study's ecological validity [53]. We designed the activities to minimize physical effort to avoid activity-induced variations in the recorded signals. After each task in sessions A and B, participants self-reported their perceived emotions. They were instructed to report their true emotion, not the one they perceived as being the 'correct' one. The questionnaires completed, they watched a neutral video of clouds to mitigate any carry-over effect of the previous emotional stimulus. The task order in both sessions was randomized for each participant.

3.1.2 Data Annotation

The experiment was performed on a graphical user interface coded using the `PyQt5` Python library, which would successively show washout, emotional stimulus, and self-report. For session B, the

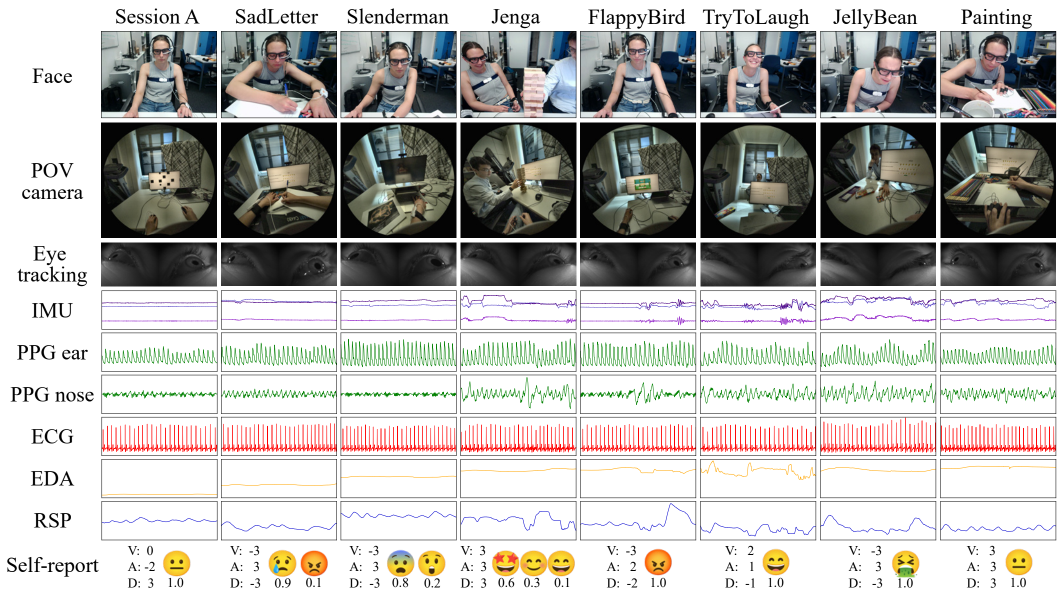

Figure 2: **Data collection** from the egocentric glasses and physiological sensors during each task with their associated self-reports. Further information about the study protocol is available in Appendix A.

experimenter would explain and setup the upcoming activity once the washout video was completed. Participants used their dominant hand to navigate through two questionnaires using a serial mouse. The first questionnaire, built on the Circumplex Model of Affect [54], comprised a self-assessment manikin (SAM) where participants reported the arousal (A), valence (V), and dominance (D) of their emotion. We used the 7-point emoji-based emoti-SAM [20], which balanced response granularity with cognitive load and was intuitive given the ubiquity of emojis. If SAM ratings are standard in emotion recognition studies, they are usually reduced to binary labels (e.g., *high* / *low*), which oversimplifies emotions. As exemplified in Figure 2, the distinct emotions of fear, sadness, disgust, and anger all fall into the low-valence / high-arousal quadrant, making them difficult to distinguish. Some studies have introduced binary emotional tags to address this [16, 42, 60], but these lack nuance, particularly when mixed emotions are present, since each emotion carries equal weight in the analysis.

To gain nuance, we used as second questionnaire a weighted version of emotional tags. The participants distributed 100% across nine emotions (eight from Mikels' wheel [41] plus a neutral option) in increments of 10%, ensuring the weights sum to unity for every report. The emotions were Amusement (Amu), Content (Con), Excitement (Exc), Awe, Fear (Fea), Sadness (Sad), Disgust (Dis), Anger (Ang), and Neutral (Neu). This captured the relative emotional strength perceived by the user, distinguishing between stimuli that have one dominating emotion and others where emotions are more homogeneous. This annotation allowed complex emotions to be represented as vectors with attributes such as polarity, type, intensity, similarity, and additivity, following Yang et al. [67]. It also enabled identifying the dominant emotion, leading to a more precise 9-class classification.

Finally, participants filled in the Big Five Inventory-2 (BFI-2) personality questionnaire online [61] before the experiment. The BFI-2 assesses five major personality traits: Extraversion (*Ex*), Agreeableness (*Ag*), Conscientiousness (*Co*), Negative Emotionality (*NE*), and Open-Mindedness (*OM*).

3.1.3 Sensors

Our study used mobile wearable sensors to capture participants emotional responses, as shown in Figure 1. We used the Project Aria glasses [13] for their significant promise in capturing ecologically valid data that does not inhibit natural activities and behavior of the participants. Using the device's 'Profile 16', we recorded eye-tracking (ET) videos with a 640 $\times$ 480 pixel resolution per eye at 90 fps, egocentric vision through a 1408 $\times$ 1408 POV RGB camera at 10 fps, and head movements through two IMUs sampling at 1000 Hz and 800 Hz. We supplemented the egocentric glasses with an in-house nosepad PPG sensor sampling at 128 Hz. A Shimmer3 unit recorded PPG and EDA signals at the ear and fingers, respectively, at 256 Hz. A 1024 Hz Movisens ECG4Move4 chest belt measured the participant's ECG data while a plux respiBAN respiratory belt measured their

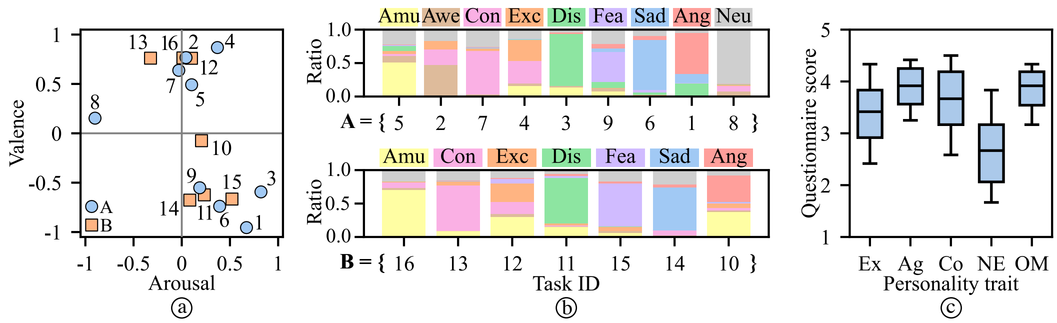

Figure 3: **Participant self-reports across tasks**. **(a)** Mean arousal-valence ratings. **(b)** Proportions of discrete emotions reported in Sessions A and B. **(c)** Boxplots of Big Five personality trait scores.

respiration pattern (RSP) at 400 Hz. We recorded participants' facial expressions with a 60 fps 1280×720 webcam for external labeling of emotions.

3.2 Recruitment and Recording

We recruited 43 healthy participants, mostly students, voluntarily with a CHF 30 compensation. The 24 female and 19 male participants were between 19 and 29 years old (μ = 26, σ = 2). Based on the Fitzpatrick scale [14], 3 participants had skin type I, 19 had skin type II, 9 had skin type III, 8 had skin type IV, and 5 had skin type V. Each participant was recorded in a single session that lasted approximately 105 minutes. They had to confirm that they were not taking tranquilizers, psychotropic drugs, or narcotics, and were not diagnosed with any cardiovascular disease. They were also informed that they would have to carry two belts (ECG and RSP) on their chest. We ensured that all participants had sufficient English proficiency to understand the videos that they were shown.

3.3 Dataset Composition

Participant recordings were cut to the duration of session A (μ = 20 min) and session B (μ = 49 min). The dataset contains all raw sensor streams presented in Figure 2, each preserved at its sampling frequency. Since all sensors were equipped with IMUs, they were synchronized at the start and end of each experiment by simultaneously shaking them. This yields egoEMOTION, a dataset composed of 43 participant recordings, each completing 16 emotional tasks. In total, the dataset offers over 50 hours of synchronized (90 Hz) multimodal data of egocentric and physiological signals. The dataset is structured by participant, with each folder containing the corresponding sensor streams. The start and end of each task were manually labelled to enable task-specific analyses.

4 Dataset Descriptives

4.1 Analysis of self-reports

Figure 3 shows the self-reports across all participants of (a) mean arousal-valence ratings for each video clip and task, (b) discrete emotions (dominant emotion indicated above task), and (c) personality traits. While participants reported a wide range of valence, arousal ratings were less varied and consistently high across tasks. The video clips and naturalistic activities elicited a diverse range of emotions (see Figure 3b). The naturalistic activities elicited stronger emotional responses, evidenced by a lower proportion of neutral tags. More detailed information is provided in Appendix B.

4.2 Correlations

Figure 4 presents the Pearson correlation matrices between continuous affect self-ratings (A-V-D), discrete emotions, and personality traits. Focusing on significant correlations, *Co* was negatively correlated with both V and D. *Ag* showed a moderate positive correlation with A. The strongest relationships for discrete emotions and personality were between *Ag* and Sadness and Disgust. The correlations between discrete emotional states and the continuous affective dimensions were the following: V was positively associated with Amusement and Content, while negatively associated

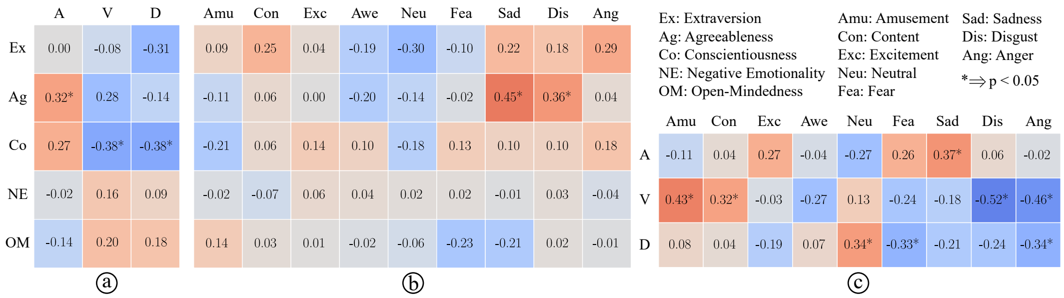

Figure 4: **Pearson correlations between self-reports.** **(a)** continuous self-ratings and personality scores **(b)** discrete emotions and personality scores **(c)** discrete emotions and continuous self-ratings.

with Disgust and Anger, aligning with expectations. D showed significant negative correlations with Disgust and Anger, while A was positively linked to Excitement and Sadness. Appendix B contains more details on the individual correlations between the self-reported annotations in Sessions A and B.

5 Baselines

To demonstrate the benefits of egoEMOTION and motivate follow-up research, we propose three benchmarking tasks: predicting a participant's self-reported *affective state*, *discrete emotions*, and *personality traits*. We evaluate classical machine learning methods using data from wearable sensors (ECG, EDA, RSP) and the Aria glasses (accelerometers, eye-tracking, nosepad PPG). We contrast these classical methods with deep learning methods to highlight potential future research directions.

5.1 Feature Extraction

We extracted a total of 612 features from all data modalities (see Appendix C.1) across the duration of each video clip in session A and each activity in session B . Following prior work, we extracted 77 features for ECG and PPG (green channel nose-pad PPG) [42], 31 features for EDA [42, 62], and 14 features for respiratory rate [26].

Pupil size was inferred over time from the eye-tracking video footage using an open-source eye-tracking algorithm [24]. We also computed the mean pixel intensity of each eye for each video frame as a basic visual descriptor. Additionally, we trained a Fisherface model (PCA followed by LDA) [1] on each training split for each target variable (affective state, emotion, and personality), and used it to project each video frame into a one-dimensional space. The resulting per-frame projections (Fisherface features) were included in our analysis. We used the open-source eye gaze extraction for the Project Aria glasses from Meta [39] to obtain the eye gaze (yaw and pitch). As there is no publicly available model yet for blinking detections from Project Aria glasses, we implemented a signal-processing-based approach using the variance map of the eye tracking videos to detect blinks [44]. To detect micro-expressions from the eye-tracking videos, we extracted features using LBP-TOP [69] with a window size of 10 frames (i.e., 111 ms) similar to previous work on facial videos [66]. For the acceleration signal from the Aria glasses, we calculated the magnitude across all three axis. All computations were run on AMD EPYC CPUs.

For each of the resulting time-series signals—pupil size, eye gaze, video pixel intensity, Fisherface features, and acceleration magnitude—we computed 15 statistical descriptors: mean, minimum, maximum, standard deviation, median, 5th percentile, 95th percentile, range, interquartile range (IQR), sum, energy, skewness, kurtosis, root mean square (RMS), and line integral. For the micro-expressions, we averaged each of the LBP-TOP features. The pupil detection and eye-tracking video preprocessing took 2 hours and about 50 GB of RAM per participant, with the micro-expressions taking 10 minutes. The rest of the feature extraction took under 1 minute per participant.

5.2 Continuous Affect Recognition

For continuous affect recognition, we focused on predicting a participant's self-reported *arousal*, *valence* and *dominance* levels. To enable classification, we binarized these continuous ratings into *low* and *high* categories using the median value across the training set, following prior work [42, 62].

Table 3: **Predictions for continuous affect ratings, discrete emotions, and personality traits.**

		Wearable devices				Egocentric glasses									All	Baseline
						ET video										
Benchmark	**Domain**	ECG	EDA	RSP	$\bowtie$	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	$\bowtie$	$\bowtie$	Random
Continuous Affect	Arousal	0.76	0.76	0.75	0.76	0.77	0.76	0.76	**0.78**	0.76	0.76	0.76	0.75	**0.78**	**0.78**	0.64
	Valence	0.67	0.64	0.69	0.69	0.73	0.72	0.69	0.63	0.66	0.68	0.66	0.75	0.76	**0.77**	0.55
	Dominance	0.63	0.66	0.66	0.66	0.67	0.66	0.65	0.65	**0.69**	0.66	0.67	0.67	0.68	0.68	0.57
	Mean	0.69	0.69	0.70	0.70	0.72	0.71	0.70	0.69	0.70	0.69	0.70	0.72	0.74	**0.75**	0.59
Discrete Emotions	Amused	0.37	0.44	0.45	0.45	0.39	0.50	0.43	0.36	0.23	0.32	0.31	**0.58**	0.50	0.52	0.21
	Content	0.28	0.20	0.29	0.29	0.37	0.49	0.31	0.31	0.23	0.20	0.20	**0.54**	0.52	0.50	0.16
	Excited	0.00	0.05	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	**0.12**	**0.12**	0.08	0.05
	Awe	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.06	0.05	0.00	0.00	0.23	**0.31**	0.28	0.04
	Neutral	0.18	0.29	0.22	0.15	0.36	0.34	0.34	0.36	0.16	0.17	0.17	0.37	**0.41**	0.40	0.17
	Fear	0.06	0.14	0.17	0.28	0.48	0.40	0.08	0.24	0.04	0.20	0.10	0.42	0.55	**0.59**	0.08
	Sad	0.15	0.42	0.17	0.46	0.45	0.52	0.32	0.37	0.11	0.12	0.10	**0.60**	0.57	0.57	0.10
	Disgust	0.08	0.40	0.27	0.39	0.40	0.61	0.34	0.40	0.08	0.20	0.18	0.60	**0.65**	0.61	0.12
	Anger	0.03	0.05	0.11	0.11	0.26	0.17	0.17	0.12	0.09	0.03	0.00	0.48	**0.53**	0.50	0.08
	Mean	0.13	0.22	0.19	0.24	0.34	0.34	0.22	0.25	0.11	0.14	0.12	0.44	**0.46**	**0.46**	0.11
Personality Traits	Ex	0.28	0.52	0.32	0.22	0.40	**0.60**	0.50	0.58	0.43	0.48	0.30	0.55	0.55	0.48	0.55
	Ag	0.38	0.42	0.48	0.55	0.45	0.40	**0.60**	**0.60**	0.35	0.43	0.40	0.57	0.30	0.55	0.52
	Co	0.55	0.55	0.30	0.50	0.55	**0.65**	0.45	0.48	0.58	0.55	0.57	0.40	0.55	**0.65**	0.55
	NE	0.52	0.50	0.65	0.68	0.68	0.60	0.55	0.60	0.50	0.58	0.42	0.30	0.68	**0.70**	0.52
	OM	0.32	0.55	0.50	0.57	0.48	0.30	0.62	0.53	0.38	0.33	0.60	0.57	**0.70**	0.58	0.52
	Mean	0.41	0.51	0.45	0.50	0.51	0.51	0.54	0.56	0.45	0.47	0.46	0.48	0.57	**0.59**	0.53

$\bowtie$ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions. The error bars are not displayed in this table for clarity purposes. They are available in Appendix C.

We trained a separate Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel (default settings [50]) for each target (arousal and valence). Features were standardized to the $[0, 1]$ range on a per-participant basis. No feature selection was applied for this task, as the SVM model was shown to perform robustly with the full set of features. Classification was performed using a leave-one-subject-out (LOSO) cross-validation strategy to ensure generalization across participants. We report the mean F1 score across all participants, averaged over the two binary classification tasks (see Table 3 and Appendix Table 6).

5.3 Discrete Emotion Recognition

In the discrete emotion recognition task, we aimed to classify one of nine basic emotions as reported by participants: *amusement*, *content*, *excitement*, *awe*, *neutral*, *fear*, *sadness*, *disgust*, and *anger*. For each participant and task, the ground-truth label corresponds to the strongest self-reported emotion. We used a Random Forest classifier with standardized features. To reduce dimensionality and focus on the most relevant inputs, we applied SelectKBest [50] feature selection using mutual information, retaining the top 10 features from the training set. As with the affect recognition task, we employed leave-one-subject-out cross-validation to assess generalization. We trained a single multi-class classifier and evaluated performance using the mean F1 score across participants (see Table 3 and Table 8). The 9-class classification task had a random baseline F1 score of 0.11.

5.4 Personality Prediction

The personality prediction task involves estimating each participant's Big Five personality traits: *open-mindedness*, *conscientiousness*, *extraversion*, *agreeableness*, and *negative emotionality*. For each trait, we binarized the self-reported score into *low* and *high* categories using the median across the training set. We trained a separate Random Forest classifier for each trait. Unlike the other tasks, we did not apply feature standardization, as the absolute magnitude of certain features was found to be more informative for personality prediction. For each classifier, we applied SelectKBest feature selection using mutual information and retained the top 10 features from the training set. Feature vectors were constructed by averaging the features for all samples belonging to a participant. We evaluated the model using leave-one-subject-out cross-validation and report the mean F1 score averaged across all five traits (see Table 3 and Appendix Table 10).

Table 4: **Performance comparison between classical and deep learning approaches.**

Benchmark	Model	Wearable devices	Egocentric glasses	All
Continuous Affect	Classical	0.70±0.14	0.74±0.13	0.75±0.13
	CNN [55]	0.63±0.05	0.68±0.05	0.68±0.07
	WER [65]	0.49±0.21	0.65±0.11	0.60±0.16
Discrete Emotions	Classical	0.24±0.08	0.46±0.18	0.46±0.17
	CNN [55]	0.12±0.01	0.23±0.03	0.22±0.02
	WER [65]	0.13±0.02	0.22±0.03	0.21±0.04
Personality Traits	Classical	0.50±0.48	0.57±0.49	0.59±0.49
	CNN [55]	0.43±0.26	0.42±0.20	0.41±0.25
	WER [65]	0.38±0.28	0.47±0.24	0.44±0.28

5.5 Use of deep learning models

To ground the above results in contemporary approaches, we implemented two deep learning-based models from previous works for wearable emotion recognition: one classical convolutional neural network (CNN) [55] and one state-of-the-art transformer-based architecture (WER) [65]. As input, we use the filtered continuous signals (without Fisherfaces), similar to previous work [55, 65]. We trained all models using a five-fold cross-validation approach. The training was conducted with a batch size of 128 for 30 epochs, a learning rate of 0.0001, and cross-entropy loss as the loss function. Each model was trained on a NVIDIA H200 with a total runtime of about 8 hours for the CNN and 30 hours for the transformer-based architecture.

For all proposed benchmark tasks, our implemented classical methods perform better than the deep learning-based approaches (see Table 4). Using the classical methods, we obtain maximum F1 scores of 0.75 (continuous affect), 0.46 (emotion prediction) and 0.59 (personality prediction) compared to maximum F1 scores of 0.68, 0.23 and 0.47 using the deep learning-based approaches, respectively.

5.6 Discussion

The results in Table 3 highlight the value of incorporating data from the Aria headset alongside traditional physiological modalities such as ECG, EDA, and RSP. For continuous affect recognition, the SVM model achieves a mean F1 score of 0.75 when using all modalities. Signals captured exclusively from the headset reach a comparable mean F1 score of 0.74, slightly outperforming traditional wearable signals ($F_1 = 0.70$), with pupil size features contributing strongly. In the more challenging discrete emotion recognition task, head-mounted signals alone yield a mean F1 score of 0.46, which is substantially above the random baseline of 0.11. Notably, acceleration magnitude from the Aria IMU achieves $F_1 = 0.44$ on its own, and pupil intensity reaches 0.34, while wearable signals perform significantly lower (e.g., $F_1 = 0.13$ for ECG, $F_1 = 0.22$ for EDA). For personality prediction, combining all modalities results in a mean F1 score of 0.59 versus 0.53 for the baseline. Signals from the egocentric glasses alone yield $F_1 = 0.57$, outperforming wearable-only inputs ($F_1 = 0.50$), with eye gaze being the best-performing individual modality.

These findings suggest that egocentric signals from head-mounted devices, such as eye-tracking video and head motion, capture rich behavioral information beyond traditional physiological sensors. While such modalities were once impractical in mobile settings, the growing availability of smartglasses and augmented reality headsets makes their use increasingly practical. Coupled with more expressive models, such as temporal neural networks or multimodal foundation models, these data sources offer promising directions for real-time user state inference and next-generation human-centered systems.

6 Limitations

While egoEMOTION offers a rich multimodal dataset for emotion and personality recognition in induced and naturalistic settings, several limitations must be acknowledged. First, the ground truth labels rely on retrospective self-reports after each task, which may be affected by recall bias and do not capture the dynamic nature of emotional responses over time [3, 34]. More fine-grained labeling (e.g., via facial expression analysis from our facial recordings) could further improve the temporal resolution of the annotations. Second, the dataset lacks longitudinal recordings, which may limit the study of emotional and personality state changes over extended periods. While our study was designed for identifying distinct emotions rather than mapping them to the arousal-valence scale in order to get finer emotion labels, we acknowledge that it has limited representation in the low-arousal, low-valence quadrant. We also recognize that some modalities like IMU may primarily capture task-related motor activity rather than affective states due to inherent coupling between behavior and emotion, which could confound emotion recognition with task classification. However, our results show IMU-based prediction performs better in Session A (identical participant behavior across emotions) than in Session B (different participant behavior across emotions), suggesting the IMU captures more than just overt behavioral differences, and is informative for emotion prediction even when behavior is held constant.

Additionally, despite recording eye-tracking and facial video data, we only extracted pupil diameter, pixel intensity, Fisherface features, gaze fixations, blink rate, and micro-expressions. Designing emotion-specific features (e.g., to recognize narrowed eyes when smiling, or teary eyes when sad) would further enhance the performance of the models. Moreover, while we leveraged end-to-end deep learning networks [35] in the CNN [55] and WER [65] models we used, we expect that incorporating pre-training on large-scale wearable physiological datasets, as well as future advances in model design and training, will improve the results. We believe our dataset will motivate future research in these directions. Finally, our participant pool was primarily composed of young adults. While this may support training stability, it introduces some demographic bias and potentially limits generalization to more diverse populations.

7 Ethical Considerations and Data Accessibility

The collection of the egoEMOTION dataset was approved by the ETH Zürich Ethics Commission (no. `23 ETHICS-008`). All participants provided informed consent for the recording of their sessions, the creation of the dataset, and its use for research purposes. To protect participants' privacy, all personally identifiable information (e.g., age, sex, skin type) and physiological data were anonymized using a numeric participant ID. However, given the inherently identifiable nature of egocentric, eye-tracking, and external video data, this information is treated as sensitive. While emotion and personality recognition can improve mental health monitoring, adaptive interfaces, and user-centric technologies, our dataset could be misused for behavioral profiling or targeted advertising. As such, access to this dataset requires users to be permanent staff members of an academic research institution and sign a Data Transfer and Use Agreement to adhere to the terms and conditions of the usage of this dataset. The dataset is hosted on servers from ETH Zurich for long-term availability and will be transferred using *sett* (the secure encryption and transfer tool) to minimize the risk of compromised data. Code to analyze the dataset is released under an open-source license.

8 Conclusion

We introduce egoEMOTION, the first publicly available dataset combining egocentric vision and physiological signals for emotion and personality recognition across both induced and naturalistic tasks. Capturing over 50 hours of synchronized multimodal recordings from 43 participants engaged in 16 emotionally diverse activities, egoEMOTION sets itself apart by covering a broad spectrum of real-world individual and social scenarios. It proposes three benchmark tasks: continuous affect regression, discrete emotion classification, and personality inference. Our results demonstrate that signals from egocentric devices—particularly eye-tracking features and head motion—outperform traditional physiological baselines in emotion and personality recognition tasks. These findings highlight the potential of egocentric vision systems to move beyond modeling observable behavior and towards capturing the underlying affective and dispositional states that shape human interaction. We envision egoEMOTION as a foundation for advancing affect-aware human-computer interaction and real-time user state estimation in the wild, enabling more personalized and emotionally intelligent systems across domains such as healthcare, education, and immersive computing.

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   Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: We specify all details of our employed approach in Section 5. We use a leave-one-subject-out cross-validation approach, ensuring no data leakage between participants, and use the default settings for all deployed SciPy classifiers. Furthermore, we provide the entire preprocessing, feature calculation, and training and testing pipeline in our code, which can be accessed with the link in the abstract.

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- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
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8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   We provide all compute details in Section 5. All computations were run on AMD EPYC CPUs. One CPU is enough to process each participant individually, with about 50 GB of RAM necessary. Processing of the pupils and video data took about 2 hours per participant. The rest of the feature extraction and training/testing took under 1 minute per participant and feature.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
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    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

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Appendix

A Study Protocol

Before starting the experiment, an explanation of the study protocol, illustrated in Figure 5, was given to each participant. The experiment consisted in participants watching 9 videos and performing 7 tasks, as listed in Table 2. Details of the videos are provided in Table 12. We informed participants that each target emotion would be experienced only once during session A. This ensured that, after viewing a disturbing video, such as one eliciting disgust or fear, they would not anticipate encountering a similar emotional stimulus in the remaining videos. Between each stimulus, a washout video of clouds was shown to mitigate any emotional carry-over effect. Washouts lasted 40 seconds in session A and 1 minute in session B.

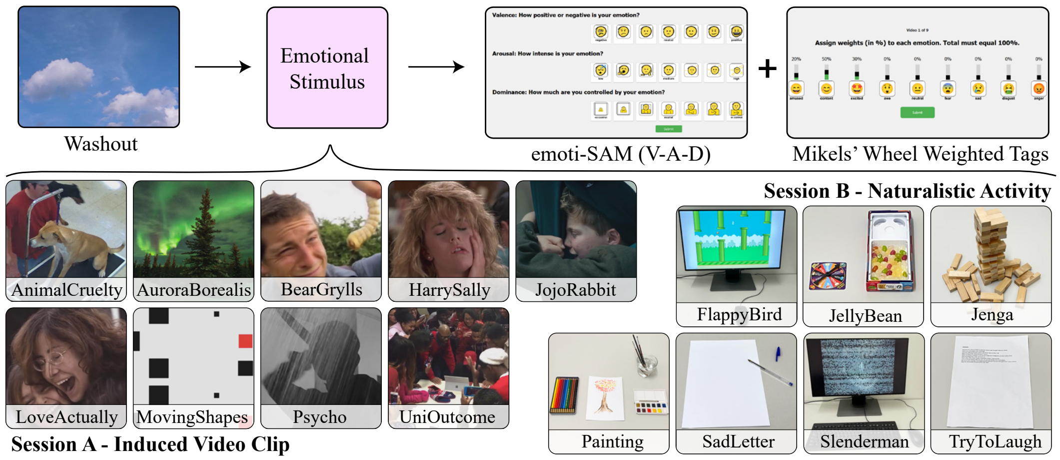


Figure 5: **Overview of the experimental protocol**. The experiment consisted of two sessions. In session A, participants watched 9 video clips, with a 40 s washout between clips and a 5 s video of a cross preceding each clip. In session B, participants performed 7 real-world tasks. Each task was spaced by a 1-min washout clip. Two questionnaires, corresponding to the emoti-SAM [20] and a weighted Mikels' Wheel [41] were answered after each emotional stimulus.

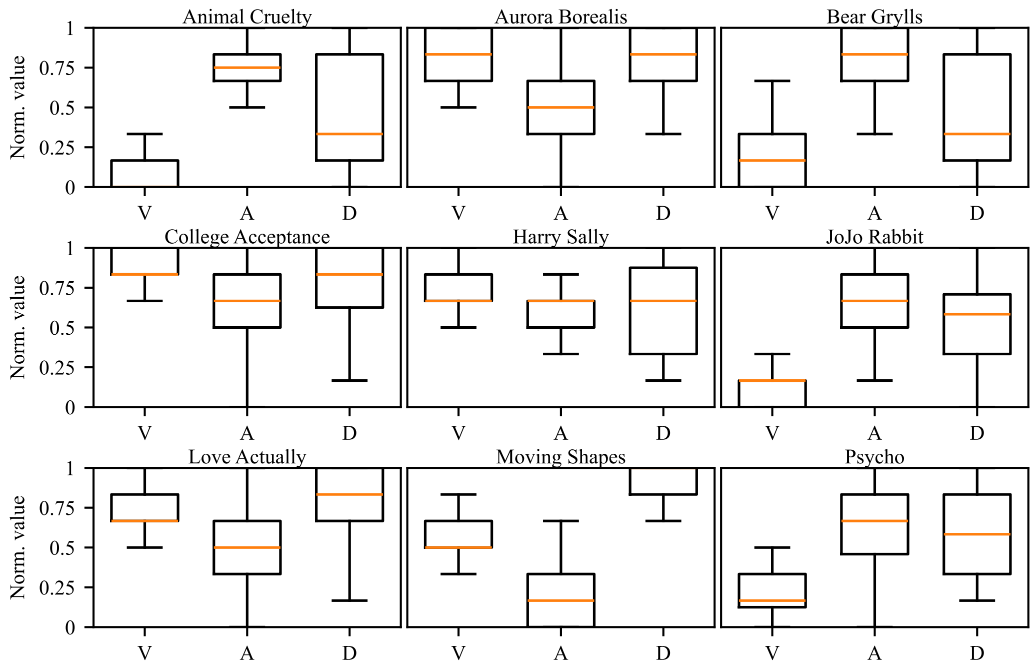
Following each emotional stimulus, participants rated their emotions using an emoti-SAM [20] and a weighted Mikels' Wheel [41], as shown in Figure 6. To familiarise the participant with each questionnaire, we explained what each term in the emoti-SAM meant i.e., *arousal*, *valence*, *dominance* and provided a definition for each emotion on Mikels' Wheel. In addition, we gave two examples of emotions and their associated self-reports. For the weighted Mikels' Wheel questionnaire, we indicated to the participant that they could gauge the intensity of their emotion using the neutral emotion. For example, if only feeling a single emotion but in low intensity, the participant could distribute the remaining weights in the neutral emotion. (e.g., 20% amused and 80% neutral indicates low amusement).

Figure 6: **Close-up view of the self-report questionnaires**. In the emoti-SAM [20], participants rated their arousal, valence and dominance using a 7-point scale. In the weighted Mikels' Wheel [41], participants distributed a 100% weight across emotions in 10% increments.

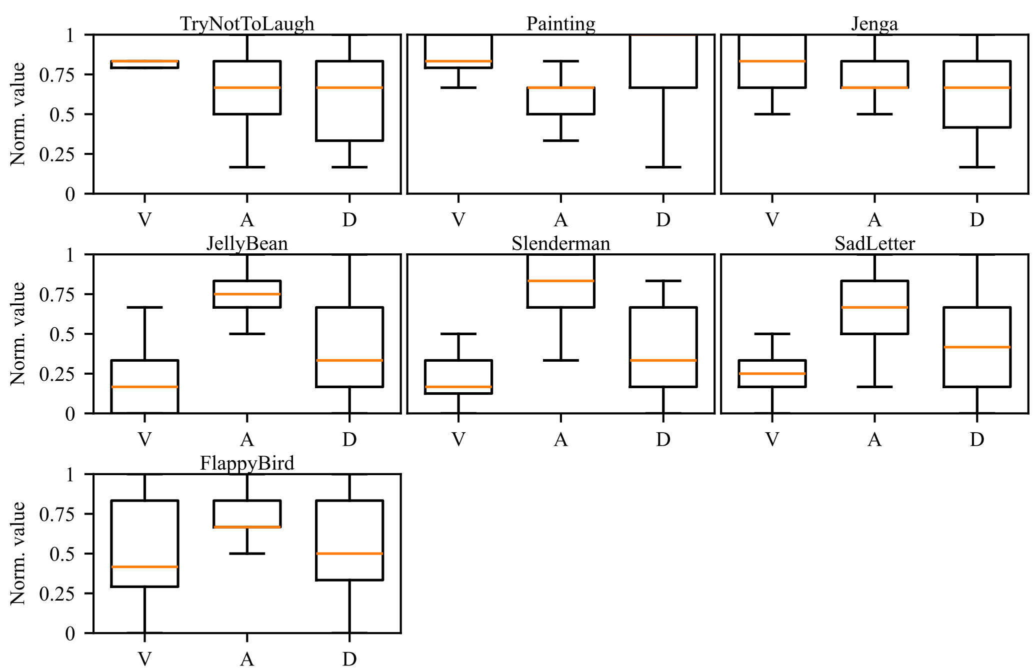
B Additional Dataset Descriptives

B.1 Mean self-ratings per task

The normalized continuous affect self-ratings for all video clips, averaged across participants, is displayed in Figure 7a. Similarly, the mean continuous affect self-ratings for the naturalistic activities of session B are displayed in Figure 7b.



(a)



(b)

Figure 7: Box plots of affect self-ratings **a)** per video clip **b)** per naturalistic task.

B.2 Self-correlations of continuous self-ratings

Figure 8 presents the Pearson correlation matrices between continuous affect self-ratings (A-V-D) across sessions A, B and A+B. Across all sessions, a strong negative relationship between arousal and dominance was observed, as well as a moderate positive relationship between valence and dominance. This indicated participants associated intense emotions with low dominance and vice-versa, while associating negative emotions to low dominance.

(a)

	Arousal	Valence	Dominance
Arousal	1.00	-0.24	-0.52*
Valence		1.00	0.40*
Dominance			1.00

(b)

	Arousal	Valence	Dominance
Arousal	1.00	-0.19	-0.53*
Valence		1.00	0.49*
Dominance			1.00

(c)

	Arousal	Valence	Dominance
Arousal	1.00	-0.20	-0.54*
Valence		1.00	0.42*
Dominance			1.00

Figure 8: Pearson correlations between continuous self-ratings in **a)** session A **b)** session B **c)** session A+B.

B.3 Self-correlations of discrete emotions

Figures 9, 10, 11 present the Pearson correlation matrices between discrete emotions across sessions A, B and A+B, respectively. The video clips of session A resulted in significant negative relationships between the neutral emotions and all other emotions excluding amused and disgust. Fear had a positive correlation with excitement and anger, while anger had a negative relationship with disgust. In session B, amusement had a strong negative correlation with anger and a moderate negative correlation with disgust.

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Amused	1.00*	0.00	-0.18	-0.10	-0.19	-0.13	-0.07	-0.08	-0.09
Content		1.00*	-0.24	-0.23	-0.33*	0.02	0.07	-0.15	0.20
Excited			1.00*	0.07	-0.47*	0.33*	0.10	0.05	0.27
Awe				1.00*	-0.41*	0.29	0.03	0.11	0.10
Neutral					1.00*	-0.54*	-0.33*	-0.16	-0.43*
Fear						1.00*	0.00	-0.24	0.32*
Sad							1.00*	0.27	-0.14
Disgust								1.00*	-0.37*
Anger									1.00*

Figure 9: Pearson correlations between discrete emotions (session A).

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Amused	1.00*	0.11	0.02	0.02	-0.29	-0.18	-0.02	-0.38*	-0.66*
Content		1.00*	-0.20	-0.28	-0.25	-0.33*	0.05	-0.10	-0.17
Excited			1.00*	-0.27	-0.26	-0.22	0.13	0.07	-0.02
Awe				1.00*	-0.11	0.37*	-0.06	-0.13	-0.09
Neutral					1.00*	-0.33*	-0.60*	-0.03	-0.05
Fear						1.00*	0.33*	-0.07	0.15
Sad							1.00*	-0.07	0.03
Disgust								1.00*	0.20
Anger									1.00*

Figure 10: Pearson correlations between discrete emotions (session B).

Fear had a moderate positive relationship with content and neutral, while having a negative relationship with awe and sadness. Finally, sadness had a strong positive relationship with the neutral emotion.

After combining the self-reports of discrete emotions from session A and B, amusement was negatively correlated with disgust and anger, while fear was positively correlated with awe. The neutral emotion was negatively correlated with excitement, awe, fear, sadness and anger.

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Amused	1.00*	0.07	-0.21	-0.17	-0.14	-0.16	0.04	-0.39*	-0.36*
Content		1.00*	-0.29	-0.23	-0.29	-0.19	0.07	-0.09	-0.13
Excited			1.00*	-0.07	-0.33*	0.13	0.25	0.15	0.28
Awe				1.00*	-0.33*	0.35*	0.06	0.01	0.21
Neutral					1.00*	-0.48*	-0.57*	-0.17	-0.42*
Fear						1.00*	0.20	-0.11	0.26
Sad							1.00*	0.07	0.08
Disgust								1.00*	0.31
Anger									1.00*

Figure 11: Pearson correlations between discrete emotions (session A+B).

B.4 Self-correlations of personality traits

Figure 12 presents the Pearson correlations between personality traits. No significant correlation was found between personality traits.

	Ex	Ag	Co	NE	OM
Ex	1.00	0.20	0.17	-0.28	0.13
Ag		1.00	0.12	-0.09	-0.08
Co			1.00	-0.26	-0.02
NE				1.00	0.28
OM					1.00

Figure 12: Pearson correlations between personality traits.

B.5 Correlations between continuous self-ratings and personality traits.

Figures 13a and 13b display the correlations between the continuous self-ratings and personality traits in session A and session B, respectively. In session A, significant negative correlations are found between dominance and *Ex* and *Co*, as well as arousal and *OM*. In session B, a negative relationship between dominance and *Co* was observed.

	Ex	Ag	Co	NE	OM
Arousal	0.20	0.20	0.20	-0.30	-0.42*
Valence	-0.07	-0.13	-0.01	-0.01	0.03
Dominance	-0.31*	-0.12	-0.34*	0.17	0.22

(a)

	Ex	Ag	Co	NE	OM
Arousal	-0.01	0.10	-0.10	0.07	0.08
Valence	-0.10	-0.05	-0.30	0.20	0.30
Dominance	-0.24	-0.16	-0.37*	-0.05	0.09

(b)

Figure 13: Pearson correlations between continuous self-ratings and personality scores in **a)** session A **b)** session B.

B.6 Correlations between continuous self-ratings and discrete emotions.

Figures 14a and 14b present the Pearson correlations between continuous self-ratings and discrete emotions in session A and session B, respectively. In session A, arousal was positively correlated with excitement, fear, sadness and anger, while being negatively correlated with the neutral emotion. Valence was positively correlated with amusement and negatively correlated with disgust. In session B, arousal was positively correlated with excitement and negatively correlated with the neutral emotion. Valence was strongly positively correlated to amusement, while being strongly negatively correlated with fear and anger. Dominance was negatively correlated with fear, sadness and disgust, while being positively correlated with the neutral emotion.

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Arousal	0.03	0.06	0.39*	0.18	-0.63*	0.32*	0.41*	0.28	0.32*
Valence	0.49*	0.27	0.01	-0.17	-0.02	-0.26	-0.24	-0.34*	-0.04
Dominance	-0.18	-0.03	0.00	-0.02	0.25	-0.18	0.03	-0.16	-0.24

(a)

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Arousal	-0.06	-0.13	0.37*	0.07	-0.42*	0.22	0.25	0.22	0.10
Valence	0.65*	0.39*	0.18	-0.08	-0.05	-0.55*	-0.20	-0.27	-0.62*
Dominance	0.06	0.08	-0.30	0.09	0.44*	-0.32*	-0.32*	-0.32*	-0.04

(b)

Figure 14: Pearson correlations between continuous self-ratings and discrete emotions in **a)** session A **b)** session B.

B.7 Pearson correlations between personality scores and discrete emotions.

Figures 15a and 15b present the Pearson correlations between personality traits and discrete emotions in session A and session B, respectively. In session A, significant positive correlations were observed between *Ag* and sadness and disgust. In session B, *Ex* was positively correlated with content. *Ag* was positively correlated with sadness and negatively correlated with awe.

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Ex	0.23	0.13	0.09	-0.15	-0.27	-0.11	0.08	0.30	0.22
Ag	-0.05	-0.02	-0.05	-0.05	-0.12	-0.02	0.35*	0.42*	-0.02
Co	-0.11	0.06	0.13	0.14	-0.22	0.15	0.14	0.19	-0.06
NE	-0.10	-0.01	-0.09	-0.06	0.15	0.04	-0.04	-0.15	-0.01
OM	0.03	-0.07	-0.02	-0.13	0.15	-0.22	-0.10	0.15	-0.06

(a)

	Amused	Content	Excited	Awe	Neutral	Fear	Sad	Disgust	Anger
Ex	-0.05	0.32*	-0.04	-0.16	-0.24	-0.06	0.28	-0.08	0.17
Ag	-0.10	0.13	0.07	-0.35*	-0.12	-0.02	0.42*	0.08	0.06
Co	-0.21	0.06	0.06	-0.02	-0.05	0.08	0.03	-0.07	0.23
NE	0.05	-0.13	0.21	0.18	-0.20	-0.01	0.02	0.24	-0.04
OM	0.17	0.15	0.04	0.17	-0.10	-0.17	-0.25	-0.18	0.03

(b)

Figure 15: Pearson correlation between personality scores and discrete emotions in **a)** session A **b)** session B.

C Additional Descriptions

C.1 Detailed Description of Baseline Features

A detailed overview of the features extracted from each modality is presented in Table 5.

Table 5: **Overview of features extracted from the recorded physiological time-series signals.** Recorded physiological signals include respiration rate, ECG, EDA, PPG recorded using a nosepad sensor and acceleration magnitude from the Aria-integrated IMU sensor. We further compute statistical descriptors of the time-series signals inferred from the video data captured by the eye-tracking cameras, including pupil size, video pixel intensity, and Fisherface feature coefficients.

Time-series signal	**Features extracted**
Acceleration Magnitude (Aria IMU)	Mean, min, max, standard deviation, median, 5th and 95th percentiles, range, interquartile range, sum, energy, skewness, kurtosis, RMS, and line integral.
Blinking (ET camera)	Number of blinks of the left eye and the right eye.
ECG	Root mean square of the mean squared IBIs, mean IBI, 60 spectral power values in the [0–6] Hz band of the ECG signal, low-frequency [0.01–0.08] Hz, medium-frequency [0.08–0.15] Hz, and high-frequency [0.15–0.5] Hz components of HRV spectral power, HR and HRV statistics.
EDA	Mean skin resistance and mean of derivative, mean differential for negative values only (mean decrease rate during decay time), proportion of negative derivative samples, number of local minima in the GSR signal, average rising time of the GSR signal, spectral power in the [0–2.4] Hz band, zero crossing rate of skin conductance slow response (SCSR) [0–0.2] Hz, zero crossing rate of skin conductance very slow response (SCVSR) [0–0.08] Hz, mean SCSR and SCVSR peak magnitude.
Eye Gaze (Yaw and Pitch)	Mean, min, max, standard deviation, median, 5th and 95th percentiles, range, interquartile range, sum, energy, skewness, kurtosis, RMS, and line integral.
Fisherface Features (ET camera)	Mean, min, max, standard deviation, median, 5th and 95th percentiles, range, interquartile range, sum, energy, skewness, kurtosis, RMS, and line integral.
Micro-expressions (ET camera)	Mean of each LBP-TOP feature.
PPG (Nosepad Sensor)	Root mean square of the mean squared IBIs, mean IBI, 60 spectral power values in the [0–6] Hz band of the PPG signal, low-frequency [0.01–0.08] Hz, medium-frequency [0.08–0.15] Hz, and high-frequency [0.15–0.5] Hz components of HRV spectral power, HR and HRV statistics.
Pupil Size (ET camera)	Mean, min, max, standard deviation, median, 5th and 95th percentiles, range, interquartile range, sum, energy, skewness, kurtosis, RMS, and line integral.
RSP	Band energy ratio (difference between the logarithm of energy between the lower (0.05–0.25 Hz) and the higher (0.25–5 Hz) bands), average respiration signal, mean of derivative (variation of the respiration signal), standard deviation, range or greatest breath, breathing rhythm (spectral centroid), breathing rate, 10 spectral power values in the bands from 0 to 2.4 Hz, average peak-to-peak time, median peak-to-peak time.
Video Pixel Intensity (ET camera)	Mean, min, max, standard deviation, median, 5th and 95th percentiles, range, interquartile range, sum, energy, skewness, kurtosis, RMS, and line integral.

C.2 Continuous Affect Prediction

Table 6 presents the continuous affect domain prediction results for session A and session B. The egocentric glasses provided better predictions of the continuous affect self-reports than the physiological sensors. The glasses had a F_1 score of 0.72 and 0.73 in session A and B, respectively, while the physiological sensors reported an F_1 score of 0.68 in session A and session B. Notably, all sensors had a strong performance when predicting arousal in session B.

Table 7 presents the standard deviation results of the continuous affect domain predictions across all sessions. Session A displays greater variability, particularly within the arousal and dominance self-reports. In contrast, Session B demonstrates lower and more uniform standard deviations across all modalities. When aggregating session A with session B, the lowest standard deviations are achieved.

Table 6: **Continuous affect domain prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	⋈	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	⋈	⋈	Random
A	Arousal	0.64	0.65	0.60	0.63	0.67	0.62	0.64	0.69	0.66	0.64	0.64	0.65	0.68	**0.69**	0.56
	Valence	0.71	0.68	0.62	0.71	0.71	0.66	**0.78**	0.64	0.71	0.63	0.77	0.66	**0.78**	**0.78**	0.56
	Dominance	0.70	0.70	0.71	0.71	0.68	**0.72**	0.68	0.71	0.72	0.71	0.69	0.71	0.71	0.71	0.61
	Mean	0.68	0.68	0.65	0.68	0.69	0.67	0.70	0.68	0.70	0.66	0.71	0.68	0.72	**0.73**	0.58
B	Arousal	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	**0.83**	0.74
	Valence	0.64	0.57	0.62	0.68	0.72	0.66	**0.78**	0.66	0.70	0.67	0.71	0.71	0.77	0.72	0.53
	Dominance	0.51	0.50	0.55	0.54	0.56	0.55	0.58	0.44	0.56	0.60	0.58	0.46	**0.59**	0.57	0.50
	Mean	0.66	0.63	0.67	0.68	0.70	0.68	**0.73**	0.64	0.70	0.70	0.71	0.65	**0.73**	0.71	0.59

⋈ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

Table 7: **Standard deviation of continuous affect domain prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	⋈	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	⋈	⋈	Random
A	Arousal	0.22	0.22	0.20	0.20	0.22	0.22	0.22	0.24	0.23	0.22	0.21	0.24	0.22	0.20	
	Valence	0.12	0.10	0.16	0.15	0.27	0.19	0.08	0.15	0.05	0.10	0.08	0.11	0.14	0.14	
	Dominance	0.23	0.24	0.24	0.24	0.22	0.23	0.22	0.24	0.24	0.24	0.23	0.24	0.24	0.24	
	Mean	0.19	0.19	0.20	0.20	0.24	0.21	0.17	0.21	0.17	0.19	0.17	0.20	0.20	0.20	
B	Arousal	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16	
	Valence	0.16	0.16	0.16	0.15	0.14	0.13	0.14	0.16	0.19	0.18	0.15	0.18	0.14	0.14	
	Dominance	0.23	0.26	0.23	0.25	0.25	0.22	0.26	0.25	0.23	0.26	0.22	0.22	0.26	0.22	
	Mean	0.18	0.19	0.18	0.19	0.18	0.17	0.19	0.19	0.19	0.20	0.18	0.19	0.19	0.17	
A+B	Arousal	0.14	0.13	0.13	0.14	0.14	0.14	0.13	0.14	0.14	0.13	0.14	0.13	0.15	0.14	
	Valence	0.10	0.11	0.10	0.09	0.10	0.10	0.06	0.09	0.09	0.09	0.09	0.10	0.10	0.09	
	Dominance	0.18	0.18	0.17	0.18	0.17	0.19	0.16	0.19	0.19	0.20	0.17	0.18	0.18	0.17	
	Mean	0.14	0.14	0.13	0.14	0.14	0.14	0.12	0.14	0.14	0.14	0.14	0.14	0.14	0.13	

⋈ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

C.3 Discrete Emotion Prediction

Table 8 presents the discrete emotion prediction results in session A and session B. The egocentric glasses significantly exceeded the physiological sensors in predicting 9 discrete emotions ($F_1 = 0.55$ vs. $F_1 = 0.25$) in session A. In the naturalistic tasks, the egocentric glasses and the wearable devices had comparable results, with $F_1 = 0.40$ and $F_1 = 0.33$, respectively. With the current feature extraction, emotions such as sadness (0.87) and anger (0.68) had high prediction scores in session A using the combined sensors from the egocentric glasses. The emotion of awe proved to be difficult to predict across experiments, with discrete emotions in session A achieving higher prediction results in comparison to session B. Disgust has a high F_1 score in session B (0.75) when predicting it from the egocentric glasses. The eye pupil size was highly informative for predicting fear in participants during session B ($F_1 = 0.66$).

Table 9 presents the standard deviations of the discrete emotion prediction results. Session A tends to be noisier, with larger fluctuations in certain cases (e.g., IMU and F.f.), while Session B looks more consistent overall.

Table 8: **Discrete emotion prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	⋈	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	⋈	⋈	Random
A	Amused	0.05	0.52	0.37	0.50	0.60	0.19	**0.62**	0.47	0.17	0.17	0.52	0.54	0.52	0.57	0.12
	Content	0.25	0.19	0.20	0.26	0.38	0.13	0.56	0.26	0.13	0.13	0.44	0.40	**0.61**	**0.61**	0.16
	Excited	0.00	0.00	0.00	0.00	0.09	0.00	0.25	0.00	0.06	0.00	0.07	0.00	**0.29**	0.24	0.05
	Awe	0.05	0.00	0.07	0.00	**0.38**	0.06	0.28	0.00	0.05	0.05	0.00	0.06	0.25	0.34	0.07
	Neutral	0.23	0.36	0.31	0.32	0.40	0.24	0.49	0.44	0.27	0.32	0.37	0.41	0.51	**0.52**	0.21
	Fear	0.00	0.24	0.00	0.06	0.48	0.08	0.52	0.11	0.00	0.00	**0.60**	0.12	0.57	0.53	0.06
	Sad	0.25	0.82	0.23	**0.88**	0.77	0.07	0.85	0.68	0.13	0.13	**0.88**	0.75	0.87	0.87	0.10
	Disgust	0.07	0.18	0.17	0.12	0.20	0.19	0.47	0.09	0.15	0.16	0.57	0.27	**0.63**	0.60	0.13
	Anger	0.12	0.00	0.12	0.14	0.32	0.08	0.66	0.06	0.16	0.05	0.14	0.12	**0.68**	**0.68**	0.09
	Mean	0.11	0.26	0.16	0.25	0.40	0.12	0.52	0.23	0.12	0.11	0.40	0.30	**0.55**	**0.55**	0.11
B	Amused	0.57	0.50	0.58	0.60	0.50	0.48	**0.62**	0.44	0.44	0.51	0.58	0.52	0.61	0.60	0.32
	Content	0.44	0.19	0.38	0.48	0.24	0.24	**0.58**	0.24	0.18	0.28	0.46	0.28	0.57	0.57	0.15
	Excited	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.13	0.00	0.00	0.00	**0.19**	0.10	0.05
	Awe	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.01**
	Neutral	0.04	**0.25**	0.13	0.05	0.10	0.14	0.00	0.32	0.11	0.04	0.04	0.09	0.00	0.00	0.11
	Fear	0.14	0.33	0.33	0.60	0.66	0.04	0.64	0.22	0.14	0.26	0.57	0.28	**0.67**	0.66	0.11
	Sad	0.16	0.26	0.34	0.39	0.19	0.26	**0.49**	0.47	0.20	0.29	0.37	0.05	0.44	0.42	0.10
	Disgust	0.27	0.70	0.50	0.74	0.61	0.26	0.73	0.25	0.15	0.55	0.75	0.72	0.75	**0.77**	0.10
	Anger	0.00	0.00	0.00	0.15	0.00	0.08	0.27	0.17	0.07	0.00	0.18	0.00	**0.34**	0.24	0.06
	Mean	0.18	0.25	0.25	0.33	0.26	0.17	0.38	0.12	0.16	0.21	0.33	0.22	**0.40**	0.37	0.11

⋈ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

Table 9: **Standard deviation of discrete emotion prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	⋈	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	⋈	⋈	Random
A	Amused	0.16	0.46	0.40	0.45	0.44	0.32	0.46	0.44	0.25	0.25	0.44	0.45	0.46	0.47	
	Content	0.26	0.23	0.24	0.31	0.32	0.25	0.35	0.24	0.15	0.20	0.39	0.32	0.34	0.35	
	Excited	0.00	0.00	0.00	0.00	0.10	0.00	0.28	0.00	0.11	0.00	0.16	0.00	0.28	0.28	
	Awe	0.16	0.00	0.10	0.00	0.41	0.10	0.34	0.00	0.06	0.11	0.00	0.16	0.36	0.42	
	Neutral	0.26	0.32	0.25	0.26	0.28	0.23	0.33	0.32	0.26	0.28	0.32	0.29	0.32	0.33	
	Fear	0.00	0.28	0.00	0.16	0.43	0.16	0.47	0.22	0.00	0.00	0.47	0.22	0.47	0.46	
	Sad	0.32	0.42	0.33	0.38	0.45	0.19	0.40	0.47	0.17	0.28	0.36	0.44	0.38	0.38	
	Disgust	0.16	0.32	0.30	0.21	0.29	0.31	0.45	0.25	0.21	0.28	0.47	0.38	0.44	0.44	
	Anger	0.24	0.00	0.24	0.30	0.38	0.19	0.48	0.17	0.25	0.16	0.28	0.24	0.46	0.46	
	Mean	0.17	0.23	0.21	0.23	0.34	0.19	0.40	0.11	0.08	0.11	0.32	0.28	0.39	0.40	
B	Amused	0.25	0.28	0.29	0.28	0.25	0.27	0.28	0.26	0.28	0.28	0.25	0.22	0.31	0.30	
	Content	0.39	0.32	0.40	0.44	0.29	0.36	0.43	0.23	0.31	0.34	0.44	0.37	0.41	0.42	
	Excited	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.16	0.00	0.00	0.00	0.22	0.16	
	Awe	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	Neutral	0.00	0.31	0.18	0.10	0.11	0.21	0.00	0.00	0.16	0.11	0.08	0.13	0.00	0.00	
	Fear	0.30	0.39	0.36	0.49	0.49	0.08	0.50	0.46	0.28	0.30	0.48	0.36	0.49	0.49	
	Sad	0.28	0.33	0.41	0.42	0.26	0.33	0.46	0.34	0.32	0.37	0.41	0.10	0.43	0.43	
	Disgust	0.27	0.51	0.45	0.50	0.50	0.36	0.50	0.50	0.28	0.48	0.50	0.50	0.50	0.49	
	Anger	0.00	0.00	0.00	0.22	0.00	0.16	0.28	0.16	0.16	0.00	0.24	0.00	0.31	0.28	
	Mean	0.17	0.24	0.23	0.27	0.21	0.20	0.29	0.16	0.18	0.21	0.27	0.19	0.30	0.29	
A+B	Amused	0.22	0.23	0.22	0.22	0.22	0.18	0.21	0.22	0.19	0.32	0.18	0.23	0.21	0.22	
	Content	0.23	0.21	0.26	0.24	0.26	0.23	0.30	0.22	0.24	0.20	0.28	0.22	0.24	0.24	
	Excited	0.00	0.10	0.00	0.00	0.19	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.20	0.18	
	Awe	0.10	0.00	0.00	0.00	0.32	0.00	0.34	0.16	0.08	0.00	0.00	0.00	0.43	0.40	
	Neutral	0.20	0.25	0.21	0.17	0.24	0.19	0.28	0.26	0.21	0.17	0.24	0.24	0.29	0.28	
	Fear	0.18	0.24	0.26	0.38	0.39	0.25	0.38	0.36	0.13	0.20	0.41	0.16	0.38	0.40	
	Sad	0.30	0.35	0.27	0.35	0.34	0.21	0.35	0.31	0.17	0.12	0.38	0.33	0.32	0.34	
	Disgust	0.16	0.28	0.27	0.32	0.33	0.25	0.35	0.29	0.19	0.20	0.36	0.34	0.34	0.32	
	Anger	0.00	0.18	0.22	0.19	0.30	0.00	0.42	0.21	0.19	0.03	0.31	0.27	0.44	0.40	
	Mean	0.15	0.20	0.19	0.21	0.29	0.15	0.31	0.08	0.05	0.14	0.24	0.20	0.32	0.31	

⋈ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

C.4 Personality Prediction

Table 10 presents the personality trait predictions for session A and session B. The pupil size and blink rate achieved the highest F_1 score in session A, while ECG performed best in session B ($F_1 = 0.60$). Table 11 presents the standard deviations of the personality prediction results.

Table 10: **Personality prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	$\bowtie$	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	$\bowtie$	$\bowtie$	Random
	Ex	0.48	0.48	0.42	0.30	0.48	0.48	0.45	0.48	**0.58**	0.38	0.45	0.48	0.38	0.25	**0.55**
	Ag	0.45	0.42	0.48	0.38	0.42	0.32	0.22	0.40	**0.58**	0.45	0.57	0.50	0.48	0.52	0.52
A	Co	0.42	0.52	0.28	0.42	**0.65**	0.48	0.52	0.58	0.63	0.63	0.52	0.40	0.35	0.38	0.55
	NE	0.50	0.52	0.50	0.52	**0.68**	0.45	0.30	0.58	0.45	0.53	0.50	0.57	0.62	0.48	0.52
	OM	0.30	0.60	**0.62**	0.48	0.52	0.55	0.42	0.60	0.53	0.45	0.28	0.60	0.60	0.45	0.52
	Mean	0.43	0.51	0.46	0.42	**0.55**	0.46	0.38	0.53	**0.55**	0.49	0.46	0.51	0.49	0.42	0.53
	Ex	0.45	0.50	0.48	0.55	0.45	**0.75**	0.53	0.45	0.73	0.52	0.55	**0.75**	0.48	0.55	
	Ag	0.48	0.60	0.48	0.48	0.48	0.60	0.45	**0.70**	0.45	0.63	0.38	0.32	0.65	0.35	0.52
B	Co	0.68	0.40	0.35	0.62	0.45	0.28	0.40	**0.70**	0.40	0.45	0.62	0.50	0.45	0.62	0.55
	NE	**0.78**	0.52	0.65	0.70	0.60	0.52	0.42	0.53	0.43	0.73	0.48	0.65	0.40	0.72	0.52
	OM	**0.62**	0.52	0.57	0.35	0.48	0.50	0.40	0.48	0.53	0.43	0.52	0.40	0.35	0.28	0.52
	Mean	**0.60**	0.51	0.51	0.54	0.49	0.53	0.44	0.59	0.45	0.59	0.50	0.48	0.52	0.49	0.53

$\bowtie$ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

Table 11: **Standard deviation of personality prediction results.**

		Wearable devices				**Egocentric glasses**									**All**	**Baseline**
						ET video										
Session	Domain	ECG	EDA	RSP	$\bowtie$	Pup.	Int.	F.f.	Gaze	Blink	μ-E.	PPG	IMU	$\bowtie$	$\bowtie$	Random
	Ex	0.50	0.50	0.49	0.48	0.50	0.50	0.50	0.50	0.49	0.48	0.50	0.50	0.48	0.45	
	Ag	0.50	0.49	0.50	0.50	0.49	0.47	0.42	0.46	0.49	0.50	0.49	0.50	0.50	0.50	
A	Co	0.49	0.50	0.45	0.50	0.48	0.50	0.50	0.46	0.48	0.48	0.50	0.49	0.48	0.48	
	NE	0.50	0.50	0.50	0.50	0.47	0.50	0.46	0.50	0.50	0.50	0.50	0.49	0.48	0.50	
	OM	0.46	0.49	0.48	0.50	0.50	0.50	0.49	0.50	0.50	0.50	0.45	0.49	0.49	0.50	
	Mean	0.49	0.50	0.48	0.50	0.49	0.50	0.47	0.48	0.49	0.49	0.49	0.49	0.49	0.49	
	Ex	0.49	0.50	0.50	0.50	0.50	0.43	0.50	0.49	0.50	0.45	0.50	0.50	0.43	0.50	
	Ag	0.50	0.49	0.50	0.50	0.50	0.49	0.50	0.49	0.50	0.48	0.48	0.47	0.48	0.47	
B	Co	0.48	0.49	0.48	0.48	0.50	0.45	0.49	0.50	0.49	0.50	0.48	0.50	0.50	0.48	
	NE	0.47	0.50	0.48	0.46	0.49	0.50	0.49	0.49	0.49	0.45	0.50	0.48	0.49	0.47	
	OM	0.49	0.50	0.49	0.48	0.50	0.50	0.49	0.50	0.50	0.49	0.50	0.49	0.48	0.45	
	Mean	0.49	0.50	0.49	0.48	0.50	0.47	0.49	0.50	0.50	0.47	0.49	0.49	0.48	0.47	
	Ex	0.43	0.50	0.47	0.40	0.49	0.46	0.50	0.49	0.49	0.50	0.49	0.50	0.50	0.50	
	Ag	0.48	0.49	0.50	0.49	0.50	0.49	0.49	0.49	0.48	0.49	0.49	0.49	0.46	0.49	
A+B	Co	0.49	0.50	0.46	0.50	0.50	0.49	0.49	0.50	0.49	0.50	0.48	0.50	0.50	0.48	
	NE	0.50	0.50	0.48	0.47	0.47	0.49	0.46	0.49	0.50	0.49	0.49	0.50	0.48	0.45	
	OM	0.48	0.50	0.50	0.49	0.50	0.49	0.49	0.50	0.48	0.47	0.46	0.48	0.45	0.48	
	Mean	0.48	0.50	0.48	0.47	0.49	0.48	0.49	0.50	0.49	0.49	0.48	0.49	0.48	0.48	

$\bowtie$ = fusion of modalities, Pup. = Pupil size, Int. = Pixel Intensity, F.f. = Fisherface features, μ-E. = micro-expressions.

Table 12: **Detailed description of the emotion-inducing video clips.**

ID	**Video Label**	**Target Emotion**	**Description**	**Duration (s)**
1	AnimalCruelty	Anger	Televised news of a dog groomer abusing dogs.	40
2	AuroraBorealis	Awe	A timelapse of the northern lights.	40
3	BearGrylls	Disgust	A man eats a worm.	40
4	CollegeAcceptance	Excitement	A student gets accepted to his dream college.	40
5	HarrySally	Amusement	Sally shows Harry how women fake orgasms at a restaurant.	72
6	JojoRabbit	Sadness	A boy embraces his mother who has been hanged.	46
7	LoveActually	Content	Narrator purporting that "love is everywhere".	42
8	MovingShapes	Neutral	Shapes moving on a neutral background.	40
9	Psycho	Fear	A lady gets murdered in her bathtub by an intruder.	45