Supplementary Material: Nonverbal Human Signals Can Help Autonomous Agents Infer Human Preferences for Their Behavior

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A PARTICIPANT EXCLUSION INFORMATION

This section describes our three exclusion criteria, adapted from [1].

A.1 Participant withdrew consent (n=3)

Participants in the Human identity condition were debriefed towards the end of the study about the co-player being controlled automatically (not by another person). Afterwards, the participants were asked: “Do you wish to continue being a participant in the study or would you prefer to withdraw your participation at this point?”

Three participants asked to withdraw from the study after the debriefing, and their data was discarded.

A.2 Did not experience intended helping behavior of co-player (n=141)

Based on analysis of game log files, if there were no events when the co-player destroyed an enemy on the left half of the screen (enemies for which the participant received points), the participant was excluded. This was because the participant did not experience our intended manipulation of co-player behavior.

We excluded 141 participants due to this criteria.

A.3 Insufficient in-game data (n=22)

We used in-game information as a proxy to estimate the quality of the participant’s Internet connection during the gameplay or their attention to the game. This information included game statistics but also videos of the participants recorded with their own webcams (with the participants’ consent) during the study.

We defined the following variables:

- *wc_CPS*: "webcam captures per second"; calculated as the number of webcam images divided by the elapsed seconds between first and last captured image

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- *wc_FPS*: "webcam frames per second"; calculated as the max frame number (rendered frame in Space Invaders game) in recording divided by the elapsed seconds
- *num_wc*: number of webcam images captured for a game of Space Invaders
- *num_gs*: number of gamescreen images for a game of Space Invaders
- *OF_detections*: number of frames in which OpenFace detected a human face

Participants were excluded if any of the following conditions were met:

- $OF\_detections/num\_wc < 0.7$: participants were excluded if the percentage of webcam images in which OpenFace 2.0 was able to detect faces was less than 70
- $num\_wc/num\_gs < 0.7$: participants were excluded if less than 70% of captured gamescreen images had a corresponding webcam image
- $wc\_CPS < 10$: participants were excluded if "webcam captures per second" indicated the rate at which images were captured was slow (indicating possible technical difficulties and/or slow internet connection)
- $wc\_FPS < 30$: participants were excluded if "webcam frames per second" indicated the rate at the game was updating was slow (indicating possible technical difficulties and/or slow internet connection)

We excluded 22 participants due to meeting one of the above conditions.

B ADDITIONAL INFORMATION ABOUT INPUTS TO PREFERENCE CLASSIFIERS

This section provides additional information on feature processing.

B.1 Post-Game Survey Responses

Post-game survey response data consisted of 18 features composed of the following data from the questions presented to the participant after completing each game of Space Invaders:

- (4 features) Game Experience (1: strongly disagree to 7: strongly agree) – scaled via dividing by 7.
  - "I enjoyed the game"
  - "The game was difficult"
  - "The game was boring"
  - "I would play this game for fun"
- (5 features) Co-player perception (1: strongly disagree to 7: strongly agree) – scaled via dividing by 7.
  - "The co-player was helpful"
  - "The co-player was proficient"
  - "The co-player was intelligent"
  - "The co-player was annoying"
  - "I liked the behavior of the co-player in the game"
- (3 features) RoSAS subscales (1:not at all to 7: very much so) – scaled via dividing by 7.
  - Warmth
  - Competence
  - Discomfort
- (3 features) Did anything about the behavior of the co-player seem unusual to you? – one-hot encoded.
  - Yes
  - No
  - Not sure
- (3 features) Did you help the co-player? – one-hot encoded.

- Yes
- No
- Not sure

B.2 Demographics

Demographics data consisted of 20 features composed of the following data:

- (1 feature) Age – divided by maximum age.
- (4 features) Gender – one-hot encoded.
  - Male
  - Female
  - Nonbinary
  - Prefer not to say
- (1 feature) How often the participant reported using a computer – ordinal responses scaled to [0,1].
- (1 feature) How often the participant reported playing video games – ordinal responses scaled to [0,1].
- (3 features) Has the participant played Space Invaders previously? – one-hot encoded.
  - Yes
  - No
  - Not sure
- (1 feature) Competitiveness Index [4] – scaled via dividing by 45.
- (4 features) BEQ [3] – scaled via dividing by 7.
  - NEX
  - PEX
  - STR
  - BEQ
- (5 features) TIPI [2] – scaled via dividing by 7.
  - Extraversion
  - Agreeableness
  - Conscientiousness
  - Emotional Stability
  - Openness

C GRIDSEARCH HYPERPARAMETERS

C.1 Support Vector Machines (SVM)

- Kernel: rbf
- Regularization parameter C: 0.1, 1, 10, 100, 1000
- Kernel coefficient Gamma: 1, 0.1, 0.01, 0.001, 0.0001

C.2 Random Forests (RF)

- Number of trees in the forest: 100, 500, 1000, 2000
- Minimum number of samples required to be at a leaf node: 2, 4, 8

C.3 K-Nearest Neighbors (KNN)

- Number of neighbors: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20
- Minkowski metric power parameter: 1, 2

C.4 Multi-Layer Perceptron (MLP)

- Optimizer: adam
- Learning rate: 0.0001, 0.001, 0.01
- Activation: relu, tanh
- Hidden layer sizes: [200, 50], [100, 50], [200, 100, 32]
- L2 Regularization: 0.0001, 0.05
- Batch size: 32, 64, 128
- Total number of epochs: 1000, 2000

D INPUT FEATURE INFORMATION FOR CONTEXT RESULTS

Table 1 includes information about the input features that resulted in the highest F_1-Score for each type of classifier for the results presenting in Figure 3 of the main paper.

Table 1. Information about input features for the set of models with the highest F_1-Scores for each ML algorithm. See Section 3.2.1 of main paper for descriptions of feature information.

Classifier	Survey	Nonverbal (# PC)	Demo	Game
SVM	Full-Diff	Visit-Hadamard (20)	None	Diff
RF	Selected-Diff	Visit-Diff (10)	Selected	Diff
MLP	Full-Diff	Full (20)	Selected	Diff
KNN	Selected-Diff	Full (10)	Selected	None

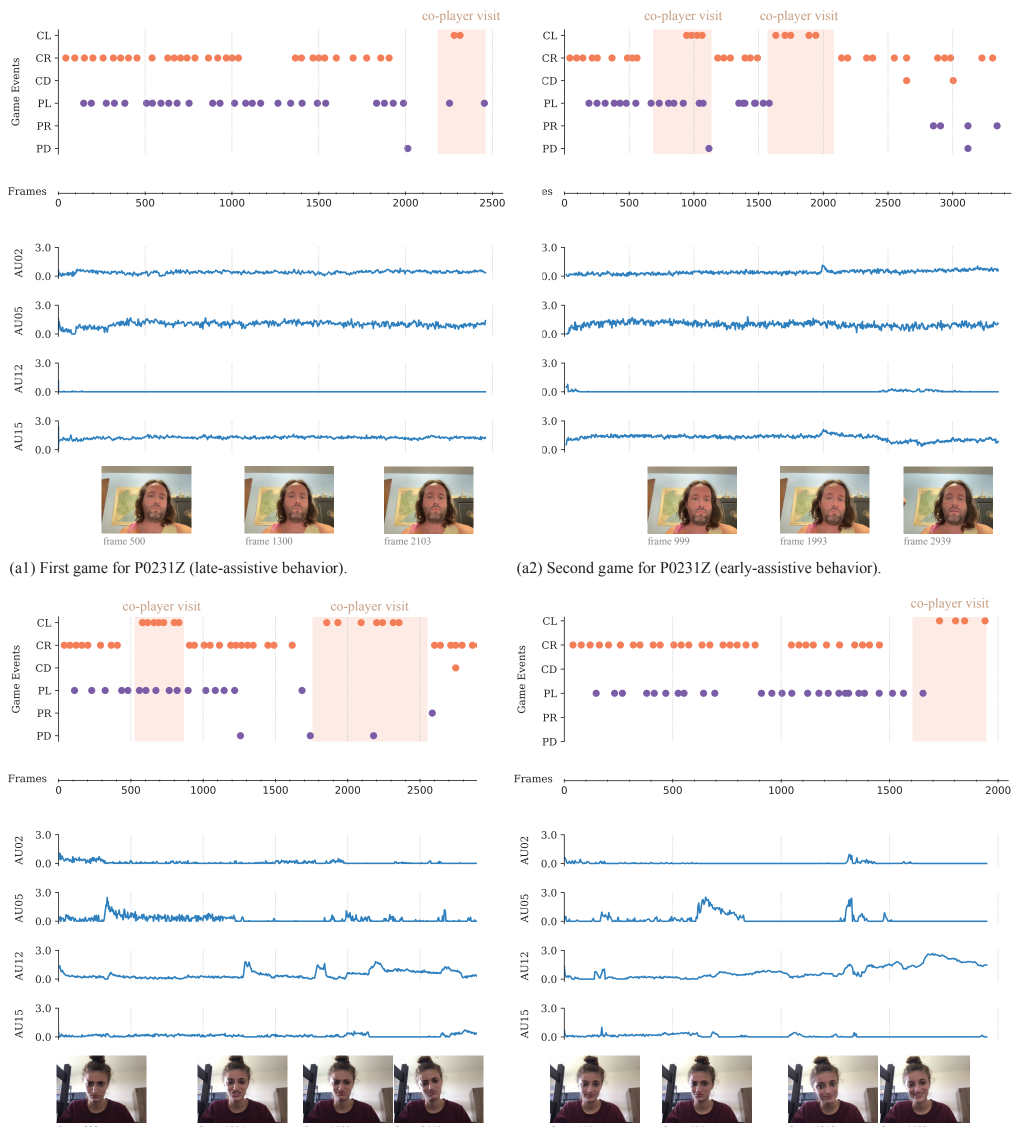
E ADDITIONAL COMPARISON FOR RESULTS

We began our investigation using survey data because survey ratings are common for understanding human preferences over agent behavior. However, it is possible to train classifiers without using survey features. For example, we found that a SVM with nonverbal features and different context combinations resulted in an F-1 score around 0.46. This was higher than the sampling baselines described in Section 4.1 of the main paper, but lower than the results with survey features (Fig. 3 of the main paper). One explanation for this outcome is that our simple summary features missed key information that is critical without survey data. Another explanation could be that we need to better understand individuals to make sense of nonverbal behavior in context. In our results, an approximation of this understanding could have been provided by survey features (e.g., with participant responses about unusual and helpful co-player behavior). To achieve better performance without them, we might need more data per individual user, from which more personalized preference models can be built in the future. We leave this for future work.

F VISUALIZATION OF IMPLICIT HUMAN FEEDBACK

Figure 1 (next page) provides an additional illustrative example, alongside the example presented in Figure 5 of the main paper, to highlight the value of implicit human feedback.

The figure shows two participants who experienced the co-player behaviors in opposite order. The participant with identifier P0231Z in Figures 1(a1) and 1(a2) preferred the early-assistive behavior. Although they did not react as much as other participants, they seemed pleasantly surprised about the co-player helping destroy their enemies (e.g., as shown in the image from frame 1993 in Figure 1(a2)). As noted in Section 5 of the main paper, participant P0354Z preferred the late-assistive behavior, which she experienced after the early-assistive behavior. This participant was very expressive as can be seen in Fig. 1(b1) and 1(b2). They moved their eyebrows, changed the expression of their mouth, and opened their eyes wide.



(a1) First game for P0231Z (late-assistive behavior).

(a2) Second game for P0231Z (early-assistive behavior).

(b1) First game for P0354Z (early-assistive behavior).

(b2) Second game for P0354Z (late-assistive behavior).

Fig. 1. Visualization of the data for two participants (P0231Z and P0354Z). Each plot shows game data (top) and webcam data (bottom). Game data includes six game events: co-player destroys enemy on the left side of the game screen (CL), co-player destroys enemy on the right side (CR), co-player dies (CD), participant destroys enemy on the left side (PL), participant destroys enemy on the right side (PL), and participant dies (PD). The orange highlight identifies the times when the co-player is on the participants' side (the left side). Webcam data includes predicted action units (AU) by OpenFace: AU02 (outer eyebrow raiser), AU05 (upper eyelid raiser), AU12 (lip corner puller), and AU15 (lip corner depressor). OpenFace assigns AU activity levels on [0, 5], but the figures focus on the [0, 3] ranges for better visibility. The webcam images below the AU activations show the participant as recorded during the study. For all plots, the x-axis corresponds to frame number as the game progresses from start to finish. All participants consented to having their images shared publicly.

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