

STEER: Steerable Dyadic Head Avatars

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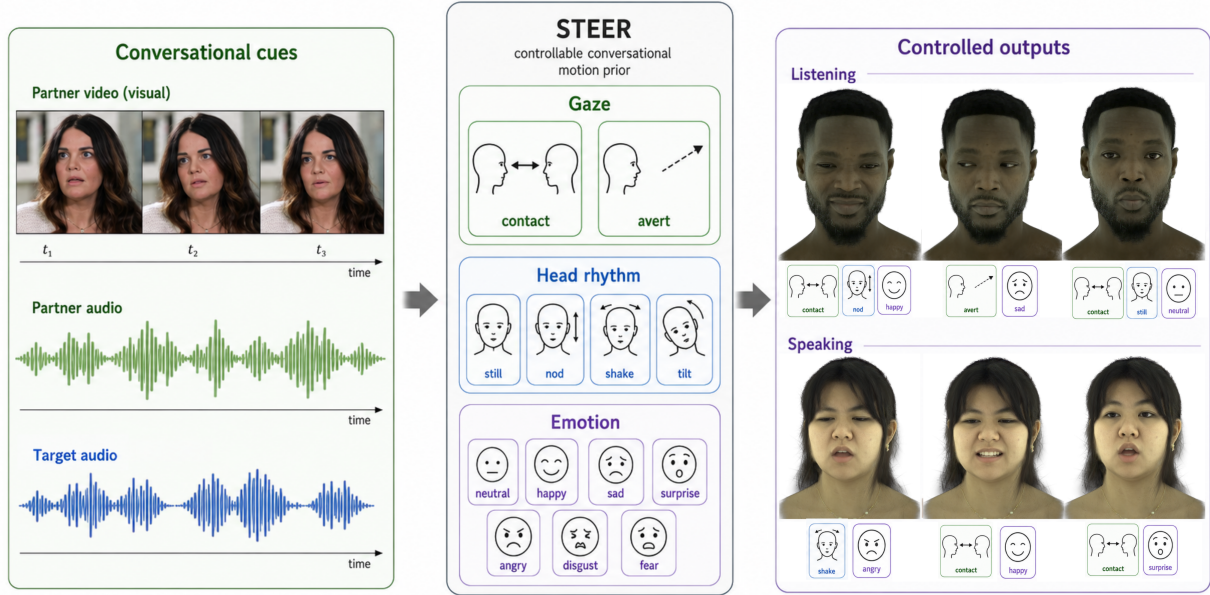


Fig. 1. STEER takes partner visual/audio cues and the target’s own audio, then generates target motion with explicit semantic controls over gaze, head rhythm, and emotion. The generated motion drives a photoreal Gaussian head avatar, enabling diverse controllable behavior for both listening and speaking roles.

Facial movement and expression are central to face-to-face communication, conveying turn-taking, attention, agreement, and engagement alongside speech. While speech-driven facial animation has made strong progress in lip synchronization and audio-conditioned motion generation, most methods treat conversational behavior as an emergent byproduct of audio, or expose only coarse sequence-level affect control. As a result, key non-verbal channels such as gaze contact and aversion, rhythmic head motion, and emotion remain difficult to explicitly control.

We present STEER, a controllable 3D dyadic motion prior for reactive conversational head avatars. STEER factorizes conversational behavior into explicit controls for gaze, head rhythm, and emotion, allowing users to steer how an avatar listens, reacts, and engages with a conversation partner. Since temporally aligned annotations for these behaviors are not available in public dyadic

corpora, we introduce a tracking and annotation pipeline that recovers behavioral pseudo-labels from in-the-wild dyadic video. A causal flow-matching transformer then learns partner-aware target motion conditioned on audio, partner motion, emotion and the proposed behavioral controls.

We further embed STEER in a photorealistic avatar pipeline by extending a Universal Gaussian Head-Avatar Prior with a learned mapping from tracked parametric motion into its avatar-driving space. This enables controllable animation of high-fidelity Gaussian head avatars without re-training the underlying avatar model. STEER outperforms recent dyadic motion baselines on motion quality, dynamics, and diversity, remains competitive on partner coupling, and enables gaze, head-rhythm, and emotion edits together with an interactive live deployment.

Additional Key Words and Phrases: Dyadic head avatars, conversational facial motion, flow matching, semantic control, 3D Gaussian avatars

1 INTRODUCTION

Photoreal conversational head avatars require both responsive dyadic motion and fine-grained semantic control over how the target responds. To the best of our knowledge, no

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existing system jointly provides partner-aware dyadic generation, explicit temporally local gaze/head-rhythm control, categorical emotion control, and photoreal Gaussian-avatar rendering.

Recent 3D dyadic head motion methods [Agrawal et al. 2025; Chatziagapi et al. 2025; Chu et al. 2025; Peng et al. 2025] have shown that plausible listener and unified speak-listen behavior can be generated from dyadic conversational signals. However, their non-verbal channel is either shaped implicitly by the conversational input — AV-Flow [Chatziagapi et al. 2025], for example, produces emergent backchannels with no exposed control and is trained as an identity-specific prior — or, where control is exposed at all, only at a global level: Seamless Interaction [Agrawal et al. 2025] offers controllable variants over global emotion and expressivity, but no factorized interface over non-verbal axes such as gaze contact/aversion or head-rhythm state.

We present STEER, a controllable dyadic motion prior for conversational head avatars.

Annotation pipeline. Existing public dyadic video corpora do not provide the temporally aligned behavioral annotations needed for explicit control. We therefore introduce an annotation pipeline for in-the-wild dyadic conversations (Sec. 3.1) that combines face and head-pose tracking [Hempel et al. 2022; Retsinas et al. 2024], kinematic decomposition [Pan et al. 2024], and facial-expression analysis [Chang et al. 2024] to recover gaze, head-rhythm, and emotion labels. These pseudo-labels provide the supervision needed to train STEER with explicit control over how an avatar looks, reacts, and expresses affect.

Generative prior. A causal flow-matching transformer consumes these labels jointly with the target’s own audio, partner audio, and partner motion, generating partner-aware target motion while exposing the labels as explicit user controls at inference.

Photoreal avatar bridge. A separate challenge is realizing this conversational prior in a photoreal avatar pipeline. Speech-driven Gaussian head-avatar models such as UniGAHA [Teotia et al. 2025], GaussianSpeech [Aneja et al. 2025], and AudioRTA [Lee et al. 2025] achieve high-fidelity rendering, but they target monadic speech and are not equipped with a controllable conversational motion prior. Rather than reusing UniGAHA [Teotia et al. 2025] as a black-box renderer, we extend its Universal Head-Avatar Prior (UHAP) with a translator that maps our tracked FLAME [Li et al. 2017] motion space into UHAP’s driving latent and adds an explicit gaze-conditioning path that the original UHAP encoder does not expose, allowing our controllable conversational prior to drive a high-fidelity Gaussian avatar without re-training the underlying avatar model.

Our contributions are:

- STEER, a dyadic conversational motion prior that exposes interpretable control channels over gaze (contact, avert), head-rhythm (still, nod, shake, tilt), and

a seven-class emotion axis, making gaze and head-rhythm directly controllable instead of leaving them implicit in the audio-conditioned prior.

- A tracking and annotation pipeline for in-the-wild dyadic video that produces temporally aligned labels over gaze, head-rhythm, and emotion, enabling supervised conversational behavior modeling.
- An extension of a universal photoreal Gaussian head-avatar prior with a learned mapping from tracked FLAME motion to its driving space, embedding our controllable conversational prior in a high-fidelity rendering pipeline without retraining the underlying avatar model.

Together, these components make STEER both a stronger dyadic motion prior and a controllable photoreal avatar system. Quantitatively, STEER outperforms recent dyadic motion baselines on motion quality, dynamics, and diversity metrics, while remaining competitive on partner coupling. Qualitatively, Fig. 1 highlights the central capability of STEER: the same partner-aware conversational input can produce diverse, photorealistic target behaviors by explicitly editing gaze, head rhythm, and emotion for both listening and speaking avatars. We further demonstrate an interactive live deployment in the supplemental video, where a user can converse with the avatar and steer its behavior through text or multimodal audio-visual input at 25 fps on a single GPU.

2 RELATED WORK

Dyadic head avatars sit at the intersection of conversational motion modeling, semantic control, and photoreal rendering. Existing methods typically address only part of this problem: they may react to a partner, expose some form of control, or render high-fidelity avatars, but rarely combine all three. We review prior work along these axes.

2.1 Speech-Driven 3D Facial Animation

A long line of work generates 3D facial animation from audio by mapping acoustic features into the parameter space of a 3D Morphable Model such as FLAME [Li et al. 2017]: autoregressive and codebook priors [Fan et al. 2022; Richard et al. 2021; Xing et al. 2023], diffusion samplers [Aneja et al. 2024; Stan et al. 2023; Sun et al. 2024; Zhao et al. 2024], and emotion-conditioned variants [Danek et al. 2023; Peng et al. 2023]. More recently, photoreal speech-driven Gaussian head-avatar models couple a parametric expression code with a 3D Gaussian decoder for direct rendering: UniGAHA [Teotia et al. 2025] learns a cross-identity Gaussian decoder driven by a compact expression latent, but is trained on read-sentence audio-visual data and exposes no semantic-control surface over the non-verbal channel; GaussianSpeech [Aneja et al. 2025] learns a personalized 3D Gaussian avatar driven by audio with no exposed control; and AudioRTA [Lee et al. 2025] drives a similar avatar from audio without head pose or controllable non-verbal axes. These methods target a single active speaker and do not model the asymmetric dynamics

of dyadic listening, nor expose a factorized semantic-control interface over non-verbal channels.

2.2 Listener and Dyadic Conversational Motion Generation

Listener generation has evolved from non-deterministic mappings of speaker audio and motion to listener face sequences [Lai et al. 2025; Liu et al. 2024; Ng et al. 2022; Siniukov et al. 2025; Song et al. 2023; Wang et al. 2025] into unified dyadic frameworks that jointly model speaking and listening. INFP [Zhu et al. 2025] dynamically alternates speak/listen states from dyadic audio. DualTalk [Peng et al. 2025] jointly models both roles across multi-round dialogue using partner audio and motion and regresses FLAME blendshapes for the listener. UniLS [Chu et al. 2025] is a two-stage end-to-end dual-track audio-driven avatar. DyStream [Chen and Liu 2025] streams dyadic talking-head generation via a flow-matching autoregressive model for low-latency interactive use; its conditioning is purely audio and it does not expose semantic-control axes. AV-Flow [Chatziagapi et al. 2025] extends a text-to-audio-visual flow-matching backbone to a dyadic always-on mode that listens to a user’s audio-visual stream and emits emergent backchannels, but exposes no explicit control interface over emotion or non-verbal behavior. The recently released Seamless Interaction [Agrawal et al. 2025] pairs a 4,000-hour dyadic audiovisual corpus with controllable motion models that adapt global emotion and expressivity levels. Yet these controls remain global: they modulate the overall emotion or expressivity of the generated motion, but do not provide time-varying control over gaze contact/aversion or head-rhythm states. Thus, existing dyadic methods learn when and how a listener reacts, but leave the semantic form of that reaction largely implicit. STEER instead exposes gaze, head rhythm, and emotion as factorized controls, allowing the same conversational context to produce different directed reactions.

2.3 Controllable Conversational Semantics

Existing control interfaces for conversational face motion fall along three lines: clip-level emotion or expressivity labels [Agrawal et al. 2025; Danek et al. 2023; Peng et al. 2023; Song et al. 2023], free-form text guidance [Liu et al. 2024; Siniukov et al. 2025], and pose-expression factorization [Wang et al. 2025]. Closest to our own decomposition, the animator-centric S3 system of Pan et al. [Pan et al. 2024] splits conversational head-and-eye motion into audio-driven rhythmic head motion, script-driven gestures, and scene-refined gaze trajectories as an authoring abstraction. In the broader body-motion literature, diffusion-based priors conditioned on text, action labels, or style tokens [Guo et al. 2024; Tevet et al. 2022] show that coarse semantic control can be layered on a strong generative backbone without sacrificing motion quality. STEER takes up the gaze-versus-rhythm decomposition of S3 and promotes it from an authoring abstraction into a learned, per-token generative control interface, extending the control

surface with a window-level seven-class emotion axis within a single dyadic framework.

Summary. Across these lines, prior systems miss at least one piece STEER combines: dyadic conditioning, explicit behavioral controls, or photoreal Gaussian-avatar rendering. Speech-driven monadic methods provide a strong audio-to-motion backbone but condition on no partner stream and at most a clip-level emotion control; dyadic methods condition on the partner but do not expose explicit gaze/head-rhythm controls or a reusable bridge to a photoreal Gaussian avatar; photoreal Gaussian-avatar pipelines render high-fidelity output but assume a clean offline driving signal. STEER builds the controllable dyadic prior and the avatar-bridge translator together, so the same model that emits steerable target motion also drives a photoreal renderer at interactive latencies.

3 METHOD

STEER takes streaming partner audio, partner motion, and the target’s own audio and produces controllable target motion at 25 fps (Fig. 2). We want this motion to react to the partner and to be steerable along semantically meaningful axes — per-token gaze, per-token head-rhythm, and a window-level emotion — but existing dyadic corpora lack the supervision such controls require, so we first build an annotation pipeline that derives these labels from in-the-wild dyadic video (Sec. 3.1). Given the labeled data, we learn a causal flow-matching prior¹ over a motion latent, trained in two phases so the semantic controls do not pre-empt the audio-and-partner backbone (Sec. 3.2–3.4). The teacher’s iterative inference would prevent real-time deployment, so we distill it into a 2-step student that preserves the control surface at live rates (Sec. 3.4). Finally, the target’s motion is more useful when it can drive a photoreal avatar, so we extend UniGAHA’s Universal Head-Avatar Prior (UHAP) with a translator that maps tracked FLAME motion into its driving space and adds explicit gaze conditioning (Sec. 3.5).

3.1 Dyadic Tracking and Behavior Annotation

Training STEER’s controls requires temporally aligned pseudo-labels for gaze and head-rhythm together with a window-level emotion label — none of which are available in public dyadic corpora. We therefore process each RealTalk [Geng et al. 2023] shot into a 61-D dynamic FLAME state, extract per-frame audio, and run LibreFace [Chang et al. 2024] for two per-frame outputs: 12-D action-unit intensities and a 7-class facial-expression prediction (neutral, happy, sad, angry, surprise, disgust, fear). We filter unreliable windows, derive per-frame gaze and head-rhythm pseudo-labels and pool them to the latent-token rate downstream (Sec. 3.3), and aggregate LibreFace’s per-frame emotion predictions into a window-level label by smoothing the per-frame argmax over a 7-frame window, computing a histogram over the 7 classes, and dropping windows whose dominant class has confidence

¹By causal we mean that any token at time t depends only on inputs up to and including time t — never on future inputs.

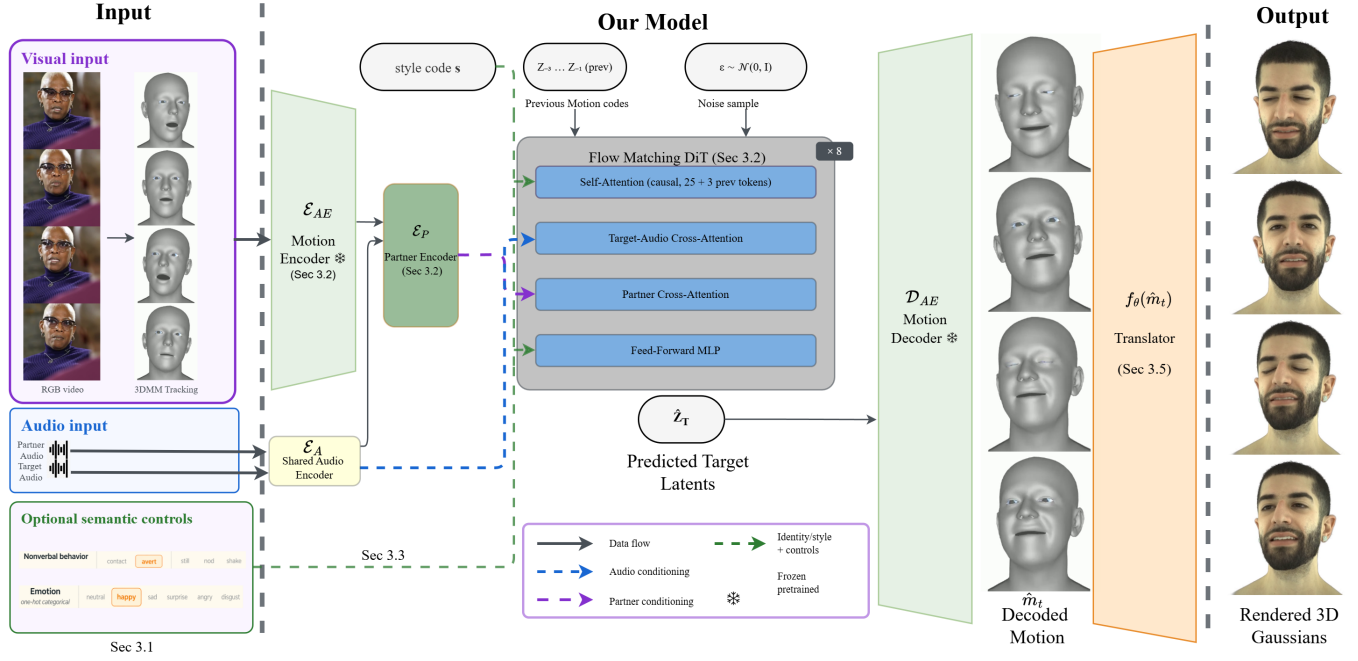


Fig. 2. Overview of STEER. A causal flow-matching DiT (center) generates the target’s motion as a sequence of $K=25$ latent tokens, conditioned on the target’s own audio and a partner context sequence (left) produced by the Partner Encoder over partner audio and partner motion, three semantic control pathways — style, behavior, emotion (top) — and a clean prefix of $n_{\text{prev}}=3$ previously committed latents for streaming continuity. The decoded motion drives a learned per-frame translator f_θ (right) into a frozen photoreal Gaussian head-avator prior. Architecture: Sec. 3.2 (motion AE + flow-matching prior), Sec. 3.3 (semantic controls), Sec. 3.4 (streaming inference), Sec. 3.5 (avator driving).

below 0.45 from the emotion supervision. Tab. 1 summarizes the per-shot extractors and the conditioning or supervision pathway each one feeds.

Per-frame motion vector. The per-frame state $\mathbf{m}_t$ stacks SMIRK [Retsinas et al. 2024] expression and jaw with neck and eye estimates from external trackers and SMIRK’s eyelid openings,

$$\mathbf{m}_t = [\mathbf{e}_t; \mathbf{j}_t; \mathbf{n}_t; \mathbf{r}_t; \mathbf{\ell}_t] \in \mathbb{R}^{61}, \quad (1)$$

where $\mathbf{e}_t \in \mathbb{R}^{50}$ are the FLAME expression coefficients, $\mathbf{j}_t, \mathbf{n}_t, \mathbf{r}_t \in \mathbb{R}^3$ are the jaw, neck, and eye axis-angle rotations with left and right eyes averaged into a single $\mathbf{r}_t$, and $\mathbf{\ell}_t \in \mathbb{R}^2$ holds the left and right eyelid openings.

Table 1. Tracking and annotation pipeline. Each per-shot signal is extracted by an off-the-shelf model and consumed by a downstream conditioning or supervision pathway.

Signal	Extractor	Output	Used for
shots	TransNetV2 [Souček and Lokoč 2020]	per-shot crops	tracking input
exp. / jaw / eyelid	SMIRK [Retsinas et al. 2024]	$\mathbf{e}, \mathbf{j}, \mathbf{\ell}$	$\mathbf{m}_t$
neck pose	6DRepNet [Hempel et al. 2022]	$\mathbf{n}$	$\mathbf{m}_t$
eye pose	MediaPipe [Lagares et al. 2019] / [Yan 2023]	$\mathbf{r}$	$\mathbf{m}_t$
per-speaker audio	VisualVoice [Gao and Grauman 2021]	16 kHz wave	audio cross-attn
AU / coarse emotion	LibreFace [Chang et al. 2024]	per-frame, 7-class	emotion control
clip filter	Qwen2-VL [Wang et al. 2024]	clean spans	training set
gaze, head-rhythm	ϕ [Pan et al. 2024]	per-frame pseudo-labels (pooled to tokens)	behavior control

Behavior labels. We obtain gaze and head-rhythm labels in two steps. First, we apply the kinematic decomposition of Pan et al. [Pan et al. 2024] to the tracked facial-motion

state, which combines expression, head pose, and eye-gaze estimates from the trackers described above. This yields smoothed partner-direction cues and pitch/yaw/roll motion statistics. Second, we discretize these signals into gaze labels (contact / avert) and head-rhythm labels (still / nod / shake / tilt) using thresholding with hysteresis; ambiguous frames are masked out of the behavior supervision. The per-token control $\mathbf{b}_k$ is a mask-weighted average of the 4 frames within each latent token’s span, re-normalized to a simplex per channel; a two-bit validity mask $\mathbf{M}_k \in \{0, 1\}^2$ marks gaze and head-rhythm independently as present or absent for that token. These labels define the control vocabulary the user steers at inference and supervise the behavior observers during training. They are reproducible kinematic proxies, not ground-truth social-intent labels. Exact thresholds, hysteresis rules, aggregation, and filtering are given in the supplemental. The final filtered corpus contains 10,555 clips, split 9,790 train and 765 test.

3.2 Latent Motion Prior

Given the behavioral labels from Sec. 3.1, we learn a partner-aware and steerable prior over target motion. To reduce the temporal sequence length, we model motion in a learned latent space: a causal motion VAE compresses each $T=100$ -frame window into $K=25$ latent tokens, and a causal flow-matching transformer models the distribution of these tokens conditioned on audio, partner context, style, and semantic

controls. The VAE is trained first and then kept frozen for all downstream prior training.

Motion autoencoder. A causal temporal VAE [Kingma and Welling 2014] encodes $T=100$ -frame windows (4s at 25 fps) into $K=25$ latent tokens of dimension $D=256$. The encoder $\mathcal{E}_{\text{AE}}$ produces a Gaussian posterior $q_{\psi}(\mathbf{Z}_{1:K} \mid \mathbf{m}^{1:T})$, sampled via the standard reparameterization,

$$(\boldsymbol{\mu}_{1:K}, \boldsymbol{\sigma}_{1:K}) = \mathcal{E}_{\text{AE}}(\mathbf{m}^{1:T}), \quad \mathbf{Z}_{1:K} = \boldsymbol{\mu}_{1:K} + \boldsymbol{\sigma}_{1:K} \odot \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}); \quad (2)$$

the decoder $\mathcal{D}_{\text{AE}}$ reconstructs $\hat{\mathbf{m}}^{1:T} = \mathcal{D}_{\text{AE}}(\mathbf{Z}_{1:K})$. Both networks are causal. The VAE is trained under

$$\mathcal{L}_{\text{AE}} = \lambda_{\text{rec}} \|\mathbf{m} - \hat{\mathbf{m}}\|_1 + \lambda_{\text{vel}} \|\Delta \mathbf{m} - \Delta \hat{\mathbf{m}}\|_1 + \lambda_{\text{KL}} D_{\text{KL}}(q_{\psi}(\mathbf{Z} \mid \mathbf{m}) \parallel \mathcal{N}(\mathbf{0}, \mathbf{I})), \quad (3)$$

where Δ denotes a one-frame finite difference. Once converged, the VAE is frozen and all downstream modeling operates on its latent space. We sample from the Gaussian posterior during training of the prior and use the posterior mean $\boldsymbol{\mu}_{1:K}$ at deployment.

Causal flow-matching prior. On top of the frozen motion autoencoder, we learn a causal latent-space prior following MotionStreamer [Xiao et al. 2025]. Unlike MotionStreamer, we use rectified-flow matching [Lipman et al. 2023; Liu et al. 2022] instead of a diffusion sampler, and condition the target motion on the target audio, partner audio, partner motion, and STEER’s semantic controls. Concretely, we learn a conditional flow-matching prior v_{θ} over target latents $\mathbf{Z}_T$ given a set of conditioning inputs

$$\mathbf{c} = \{\mathbf{a}^T, \mathbf{c}^P, \mathbf{s}, \mathbf{b}_{1:K}, \mathbf{y}^{\text{emo}}\},$$

where $\mathbf{a}^T$ is the target’s own audio feature stream, $\mathbf{c}^P = \mathcal{E}_P(\mathbf{Z}_P, \mathbf{a}^P)$ is the Partner Encoder output over the partner’s motion latents $\mathbf{Z}_P = \mathcal{E}_{\text{AE}}(\mathbf{m}_{\text{partner}})$ and audio features $\mathbf{a}^P$ ($\mathbf{m}_{\text{partner}}$ being the partner-side counterpart of $\mathbf{m}$ from Eq. 1), $\mathbf{s}$ is a motion-style code, and $\mathbf{b}_{1:K}, \mathbf{y}^{\text{emo}}$ are the two semantic controls (per-token behavior, window-level emotion; Sec. 3.3). Sampling a flow-time variable $\tau \sim \mathcal{U}(0, 1)$ and forming the rectified-flow interpolate

$$\mathbf{Z}_{\tau} = (1 - \tau) \boldsymbol{\epsilon} + \tau \mathbf{Z}_T, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{K \times D}), \quad (4)$$

we regress the velocity field with the flow-matching objective

$$\mathcal{L}_{\text{flow}} = \mathbb{E}_{\tau, \boldsymbol{\epsilon}, (\mathbf{Z}_T, \mathbf{c})} \left[\left\| v_{\theta}(\mathbf{Z}_{\tau}, \tau, \mathbf{c}) - (\mathbf{Z}_T - \boldsymbol{\epsilon}) \right\|_2^2 \right]. \quad (5)$$

The network v_{θ} is a causal DiT [Peebles and Xie 2023] with RoPE self-attention [Su et al. 2021].

Partner Encoder. $\mathcal{E}_P$ is a causal RoPE encoder that fuses $\mathbf{Z}_P$ and $\mathbf{a}^P$ into the per-token context $\mathbf{c}^P$.

Conditioning pathways. The prior receives the target audio, partner context, motion style, behavior controls, and emotion label through modality-specific conditioning paths: cross-attention for audio and partner context, FiLM modulation [Perez et al. 2018] for style, the behavior residual of Sec. 3.3, and AdaLN-Zero for emotion. To maintain streaming continuity, we prepend a clean prefix of $n_{\text{prev}}=3$ previously committed latents to the current candidate tokens. Audio features are extracted with a frozen causal Wav2Vec2 encoder [Baevski et al. 2020; Chen

and Liu 2025]; conditioning dropout follows classifier-free guidance [Ho and Salimans 2022]. Partner audio and partner motion share a joint dropout mask that replaces the partner stream as a unit. Each partner modality is additionally dropped independently (supp.), so the model also trains on partner-audio-only and partner-motion-only states.

3.3 Semantic Control Injection

We inject each control through the mechanism best suited to its temporal rate and value type: FiLM modulation [Perez et al. 2018] for the clip-level continuous style code, a gap-driven residual on the last three DiT layers for the per-token discrete behavior controls, and AdaLN-Zero [Peebles and Xie 2023] for the window-level discrete emotion class.

Style. We additionally condition the prior on a compact target-reference code $\mathbf{s} \in \mathbb{R}^{128}$, encoded from a same-speaker motion window, to capture residual target-specific motion statistics [Danek et al. 2023; Fan et al. 2022; Peng et al. 2023; Sun et al. 2024]. A KL-regularized VAE limits the capacity of this code so that dyadic dynamics must still be explained by the audio and partner streams. The code modulates the flow-matching backbone via per-block FiLM; when no reference is available, we use a learned null code.

Behavior. The user steers the target with per-token control vectors stacking a 2-class gaze softmax (contact / avert) and a 4-class head-rhythm softmax (still / nod / shake / tilt),

$$\mathbf{b}_k = [\mathbf{q}_k^g; \mathbf{q}_k^h] \in \mathbb{R}^6, \quad \mathbf{q}_k^g \in \Delta_2, \quad \mathbf{q}_k^h \in \Delta_4, \quad (6)$$

where $[\cdot; \cdot]$ denotes channel-wise concatenation; the format permits independent specification across the two channels.²

Gap-driven residual. Behavior labels often agree with what the audio-and-partner backbone already produces (e.g. a contact request when the target is already looking at the partner); concatenating $\mathbf{b}_{1:K}$ as input tokens would force the prior to re-predict that behavior even when no change is needed. We instead inject the gap between requested and currently-predicted behavior as a residual on the last three DiT layers. At each such layer, an observer ϕ_{ℓ} predicts $\hat{\mathbf{b}}_{\ell} = \phi_{\ell}(\mathbf{h}_{\ell})$ from the layer’s hidden state, supervised by a masked cross-entropy loss $\mathcal{L}_{\text{obs}}$ against the per-token labels $\mathbf{b}_{1:K}$ of Sec. 3.1. The control residual at layer ℓ is then

$$\mathbf{h}_{\ell}^{\text{ctrl}} = \mathbf{h}_{\ell} + \mathcal{R}_{\ell}([\mathbf{h}_{\ell}; (\mathbf{b}_{1:K} - \hat{\mathbf{b}}_{\ell}) \odot \mathbf{M}_{1:K}]), \quad (7)$$

where $[\cdot; \cdot]$ denotes channel-wise concatenation, $\mathcal{R}_{\ell}$ is a small MLP zero-initialized at the residual output, in the spirit of zero-initialized control adapters [Dai et al. 2024; Xie et al. 2024; Zhang et al. 2023], and $\mathbf{M}_{1:K}$ is the per-token validity mask of Sec. 3.1, broadcast across each channel and exposed at inference for per-channel masking.

Emotion. A window-level 7-class label $\mathbf{y}^{\text{emo}} \in \Delta_7$ (a soft distribution over the seven classes at training, from the window-aggregation step of Sec. 3.1; user-specified at inference) is injected through AdaLN-Zero [Peebles and Xie 2023]: at each block ℓ an adapter $\mathcal{G}_{\ell}^{\text{emo}}$ produces $(\boldsymbol{\gamma}_{\ell}, \boldsymbol{\beta}_{\ell}, \boldsymbol{\alpha}_{\ell}) = \mathcal{G}_{\ell}^{\text{emo}}(\mathbf{y}^{\text{emo}})$

²We write Δ_n for the n -vertex probability simplex, i.e. non-negative vectors in $\mathbb{R}^n$ summing to one.

that gate the block’s residual sub-branches:

$$\mathbf{h}_{\ell+1} = \mathbf{h}_{\ell} + \alpha_{\ell} \odot \mathcal{F}_{\ell}((1 + \gamma_{\ell}) \odot \text{LN}(\mathbf{h}_{\ell}) + \beta_{\ell}), \quad (8)$$

where $\mathcal{F}_{\ell}$ is the block’s self-attention or MLP sub-network. Training-time supervision on $\mathbf{y}^{\text{emo}}$ is via the observer-tracking loss of Sec. 3.4, evaluated on the model’s decoded motion against the requested class.

3.4 Training and Streaming Inference

Phase 1: backbone prior. To prevent the prior from collapsing onto the semantic labels before the audio-and-partner backbone has converged, Phase 1 trains the backbone alone under

$$\mathcal{L}_{\text{phase1}} = \lambda_{\text{flow}} \mathcal{L}_{\text{flow}} + \lambda_{\text{energy}} \mathcal{L}_{\text{energy}}, \quad (9)$$

where $\mathcal{L}_{\text{flow}}$ is Eq. 5 and $\mathcal{L}_{\text{energy}}$ is an asymmetric per-region energy regularizer $\mathcal{L}_{\text{energy}} = \sum_d \text{ReLU}(\alpha E_d^{\text{gt}} - E_d^{\text{pred}})$ [Nair and Hinton 2010], with the per-region energy $E_d(\mathbf{m}) = \sqrt{\frac{1}{T-1} \sum_{t=2}^T \|\Delta \mathbf{m}_{t,d}\|_2}$ (RMS first-difference velocity), floor ratio $\alpha=0.9$, and $d \in \{\text{exp, jaw, neck, eye}\}$. The predicted energy is computed on the clean-motion estimate $\hat{\mathbf{m}}$ obtained by a one-step flow rollout from $(\mathbf{Z}_T, \tau)$ to $\tau=1$. The ReLU activates only when the prediction under-shoots ground truth.

Phase 2: semantic steerability. Phase 2 keeps the backbone trainable at a reduced learning rate and activates the semantic-control pathways under

$$\mathcal{L}_{\text{STEER}} = \lambda_{\text{flow}} \mathcal{L}_{\text{flow}} + \lambda_{\text{emo}} \mathcal{L}_{\text{emo}} + \lambda_{\text{obs}} \mathcal{L}_{\text{obs}}, \quad (10)$$

where $\mathcal{L}_{\text{emo}}$ is the cross-entropy between the requested emotion class and the window-level logits of a frozen affect observer [Danek et al. 2023; Peng et al. 2023] — a TCN we pre-train on LibreFace labels (supp.) — applied to the decoded motion, and $\mathcal{L}_{\text{obs}}$ is masked cross-entropy on the behavior observers $\{\phi_{\ell}\}$ of Sec. 3.3. Both phases additionally apply the flow-matching loss on the decoded motion, weighted by λ_{decoded} , and penalize per-region velocity and acceleration with weights λ_{vel} and λ_{acc} . Phase 2 adds a preservation loss with weight $\lambda_{\text{preserve}}$: the backbone’s predictions under the null condition are matched to a frozen Phase-1 copy, keeping the audio-and-partner pathway stable while the control pathways train. Coefficients are listed in the supplemental. Few-step distillation for live inference. For live deployment we distil the 10-step teacher $v_{\theta}^{\text{teach}}$ into a 2-step student v_{θ}^{stud} under the same streaming protocol used at deployment: at each emit the model takes the n_{prev} -token clean prefix (Sec. 3.2) and predicts K candidate tokens of which a leading commit-stride $s=1$ is committed; the trailing $K-s$ tokens overlap with the next emit’s candidate slots and are blended with the next emit’s predictions through a raised-cosine taper of width 8 tokens. We use $s=1$ throughout, including all reported evaluations: each token spans 4 frames, so one commit decodes a 160 ms chunk at 25 fps. The student is trained with a trajectory-matching loss in the spirit of progressive distillation [Salimans and Ho 2022],

$$\mathcal{L}_{\text{distill}} = \|\mathbf{Z}_T^{\text{stud}} - \mathbf{Z}_T^{\text{teach}}\|_2^2, \quad (11)$$

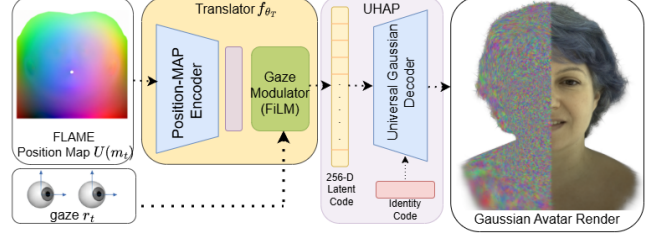


Fig. 3. Translator f_{θ} . The FLAME geometry from $\mathbf{m}_t$ — with eye rotation neutralized — is rendered as a UV position map $U(\mathbf{m}_t)$ and encoded into UHAP’s 256-D expression latent; the eye-pose vector $\mathbf{r}_t$ enters *only* via a FiLM modulator, so gaze is encoded exactly once. UHAP’s universal Gaussian decoder is kept frozen.

combined with the same semantic supervision applied to the teacher. The full per-emit budget at $s=1$ on an RTX 5090 and the resulting cue-to-render latency are reported in the supplementary.

3.5 Driving a Photoreal Gaussian Head Avatar

At inference, the target latent $\hat{\mathbf{Z}}_T$ sampled by v_{θ} (Sec. 3.2) is decoded by the frozen motion AE into per-frame FLAME state $\hat{\mathbf{m}}^{1:T} = \mathcal{D}_{\text{AE}}(\hat{\mathbf{Z}}_T)$; the rest of this section drives a photoreal head avatar from those frames. We drive UniGAHA’s Universal Head-Avatar Prior (UHAP) [Teotia et al. 2025], whose Gaussian decoder takes a 256-D expression code and an identity code. Gaze is entangled with the rest of UHAP’s expression code, so a per-frame translator $f_{\theta} : \mathbb{R}^{61} \rightarrow \mathbb{R}^{256}$ maps the FLAME [Li et al. 2017] state $\mathbf{m}_t$ into the expression code while taking gaze as an independent input (Fig. 3); the resulting disentangled control axes are visualised in Fig. 5.

Architecture. The FLAME geometry — with eye rotation held at the neutral pose, so gaze does not enter through the UV path — is rendered as a UV position map $U(\mathbf{m}_t)$ and fed to a position-map encoder $\mathcal{E}_{\text{UV}}$. The eye-pose $\mathbf{r}_t$ enters only through a gaze MLP g_{gaze} that emits FiLM parameters at the encoder bottleneck; a head h_{lat} projects the modulated features to the 256-D expression code:

$$f_{\theta}(\mathbf{m}_t) = h_{\text{lat}}(\text{FiLM}_{\gamma_t, \beta_t}(\mathcal{E}_{\text{UV}}(U(\mathbf{m}_t))))), \quad (\gamma_t, \beta_t) = g_{\text{gaze}}(\mathbf{r}_t). \quad (12)$$

UHAP’s universal Gaussian decoder, identity embedding, and FLAME forward pass are kept frozen; only f_{θ} is trained under

$\mathcal{L}_{\text{render}} = \lambda_{\text{lat}} \mathcal{L}_{\text{lat}} + \lambda_{\text{vel}} \mathcal{L}_{\text{vel}} + \lambda_{\text{acc}} \mathcal{L}_{\text{acc}} + \lambda_{\text{pix}} \mathcal{L}_{\text{pix}} + \lambda_{\text{geo}} \mathcal{L}_{\text{geo}}$. (13)
where $\mathcal{L}_{\text{lat}}$ matches the translated code $f_{\theta}(\mathbf{m}_t)$ to UHAP’s pretrained expression latent, and $\mathcal{L}_{\text{vel}}$ and $\mathcal{L}_{\text{acc}}$ enforce first- and second-order temporal consistency in the same latent space. $\mathcal{L}_{\text{pix}}$ distills UHAP’s original encoder by matching renders driven by f_{θ} to renders driven by the pretrained UHAP encoder, while $\mathcal{L}_{\text{geo}}$ preserves the positions and scales of the predicted Gaussians. At inference, the neck rotation $\mathbf{n}_t$ is applied as a rigid transform to the decoded Gaussians. Details are given in the supplemental.

4 EXPERIMENTS

We first describe the data, baselines, and metrics used throughout (Sec. 4.1), then present qualitative controllability results (Sec. 4.2) and comparisons with state-of-the-art (Sec. 4.3). Ablation studies isolate the partner-conditioning channels (Sec. 4.5); training-objective ablations are reported in the supplemental.

4.1 Datasets, Baselines, and Metrics

Data. We train STEER on the 9,790-clip training split of our filtered RealTalk corpus (Sec. 3.1) and evaluate on a held-out test set of 765 clips, partitioned by conversational role into a Speak subset ($n=170$, target purely speaking), a Listen subset ($n=330$, target purely listening), and a Mixed turn-taking subset ($n=265$, the target alternates between speaking and listening). The main-paper Tab. 2 reports the test-set average across all three subsets; the per-subset breakdown is in the supplemental. All methods consume the partner stream (audio + motion) and the target’s own audio. STEER runs in its base generation mode for this comparison — the semantic controls are dropped to their classifier-free-guidance null tokens — so every method generates target motion from the same partner+target audio inputs. Tab. 2 therefore reports the partner-input-to-motion mapping for each model under a matched input regime. The controllability eval — whether STEER’s semantic-control pathways produce the requested behavior when the controls are supplied — is reported separately in the supplemental.

Baselines. We compare against two recent dyadic motion baselines fine-tuned on our corpus: DualTalk [Peng et al. 2025], a joint speaker-listener model, and UniLS [Chu et al. 2025], an end-to-end audio-driven dyadic avatar. We additionally include DiffPoseTalk [Sun et al. 2024], a monadic speech-driven baseline that does not condition on the partner, as a non-dyadic reference, and Ours-Distill, the 2-step distilled student, alongside the full model.

Metrics. We adopt established metrics from the talking-head and listener-generation literature, organized along four axes; per-clip values are computed on the rendered FLAME mesh except where noted. Lip fidelity. LipSync(mm) ($\downarrow$) reports the lip-vertex error in millimetres against ground truth, in the spirit of the lip-vertex error of [Sun et al. 2024; Xing et al. 2023]. Realism and dynamics. vFDE ($\downarrow$) is the Fréchet distance between predicted and ground-truth motion sequences in expression-vertex space, following the L2L motion-realism protocol of Ng et al. [Ng et al. 2022]. FDD_u, PDD_h, and JDD ($\downarrow$) are the Facial Dynamics Deviation [Xing et al. 2023] on the upper-face, head pose, and FLAME jaw axis-angle respectively — the per-vertex gap between prediction and ground truth in temporal standard deviation — which captures whether the predicted motion has the same level of dynamism as ground truth in each region. Diversity. Div_E and Div_H (bits, $\uparrow$) are the Shannon-index diversity of Ng et al. [Ng et al. 2022]: with k-means cluster centers pre-fit on ground-truth expression and head-rotation sequences, we report the

Table 2. Quantitative comparison on the held-out test set ($n=765$, weighted across the SPEAK / LISTEN / MIXED subsets defined in Sec. 4.1; per-subset breakdown in the supplemental). Each method generates target motion from the partner stream (audio + motion) and target audio; STEER runs in its base mode with semantic controls dropped to the classifier-free-guidance null tokens, matching baselines’ input regime. The orthogonal controllability evaluation under *supplied* controls is in the supplemental. LipSync (mm) is the per-frame mean lip-vertex error; rPCC_{fv} is reported as $\times 10^{-4}$. Best per column in bold; cells color-shaded by per-column rank.

Method	LipSync $\downarrow$	vFDE $\downarrow$	FDD _u $\downarrow$	JDD $\downarrow$	PDD _h $\downarrow$	Div _E $\uparrow$	Div _H $\uparrow$	rPCC _n $\downarrow$	rPCC _{fv} $\downarrow$
DiffPoseTalk [Sun et al. 2024]	12.46	0.0376	0.0405	0.1415	0.3029	1.246	0.723	0.481	8.86
DualTalk-FT [Peng et al. 2025]	9.33	0.0572	0.0648	0.2011	0.3299	1.010	0.619	0.397	6.12
UniLS-FT [Chu et al. 2025]	11.67	0.0394	0.0444	0.1357	0.3169	1.143	0.923	0.458	7.38
Ours-Distill	9.18	0.0267	0.0267	0.1026	0.2430	1.562	0.980	0.419	5.62
Ours (Full)	9.15	0.0262	0.0260	0.1008	0.2343	1.595	1.086	0.406	5.65

entropy of the cluster-assignment histogram of the predicted samples, so that a uniform spread across modes scores higher than a collapsed prediction. Partner-conditioned reactivity. RPCC_n ($\downarrow$) follows [Peng et al. 2025; Song et al. 2023] and measures the ℓ_1 gap between predicted and ground-truth target-partner Pearson correlations on the neck axis-angle. rPCC_{fv} ($\downarrow$, $\times 10^{-4}$) applies the same residual-correlation metric to pose-normalized facial vertex motion induced by expression and jaw.

4.2 Qualitative Results

Fig. 4 evaluates controllability across the two conversational roles. Under four identical control inputs (base, happy, avert, avert + disgust), the target exhibits the requested gaze and emotion edits in both regimes while preserving role-specific articulation, such as listening head motion and speaking lip motion. Fig. 5 further shows that these controls transfer to the photoreal avatar stage: gaze and expression edits remain visually disentangled after mapping the generated FLAME motion into UHAP’s avatar-driving space.

4.3 Comparisons with State-of-the-art Methods

Quantitative. Tab. 2 summarizes the comparison on the full $n=765$ test set, averaged across Speak / Listen / Mixed; per-subset results are provided in the supplemental. STEER is the strongest overall model, achieving the best scores on lip accuracy, motion realism, dynamics, and diversity. The only metric not led by STEER is neck-level partner coupling, where DualTalk is marginally better, but this comes with noticeably reduced diversity. UniLS uses partner audio but does not condition on partner motion, and remains below STEER across the reported metrics, while the monadic DiffPoseTalk baseline is weakest on partner-reactivity metrics. The distilled student remains close to the full model, preserving the main quantitative gains while supporting real-time inference. **Qualitative.** Fig. 6 provides a visual comparison on representative Speak and Listen clips. With global head pose normalized, the upper-face region in our outputs contains eye-pose and brow motion that is largely absent in the baseline rows on Speak; on Listen, the target’s smile response and head

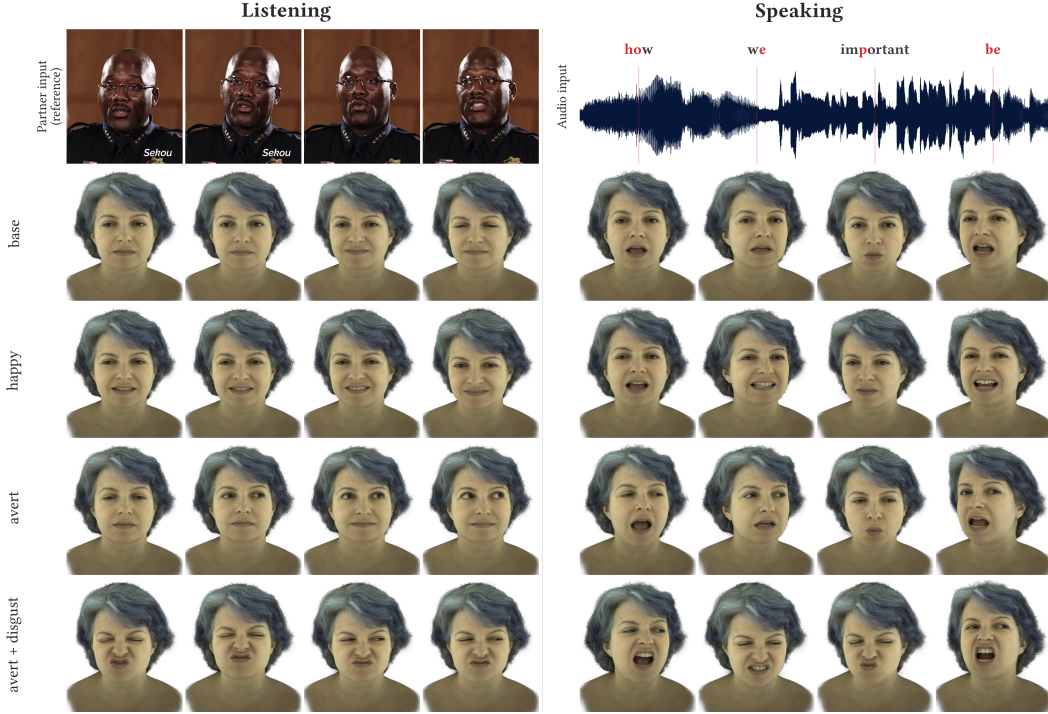


Fig. 4. Controllability across conversational roles. Top row: the dominant driving input per role (partner reference for LISTEN, target’s own audio for SPEAK). Rows 2–5: same identity under four controls (*base*, *happy*, *avert*, *avert + disgust*); the controls take effect in both regimes while role-specific behavior (listening posture, speaking lip-sync) is preserved.



Fig. 5. Disentangled FLAME controls transferred to the Gaussian avatar through f_{θ} . Independent sweeps of head yaw, eye yaw, and jaw opening produce clean, isolated changes in the rendered avatar while other motion channels remain fixed.

motion in our outputs follow the partner cue (top RGB row), whereas the baselines remain comparatively static.

Table 3. Perceptual user study: share (%) of pairwise comparisons in which raters preferred STEER over each baseline, per facet (> 50 favors STEER). In each trial of the blinded two-alternative forced-choice study, raters saw STEER and one baseline side by side on the same clip (10 raters, 18 held-out clips). Lip-sync is judged on SPEAK clips, reaction timing on LISTEN and MIXED clips, and expressions and head pose on all clips.

vs. STEER	Lip-sync	Expressions	Head pose	Reaction
UniLS	67	71	71	85
DualTalk	72	81	84	91
DiffPoseTalk	85	88	90	84
All	76	81	83	87

4.4 Perceptual User Study

In a blinded two-alternative forced-choice study, raters see STEER beside one baseline on 18 held-out clips (8 Listen, 8 Speak, 2 Mixed), judging lip-sync (Speak), reaction timing (Listen/Mixed), expressions, and head pose (all clips); 10 raters took part, and STEER is preferred on every facet against every baseline (Tab. 3).

4.5 Partner-conditioning Ablation

The partner stream carries two channels — partner audio and partner motion (latents) — on top of the target’s own audio. Fig. 7 illustrates the redundancy this gives the model on a mirror-laugh clip: the smile response is elicited even

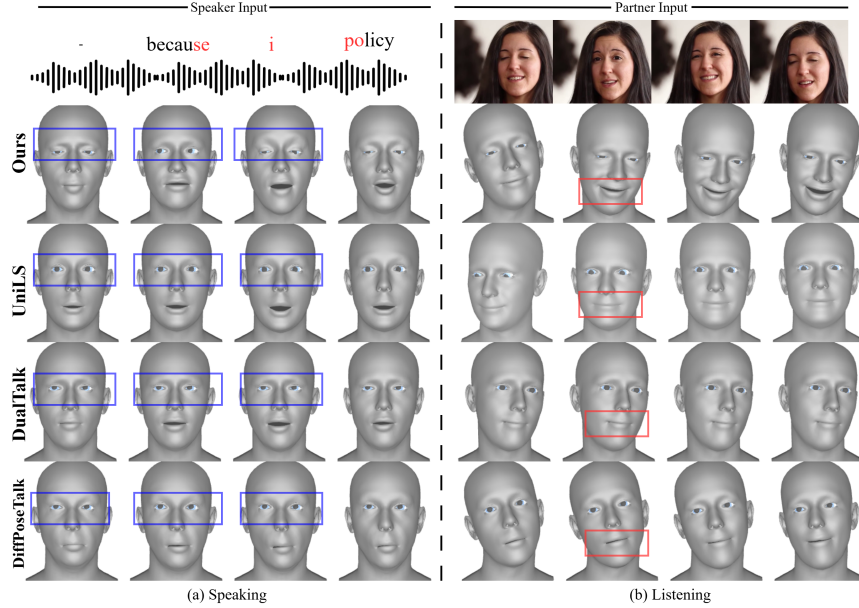


Fig. 6. Qualitative comparison; STEER (top) versus UniLS, DualTalk, DiffPoseTalk. (a) *SPEAK*: blue boxes mark the upper face — with head pose normalized, STEER shows richer eye-pose and brow motion while baselines stay static. (b) *LISTEN*: red boxes mark the mouth; STEER mirrors the smiling partner (top, RGB) more strongly and varies head motion more than baselines.

when partner audio or partner motion alone is provided; both channels carry the social cue. Removing both partner channels jointly suppresses the response, confirming the partner stream as the source of the mirroring rather than the target’s own audio. A detailed quantitative analysis of the partner-conditioning ablation is provided in the supplementary document.

4.6 Real-time System Deployment

We additionally deploy STEER as an interactive avatar that runs end-to-end at 25 fps on a single NVIDIA RTX 5090 [NVIDIA Corporation 2025]; the per-stage cue-to-render latency breakdown is reported in the supplemental. The system can be interfaced in three input modes: text (typed prompts driving the partner via Gemini 2.5 Flash [Google DeepMind 2025] TTS), audio-only (microphone input from the partner), and audio + video. At runtime the user can swap the rendered identity, change the camera viewpoint of the Gaussian avatar, and override the semantic controls; Fig. 8 reports the running HUD across these axes. We provide screen recordings of all three interaction modes, with on-screen control overlays and audio, in the supplemental video.

5 LIMITATIONS AND FUTURE WORK

STEER exposes explicit semantic controls for gaze, head rhythm, and emotion, but these axes remain discrete by design: two gaze modes, four head-rhythm modes, and seven emotion classes. This does not capture the full continuous space of human expressive variation. The decomposition is

deliberately interpretable, since controllability requires axes that a user can name and request; learned decompositions such as PCA or codebooks do not offer this. Extending the controller to continuous affect coordinates, richer behavior vocabularies, or free-form text specifications is an important direction for future work. Our interactive system runs in real time, but currently depends on a high-end GPU for the full avatar pipeline. In the live mode, motion tokens are committed before future context arrives, which can introduce high-frequency head motion that does not occur offline. Improving model efficiency, renderer throughput, and deployment on more accessible hardware would make the system more practical for broader interactive applications. STEER also assumes that the desired controls are provided externally. While this is useful for authoring and interactive steering, a natural next step is to add a higher-level behavior planner that selects gaze, head rhythm, and affect from conversational content, dialogue state, partner cues, or user intent. Finally, the model inherits biases and failure modes from the underlying tracking and annotation stack, including the RealTalk data distribution and LibreFace-derived emotion supervision. Training on a single corpus also limits demographic coverage. Behavior also varies across subjects: the style code captures this only over short windows (supp.), and a subject-conditioned behavior handle is a natural extension. Extending the data coverage, improving annotation robustness, coupling the controller to full-body motion, and learning personalized behavior preferences online are promising future directions.

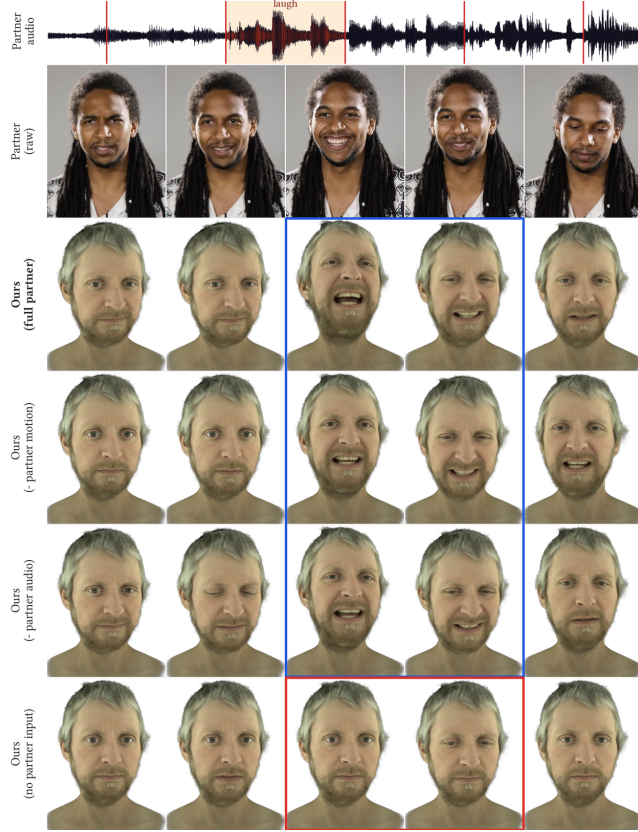


Fig. 7. Mirror-laugh ablation. Both partner channels carry the cue: partner audio or partner motion alone elicits the smile (rows 3–5, blue); removing both fails to elicit it (row 6, red).

Ethical considerations. Photoreal avatars can be misused for unauthorized depiction, privacy violations, and deceptive content; ours come from a studio-captured prior of consenting subjects, and we do not construct photoreal avatars of in-the-wild individuals: RealTalk video supervises motion, not appearance. Demographic bias from the tracking and labeling stacks remains a concern, and deployments should disclose synthesis and obtain consent.

6 CONCLUSION

We presented STEER, a controllable dyadic motion prior for photorealistic conversational head avatars. By exposing gaze, head rhythm, and emotion as explicit semantic controls, STEER moves beyond prior dyadic methods that leave non-verbal behavior largely implicit in audio and partner conditioning. To enable this control, we introduced an annotation pipeline for in-the-wild dyadic video, trained a causal flow-matching prior for partner-aware target motion, and connected the generated motion to a universal Gaussian head-avatar prior through a learned FLAME-to-avatar driving-space translator. Experiments show that STEER improves motion quality, dynamics, and diversity over recent dyadic



Fig. 8. STEER deployed in a real-time setting at 25 fps. Row 1 (*id swap*): same pose driving three different identities through UHAP. Row 2 (*view control*): free-viewpoint rendering of the same identity. Row 3 (*speaking*): live audio-driven speaking with semantic-control overlays (emotion, behavior).

baselines, while supporting controllable edits and real-time interactive deployment. We will release our training and evaluation code together with our dataset annotations.

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REFERENCES

- Ahmed A. Abdelrahman, Thorsten Hempel, Aly Khalifa, and Ayoub Al-Hamadi. 2023. L2CS-Net: Fine-Grained Gaze Estimation in Unconstrained Environments. In 2023 8th International Conference on Frontiers of Signal Processing (ICFSP). 98–102.
- Vasu Agrawal, Akinniyi Akinyemi, Kathryn Alvero, Morteza Behrooz, Julia Buffalini, Fabio Maria Carlucci, Joy Chen, Junming Chen, Zhang Chen, Shiyang Cheng, Praveen Chowdary, Joe Chuang, Antony D’Avirro, Jon Daly, Ning Dong, Mark Duppenhaler, Cynthia Gao, Jeff Girard, Martin Gleize, Sahir Gomez, Hongyu Gong, Srivathsan Govindarajan, Brandon Han, Sen He, Denise Hernandez, Yordan Hristov, Rongjie Huang, Hirofumi Inaguma, Somya Jain, Raj Janardhan, Qingyao Jia, Christopher Klaiber, Dejan Kovachev, Moneish Kumar, Hang Li, Yilei Li, Pavel Litvin, Wei Liu, Guangyao Ma, Jing Ma, Martin Ma, Xutai Ma, Lucas Mantovani, Sagar Miglani, Sreyas Mohan, Louis-Philippe Morency, Evonne Ng, Kam-Woh Ng, Tu Anh Nguyen, Amia Oberai, Benjamin Peloquin, Juan Pino, Jovan Popovic, Omid Poursaeed, Fabian Prada, Alice Rakotoarison, Rakesh Ranjan, Alexander Richard, Christophe Ropers, Safiyyah Saleem, Vasu Sharma, Alex Shcherbyna, Jia Shen, Jie Shen, Anastasis Stathopoulos, Anna Sun, Paden Tomasello, Tuan Tran, Arina Turkatenco, Bo Wan, Chao Wang, Jeff Wang, Mary Williamson, Carleigh Wood, Tao Xiang, Yilin Yang, Julien Yao, Chen Zhang, Jiemin Zhang, Xinyue Zhang, Jason Zheng, Pavlo Zhyzheria, Jan Zikes, and Michael Zollhoefer. 2025. Seamless Interaction: Dyadic Audiovisual Motion Modeling and Large-Scale Dataset. arXiv:2506.22554 [cs.CV] <https://arxiv.org/abs/2506.22554>
- Shivangi Aneja, Artem Sevastopolsky, Tobias Kirschstein, Justus Thies, Angela Dai, and Matthias Nießner. 2025. GaussianSpeech: Audio-Driven Personalized 3D Gaussian Avatars. In Proceedings

- of the IEEE/CVF International Conference on Computer Vision (ICCV). 13065–13075.
- Shivangi Aneja, Justus Thies, Angela Dai, and Matthias Nießner. 2024. FaceTalk: Audio-Driven Motion Diffusion for Neural Parametric Head Models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 21263–21273.
- Alexei Baevski, Henry Zhou, Abdelrahman Mohamed, and Michael Auli. 2020. wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations. arXiv:2006.11477 [cs.CL] <https://arxiv.org/abs/2006.11477>
- Di Chang, Yufeng Yin, Zongjian Li, Minh Tran, and Mohammad Soilemani. 2024. LibreFace: An Open-Source Toolkit for Deep Facial Expression Analysis. In IEEE/CVF Winter Conference on Applications of Computer Vision (WACV).
- Aggelina Chatziagapi, Louis-Philippe Morency, Hongyu Gong, Michael Zollhöfer, Dimitris Samaras, and Alexander Richard. 2025. AV-Flow: Transforming Text to Audio-Visual Human-like Interactions. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 14270–14282.
- Bohong Chen and Haiyang Liu. 2025. DyStream: Streaming Dyadic Talking Heads Generation via Flow Matching-based Autoregressive Model. arXiv:2512.24408 [cs.CV] <https://arxiv.org/abs/2512.24408>
- Xin Chen, Biao Jiang, Wen Liu, Zilong Huang, Bin Fu, Tao Chen, and Gang Yu. 2023. Executing your Commands via Motion Diffusion in Latent Space. In IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2023, Vancouver, BC, Canada, June 17–24, 2023. IEEE, 18000–18010. <https://doi.org/10.1109/CVPR52729.2023.01726>
- Jin Hyun Cheong, Eshin Jolly, Tiankang Xie, Sophie Byrne, Matthew Kenney, and Luke J. Chang. 2023. Py-Feat: Python Facial Expression Analysis Toolbox. *Affective Science* 4, 4 (2023), 781–796.
- Xuangeng Chu, Ruicong Liu, Yifei Huang, Yun Liu, Yichen Peng, and Bo Zheng. 2025. UniLS: End-to-End Audio-Driven Avatars for Unified Listening and Speaking. arXiv:2512.09327 [cs.CV] <https://arxiv.org/abs/2512.09327>
- Wenxun Dai, Ling-Hao Chen, Jingbo Wang, Jinpeng Liu, Bo Dai, and Yansong Tang. 2024. MotionLCM: Real-Time Controllable Motion Generation via Latent Consistency Model. In *Computer Vision - ECCV 2024 - 18th European Conference, Milan, Italy, September 29–October 4, 2024, Proceedings, Part XVI (Lecture Notes in Computer Science, Vol. 15074)*, Ales Leonardis, Elisa Ricci, Stefan Roth, Olga Russakovsky, Torsten Sattler, and Gül Varol (Eds.). Springer, 390–408. https://doi.org/10.1007/978-3-031-72640-8_22
- Radek Danek, Kiran Chhatre, Shashank Tripathi, Yandong Wen, Michael J. Black, and Timo Bolkart. 2023. Emotional Speech-Driven Animation with Content-Emotion Disentanglement. <https://doi.org/10.1145/3610548.3618183> arXiv:2306.08990 [cs.CV]
- Yingruo Fan, Zhaojiang Lin, Jun Saito, Wenping Wang, and Taku Komura. 2022. FaceFormer: Speech-Driven 3D Facial Animation With Transformers. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 18770–18780.
- Ruohan Gao and Kristen Grauman. 2021. VisualVoice: Audio-Visual Speech Separation with Cross-Modal Consistency. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
- Scott Geng, Revant Teotia, Purva Tendulkar, Sachit Menon, and Carl Vondrick. 2023. Affective Faces for Goal-Driven Dyadic Communication. arXiv:2301.10939 [cs.CV] <https://arxiv.org/abs/2301.10939>
- Google DeepMind. 2025. Gemini 2.5 Flash. <https://deepmind.google/technologies/gemini/flash/>. Large multimodal model, used for TTS in our live system.
- Chuan Guo, Yuxuan Mu, Muhammad Gohar Javed, Sen Wang, and Li Cheng. 2024. MoMask: Generative Masked Modeling of 3D Human Motions. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 1900–1910.
- Thorsten Hempel, Ahmed A. Abdelrahman, and Ayoub Al-Hamadi. 2022. 6D Rotation Representation for Unconstrained Head Pose Estimation. In IEEE International Conference on Image Processing (ICIP).
- Jonathan Ho and Tim Salimans. 2022. Classifier-Free Diffusion Guidance. arXiv:2207.12598 [cs.LG] <https://arxiv.org/abs/2207.12598>
- Diederik P Kingma and Max Welling. 2014. Auto-Encoding Variational Bayes. *International Conference on Learning Representations (ICLR)* (2014).
- Peiwen Lai, Weizhi Zhong, Yipeng Qin, Xiaohang Ren, Baoyuan Wang, and Guanbin Li. 2025. LLM-driven Multimodal and Multi-Identity Listening Head Generation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 10656–10666.
- Jiye Lee, Chenghui Li, Linh Tran, Shih-En Wei, Jason Saragih, Alexander Richard, Hanbyul Joo, and Shaojie Bai. 2025. Audio Driven Real-Time Facial Animation for Social Telepresence. arXiv preprint arXiv:2510.01176 (2025).
- Tianye Li, Timo Bolkart, Michael J. Black, Hao Li, and Javier Romero. 2017. Learning a model of facial shape and expression from 4D scans. *ACM Transactions on Graphics, (Proc. SIGGRAPH Asia)* 36, 6 (2017), 194:1–194:17. <https://doi.org/10.1145/3130800.3130813>
- Yaron Lipman, Ricky T. Q. Chen, Heli Ben-Hamu, Maximilian Nickel, and Matt Le. 2023. Flow Matching for Generative Modeling. arXiv:2210.02747 [cs.LG] <https://arxiv.org/abs/2210.02747>
- Xingchao Liu, Chengyue Gong, and Qiang Liu. 2022. Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow. arXiv:2209.03003 [cs.LG] <https://arxiv.org/abs/2209.03003>
- Xi Liu, Ying Guo, Cheng Zhen, Tong Li, Yingying Ao, and Pengfei Yan. 2024. CustomListener: Text-guided Responsive Interaction for User-friendly Listening Head Generation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2415–2424.
- Camillo Lugaresi, Jiuqiang Tang, Hadon Nash, Chris McClanahan, Esha Uboweja, Michael Hays, Fan Zhang, Chuo-Ling Chang, Ming Guang Yong, Juhyun Lee, Wan-Teh Chang, Wei Hua, Manfred Georg, and Matthias Grundmann. 2019. MediaPipe: A Framework for Building Perception Pipelines. arXiv:1906.08172 [cs.DC]
- Vinod Nair and Geoffrey E Hinton. 2010. Rectified linear units improve restricted Boltzmann machines. In *ICML*.
- Evonne Ng, Hanbyul Joo, Liwen Hu, Hao Li, Trevor Darrell, Angjoo Kanazawa, and Shiry Ginosar. 2022. Learning To Listen: Modeling Non-Deterministic Dyadic Facial Motion. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 20395–20405.
- NVIDIA Corporation. 2025. NVIDIA GeForce RTX 5090. <https://www.nvidia.com/en-us/geforce/graphics-cards/50-series/rtx-5090/>. Consumer GPU product page.
- Yifang Pan, Rishabh Agrawal, and Karan Singh. 2024. S3: Speech, Script and Scene Driven Head and Eye Animation. *ACM Transactions on Graphics* 43, 4, Article 47 (2024), 12 pages. <https://doi.org/10.1145/3658172>
- William Peebles and Saining Xie. 2023. Scalable Diffusion Models with Transformers. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 4195–4205.
- Ziqiao Peng, Yanbo Fan, Haoyu Wu, Xuan Wang, Hongyan Liu, Jun He, and Zhaoxin Fan. 2025. DualTalk: Dual-Speaker Interaction for 3D Talking Head Conversations. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 21055–21064.
- Ziqiao Peng, Haoyu Wu, Zhenbo Song, Hao Xu, Xiangyu Zhu, Jun He, Hongyan Liu, and Zhaoxin Fan. 2023. EmoTalk: Speech-Driven Emotional Disentanglement for 3D Face Animation. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 20687–20697.
- Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron Courville. 2018. FiLM: Visual Reasoning with a General Conditioning Layer. In *AAAI*.
- George Retsinas, Panagiotis P. Filntisis, Radek Danecsek, Victoria F. Abrevaya, Anastasios Roussos, Timo Bolkart, and Petros Maragos. 2024. 3D Facial Expressions through Analysis-by-Neural-Synthesis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2490–2501.
- Alexander Richard, Michael Zollhöfer, Yandong Wen, Fernando de la Torre, and Yaser Sheikh. 2021. MeshTalk: 3D Face Animation From Speech Using Cross-Modality Disentanglement. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 1173–1182.
- Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-Resolution Image Synthesis with Latent Diffusion Models. In IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18–24, 2022. IEEE, 10674–10685. <https://doi.org/10.1109/CVPR52688.2022.01042>
- Tim Salimans and Jonathan Ho. 2022. Progressive Distillation for Fast Sampling of Diffusion Models. In *International Conference on Learning Representations (ICLR)*.

- Maksim Siniukov, Di Chang, Minh Tran, Hongkun Gong, Ashutosh Chaubey, and Mohammad Soleymani. 2025. DiTailListener: Controllable High Fidelity Listener Video Generation with Diffusion. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 11991–12001.
- Luchuan Song, Guojun Yin, Zhenchao Jin, Xiaoyi Dong, and Chenliang Xu. 2023. Emotional Listener Portrait: Neural Listener Head Generation with Emotion. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). 20839–20849.
- Tomáš Souček and Jakub Lokoč. 2020. TransNet V2: An Effective Deep Network Architecture for Fast Shot Transition Detection. arXiv preprint arXiv:2008.04838 (2020).
- Stefan Stan, Kazi Injamamul Haque, and Zerrin Yumak. 2023. FaceDiffuser: Speech-Driven 3D Facial Animation Synthesis Using Diffusion. arXiv:2309.11306 [cs.CV] <https://arxiv.org/abs/2309.11306>
- Tanya Stivers, N. J. Enfield, Penelope Brown, Christina Englert, Makoto Hayashi, Trine Heinemann, Gertie Hoymann, Federico Rossano, Jan Peter de Ruiter, Kyung-Eun Yoon, and Stephen C. Levinson. 2009. Universals and cultural variation in turn-taking in conversation. *Proceedings of the National Academy of Sciences (PNAS)* 106, 26 (2009), 10587–10592.
- Jianlin Su, Yu Lu, Shengfeng Pan, Ahmed Murtadha, Bo Wen, and Yunfeng Liu. 2021. RoFormer: Enhanced Transformer with Rotary Position Embedding. arXiv preprint arXiv:2104.09864 (2021).
- Zhiyao Sun, Tian Lv, Sheng Ye, Matthieu Lin, Jenny Sheng, Yu-Hui Wen, Mingjing Yu, and Yong-Jin Liu. 2024. DiffPoseTalk: Speech-Driven Stylistic 3D Facial Animation and Head Pose Generation via Diffusion Models. arXiv:2310.00434 [cs.CV] <https://arxiv.org/abs/2310.00434>
- Kartik Teotia, Helge Rhodin, Mohit Mendiratta, Hyeonwoo Kim, Marc Habermann, and Christian Theobalt. 2025. Audio-Driven Universal Gaussian Head Avatars. arXiv:2509.18924 [cs.CV] <https://arxiv.org/abs/2509.18924>
- Guy Tevet, Sigal Raab, Brian Gordon, Yonatan Shafir, Daniel Cohen-Or, and Amit H. Bermano. 2022. Human Motion Diffusion Model. arXiv:2209.14916 [cs.CV] <https://arxiv.org/abs/2209.14916>
- Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Yang Fan, Kai Dang, Mengfei Du, Xuancheng Ren, Rui Men, Dayiheng Liu, Chang Zhou, Jingren Zhou, and Junyang Lin. 2024. Qwen2-VL: Enhancing Vision-Language Model’s Perception of the World at Any Resolution. arXiv:2409.12191
- Yinuo Wang, Yanbo Fan, Xuan Wang, Guo Yu, and Fei Wang. 2025. Diffusion-based Realistic Listening Head Generation via Hybrid Motion Modeling. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 15885–15895.
- Lixing Xiao, Shunlin Lu, Huaijin Pi, Ke Fan, Liang Pan, Yueer Zhou, Ziyong Feng, Xiaowei Zhou, Sida Peng, and Jingbo Wang. 2025. MotionStreamer: Streaming Motion Generation via Diffusion-based Autoregressive Model in Causal Latent Space. arXiv:2503.15451 [cs.CV] <https://arxiv.org/abs/2503.15451>
- Yiming Xie, Varun Jampani, Lei Zhong, Deqing Sun, and Huaizu Jiang. 2024. OmniControl: Control Any Joint at Any Time for Human Motion Generation. In The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024. OpenReview.net. <https://openreview.net/forum?id=gd0LAETWso>
- Jinbo Xing, Menghan Xia, Yuechen Zhang, Xiaodong Cun, Jue Wang, and Tien-Tsin Wong. 2023. CodeTalker: Speech-Driven 3D Facial Animation With Discrete Motion Prior. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 12780–12790.
- Peizhi Yan. 2023. MediaPipe Blendshapes to FLAME. <https://github.com/PeizhiYan/mediapipe-blendshapes-to-flame>.
- Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. 2023. Adding Conditional Control to Text-to-Image Diffusion Models. In IEEE/CVF International Conference on Computer Vision, ICCV 2023, Paris, France, October 1-6, 2023. IEEE, 3813–3824. <https://doi.org/10.1109/ICCV51070.2023.00355>
- Qingcheng Zhao, Pengyu Long, Qixuan Zhang, Dafei Qin, Han Liang, Longwen Zhang, Yingliang Zhang, Jingyi Yu, and Lan Xu. 2024. Media2Face: Co-speech Facial Animation Generation With Multi-Modality Guidance. arXiv:2401.15687 [cs.CV] <https://arxiv.org/abs/2401.15687>
- Yongming Zhu, Longhao Zhang, Zhengkun Rong, Tianshu Hu, Shuang Liang, and Zhipeng Ge. 2025. INFP: Audio-Driven Interactive Head Generation in Dyadic Conversations. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 10667–10677.

Supplementary Material

STEER: Steerable Dyadic Head Avatars

A BEHAVIOR-LABEL PIPELINE AND THRESHOLDS

The gaze and head-rhythm pseudo-labels referenced in main-paper Sec. 3.1 are derived from the kinematic motion decomposition $\tilde{\phi}$ of Pan et al. [Pan et al. 2024], which produces per-frame partner-attention and rhythmic-head signals from the tracked facial-motion state, including head-pose and eye-gaze estimates. We turn those signals into discrete categorical labels in three stages: per-frame thresholding, per-token pooling, and clip-level filtering.

Geometry assumption. RealTalk shots are filmed face-to-face but the camera distance and framing vary, so we do not assume any fixed seating geometry. Instead we estimate a per-shot partner direction for each speaker as a robust trimmed mean of their head-forward vector across the shot — i.e., where the speaker is mostly looking on average. All gaze angles below are measured in degrees relative to this shot-specific reference.

Per-frame gaze (contact / avert). For each frame we measure the angle θ between the speaker’s combined head + eye gaze vector and the partner direction. With hysteresis,

- $\theta < 11^\circ$ enters on-partner state (within a narrow cone toward the partner),
- $\theta > 19^\circ$ leaves it; in between the state is held to avoid flicker.

Each frame is then either on-partner (1) or averted (0). To require temporal consistency, we smooth this $\{0, 1\}$ signal over a 7-frame (~ 280 ms) window and label a frame contact if at least 5 of those 7 frames were on-partner, avert if at most 2 were, and mask out the gaze channels in between (the ambiguous band).

Per-frame head-rhythm (still / nod / shake / tilt). We classify each frame from the rhythmic head-pose components (pitch, yaw, roll, all in degrees) over a local window centered on that frame, with half-window $hw=12$ frames (~ 1 s total span). Let $\Delta_p, \Delta_y, \Delta_r$ be the within-window peak-to-peak range of pitch / yaw / roll, and $|\dot{p}|$ the mean per-frame absolute pitch derivative. The per-frame label is:

- still: $|\dot{p}| < 0.5^\circ/\text{frame}$ and $\Delta_p < 1^\circ$ and $\Delta_y < 1^\circ$;
- nod: $\Delta_p > 1.2 \cdot \max(\Delta_y, \Delta_r)$;
- shake: $\Delta_y > 1.2 \cdot \max(\Delta_p, \Delta_r)$;
- tilt: $\Delta_r > 1.2 \cdot \max(\Delta_p, \Delta_y)$;
- otherwise the head-rhythm channels are masked out at that frame..

The $1.2\times$ dominance multiplier suppresses noisy near-tied frames; the $0.5^\circ / 1^\circ$ stillness floors were calibrated by histogram inspection on ~ 200 training shots.

Per-token pooling. Each $T=100$ -frame window (4 s at 25 fps) is reduced to $K=25$ latent tokens by the AE; we pool the per-frame labels onto the same grid by splitting the window into 25 contiguous bins of 4 frames. For each bin we take a mask-weighted average of the per-frame labels and re-normalize the gaze channels and the head-rhythm channels to a simplex; a channel group’s bin is marked valid iff at least one frame in the bin was unmasked for that group. This yields the per-token control vector $\mathbf{b}_k$ and validity mask $\mathbf{M}_k$ used in main-paper Sec. 3.3.

Clip-level filtering. Before pseudo-labels are computed, we filter shots and windows for tracking quality: (i) a Qwen2-VL pre-pass [Wang et al. 2024] flags shots with side-views, multi-person frames, or heavy occlusion (filtering at the shot level); (ii) windows in which the kinematic decomposition $\tilde{\phi}$ is missing or incomplete are dropped; (iii) only contiguous clean spans of at least 5 seconds are retained for training. These steps reduce the 16,573 raw RealTalk shots to the 10,555-clip filtered corpus reported in the main paper. The pipeline itself is corpus-agnostic: it consumes tracked motion and per-speaker audio, so any face-to-face corpus with separable audio can be processed the same way.

B NETWORK ARCHITECTURES

This section gives the per-module specifications referenced from main-paper Sec. 3.2–3.5. All downstream modules operate at the token rate $K=25$ defined there unless noted.

B.1 Motion autoencoder ($\mathcal{E}_{\text{AE}}, \mathcal{D}_{\text{AE}}$, main-paper Sec. 3.2)

The motion AE is a standard VAE [Kingma and Welling 2014]; its design closely follows the causal motion-latent autoencoder used by MotionStreamer [Xiao et al. 2025] but is retrained on our 61-D dyadic FLAME state. The encoder $\mathcal{E}_{\text{AE}}$ stacks two stride-2 causal 1D convolutions (kernel 5, channels $61 \rightarrow 128 \rightarrow 256$), followed by a 2-layer Transformer with rotary position embeddings (RoPE) [Su et al. 2021], 4 heads, and feed-forward width 512, which produces the per-token Gaussian-posterior parameters (μ_k, σ_k) . The decoder $\mathcal{D}_{\text{AE}}$ mirrors this stack with transposed causal convolutions. The reconstruction loss in main-paper Eq. 3 is a per-region weighted ℓ_1 ($w_{\text{exp}}=1, w_{\text{jaw}}=2, w_{\text{neck}}=4, w_{\text{eye}}=3, w_{\text{eyelid}}=2$) plus first-order velocity ℓ_1 ($\lambda_{\text{vel}}=1.0$) and second-order acceleration ℓ_1 ($\lambda_{\text{acc}}=0.1$); the KL term toward $\mathcal{N}(\mathbf{0}, \mathbf{I})$ is annealed from 0 to $\beta_{\text{KL}}=10^{-5}$ over 10,000 iterations. The AE is trained for 150,000 iterations at batch size 128, lr 2×10^{-4} , and then frozen for all downstream modelling. Freezing the AE gives the prior a fixed latent distribution to model rather than a moving target, following the standard two-stage recipe in latent generative modeling [Chen et al. 2023; Rombach et al. 2022; Xiao et al. 2025]. A possible concern is that the bottleneck smooths away brief or subtle motion. In practice it does not: the smile-timing F1 (§I) and the control effect-sizes of §E are measured on motion decoded through this AE, and both depend on such events surviving decoding.

B.2 Partner Encoder ($\mathcal{E}_P$, main-paper Sec. 3.2)

The Partner Encoder turns the per-frame partner streams into the per-token context sequence $\mathbf{c}^P$ that every DiT block cross-attends to. Two streams enter: (i) AE-encoded partner motion latents $\mathbf{Z}_P$, already at the token rate; and (ii) partner audio features $\mathbf{a}^P$, mean-pooled over each 4-frame token span from the audio encoder of §B.6. Each stream is linearly projected to the shared hidden dimension and concatenated, followed by a Linear+GELU+Linear fusion. The result is processed by a Transformer with RoPE [Su et al. 2021], causal in time, 4 blocks deep, hidden dimension 448, 8 heads, MLP ratio 4. The output sequence is the partner KV consumed by the DiT.

B.3 Flow-matching prior (v_θ , main-paper Sec. 3.2–3.3)

The prior is a causal DiT [Peebles and Xie 2023] with RoPE self-attention [Su et al. 2021]: 8 blocks, hidden 448, 8 heads (head dimension 56), MLP ratio 4. Each block sequentially applies, in order: AdaLN-Zero modulation on the residual stream from the window-level emotion code $\mathbf{y}^{\text{emo}}$ [Peebles and Xie 2023], causal RoPE self-attention over the $K+n_{\text{prev}}$ tokens, cross-attention to the target’s audio features $\mathbf{a}^T$, cross-attention to the Partner-Encoder output $\mathbf{c}^P$ (§B.2), per-block FiLM [Perez et al. 2018] modulation from the style code $\mathbf{s}$, and a causal MLP. The AdaLN-Zero adapter $\mathcal{G}_\ell^{\text{emo}}$ is a 2-layer MLP from the 7=7-class emotion vector to per-block scale/shift/gate $(\gamma_\ell, \beta_\ell, \alpha_\ell)$, with α_ℓ initialised to zero so the adapter starts as a no-op [Peebles and Xie 2023]. The style FiLM adapter is a single linear projection from $\mathbf{s} \in \mathbb{R}^{128}$ to per-block (γ, β) .

Gap-driven residual ($\mathcal{R}_\ell$). The behavior residual of main-paper Sec. 3.3 (main-paper Eq. 7) lives on the last three DiT blocks. Each $\mathcal{R}_\ell$ is a 2-layer MLP, hidden 448, GELU, with its final linear layer zero-initialised so the residual is a no-op at training start. Each of the three layers carries its own observer head ϕ_ℓ — a single linear projection from the hidden state to per-channel gaze and head-rhythm softmaxes — supervised by the masked cross-entropy of main-paper Sec. 3.4.

B.4 Style VAE (main-paper Sec. 3.3)

A VAE [Kingma and Welling 2014] encodes a single T -frame target-motion window into a clip-level motion-style code $\mathbf{s} \in \mathbb{R}^{128}$. The encoder is a 1D-conv stem followed by a 2-layer Transformer, hidden 256, 4 heads, that pools to a single token and emits $\boldsymbol{\mu}, \boldsymbol{\sigma} \in \mathbb{R}^{128}$. We sample at training and use $\boldsymbol{\mu}$ at deployment. The KL term toward $\mathcal{N}(\mathbf{0}, \mathbf{I})$ caps the channel’s capacity, as discussed in the main paper.

B.5 Affect observer (main-paper Sec. 3.4)

The frozen affect observer that produces $\mathcal{L}_{\text{emo}}$ is a causal 5-block dilated TCN over per-frame motion $\mathbf{m} \in \mathbb{R}^{T \times 61}$, hidden width 192, kernel 5, GroupNorm + GELU. Two heads share the trunk: a per-frame linear head outputs 12-D action-unit intensities; a window head temporal-mean-pools the trunk features over T frames and projects to 7-class facial-expression

logits. We pre-train it for 40,000 steps with batch size 128 on (motion, LibreFace) pairs from our training corpus, with a weighted sum of per-frame MSE on action units and window-level cross-entropy on the seven-class facial-expression label. The observer is frozen for all of STEER’s training, and only the window-level emotion head is consumed by $\mathcal{L}_{\text{emo}}$; the action-unit head is retained as auxiliary supervision during the observer’s own pre-training.

B.6 Audio encoders

The target’s and partner’s audio are encoded by a shared, frozen Wav2Vec2-Large [Baeviski et al. 2020] adapted to the causal-streaming recipe of DyStream [Chen and Liu 2025]: the lower convolutional feature extractor is unchanged; the top 6 Transformer layers are made causal with a 60 ms right context. A 1024-D audio adapter projects the Wav2Vec2 output to the DiT cross-attention dimension. The per-frame embeddings are mean-pooled over the 4-frame token span before they enter the prior; the same encoder serves both the target-audio and partner-audio cross-attention paths in the DiT.

B.7 Avatar translator f_θ (main-paper Sec. 3.5)

f_θ maps the per-frame FLAME state $\mathbf{m}_t \in \mathbb{R}^{61}$ to UHAP’s 256-D expression code. The FLAME geometry is first posed with expression, jaw, and neck applied and eye rotation held at the neutral pose, so gaze does not enter the UV path; it is then rasterised into a $1024 \times 1024 \times 3$ UV position map $U(\mathbf{m}_t)$ indexed by UV. This map feeds an 8-layer weight-normalised 2D-conv encoder $\mathcal{E}_{\text{UV}}$ with kernel 4, stride 2, LeakyReLU(0.2); the channel progression is $32 \rightarrow 32 \rightarrow 64 \rightarrow 64 \rightarrow 128 \rightarrow 128 \rightarrow 256 \rightarrow 256$, downsampling $1024 \rightarrow 4$ spatially. The $256 \times 4 \times 4 = 4096$ -D bottleneck is flattened and projected by two weight-normalised linear layers ($4096 \rightarrow 512 \rightarrow 256$) with LeakyReLU between, the last layer initialised at $0.1\times$. Gaze enters as an independent control through a 2-layer MLP g_{gaze} ($4 \rightarrow 64 \rightarrow 2 \cdot 256$) that emits FiLM [Perez et al. 2018] parameters $(\gamma_t, \beta_t) \in \mathbb{R}^{256}$. The final code is

$$f_\theta(\mathbf{m}_t) = h_{\text{lat}}(\mathcal{E}_{\text{UV}}(U(\mathbf{m}_t))) \odot (1 + \gamma_t) + \beta_t.$$

The gaze MLP’s output layer is zero-initialised, so f_θ starts as a pure UV-only encoder. UHAP’s Gaussian decoder, identity embedding, and FLAME forward pass are kept frozen.

Reconstruction fidelity. We measure what the translator costs relative to the avatar’s own reconstruction ceiling on a held-out expression set (3,000 frames) with multi-view ground truth. The ceiling drives UHAP’s frozen decoder with the expression codes recovered by its native encoder; the translator path drives the same decoder with f_θ applied to the tracked FLAME state. Tab. 4 reports both against the captured images. The translator lands within 3.8 dB PSNR of the ceiling. The residual gap originates primarily in the underlying FLAME tracking, which holds back on some subtle and extreme expressions before the avatar is driven. The gap is dominated by a small geometric misalignment (+2.7 mm

mesh error) rather than by a change in appearance (LPIPS +0.044). Fig. 9 illustrates this: where the tracked FLAME state already lacks an expression, both the avatar’s own reconstruction and the translator render inherit the loss.

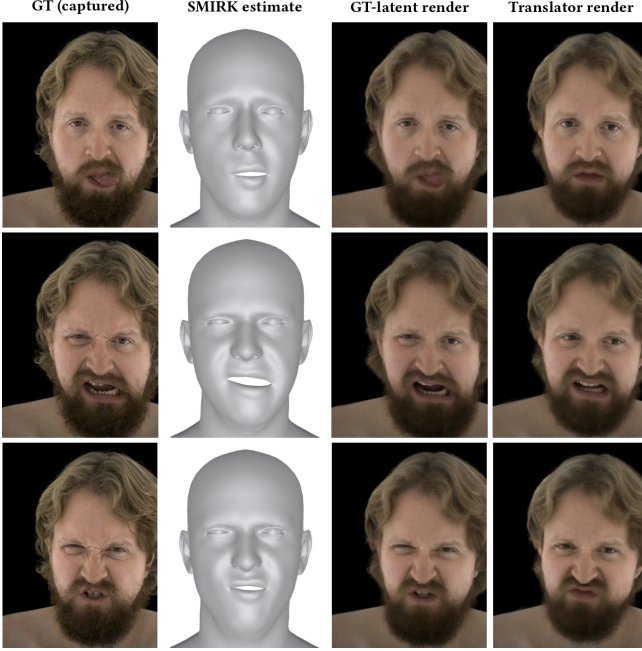


Fig. 9. Attribution of the avatar-bridge gap. Left to right: captured frame; tracked SMIRK/FLAME estimate (the translator’s input); render from UHAP’s native expression codes (the avatar’s reconstruction ceiling); render from the translator. The tracked state already misses parts of the expression: the tongue in row 1, and fine expression detail in rows 2 and 3, most visibly the nose wrinkle in row 3. Both renders inherit this loss, so the residual gap originates in tracking, before the translator.

Table 4. Translator fidelity on a held-out expression set.

	PSNR $\uparrow$	ℓ_1 $\downarrow$	LPIPS $\downarrow$	Mesh ℓ_2 $\downarrow$
GT-latent	28.05	0.023	0.165	1.09 mm
Translator	24.27	0.032	0.209	3.79 mm
Gap	-3.78	+0.010	+0.044	+2.70 mm

B.8 Preservation distillation

Fine-tuning v_θ jointly with the style, behavior, and emotion heads on top of an already-converged audio-and-partner backbone risks trunk drift. We mitigate this by holding a frozen copy of the backbone-only checkpoint as a preservation teacher and adding a per-iteration trajectory-matching loss

$$\mathcal{L}_{\text{preserve}} = \|\mathbf{z}_T^{\text{stud}, \emptyset} - \mathbf{z}_T^{\text{teach}, \emptyset}\|_2^2,$$

where both forward passes use the same noise/timestep but with all semantic controls dropped out (the null condition). We weight $\mathcal{L}_{\text{preserve}}$ at 1.0 and lower the trunk learning rate

to 6×10^{-6} , an order of magnitude below the per-head rates (§B.9). This keeps the audio-and-partner pathway aligned with its pre-fine-tune behaviour while the controls activate without overriding it.

B.9 Training schedule

We optimise the prior with AdamW. Param-group learning rates: trunk 6×10^{-6} , audio adapter 1×10^{-4} , behavior heads 1.2×10^{-4} , style and emotion adapters 1.5×10^{-4} . We use cosine decay to $0.02 \times$ of base LR with linear warmup, gradient-norm clipping at 1.0, batch size 48, and 215,000 iterations.

Classifier-free guidance dropouts. Following classifier-free guidance [Ho and Salimans 2022], each conditioning channel is replaced with a learned null token at training with the per-channel Bernoulli probabilities of Tab. 5. The joint partner mask shares a single coin across partner audio and partner motion so the partner stream is replaced as a unit; the per-modality partner dropouts apply on top of that joint mask.

Table 5. Per-channel classifier-free-guidance dropout probabilities.

Channel	Bernoulli p
Target audio	0.10
Partner stream (joint)	0.10
Partner audio / motion (per-modality)	0.05 each
Style	0.15
Behavior	0.25
Emotion	0.30
Previous-window prefix	0.10

Loss weights. Tab. 6 lists the loss coefficients used to instantiate the composite training loss of main-paper Sec. 3.4. The per-region ℓ_1 velocity and acceleration losses use the FLAME-state regions {neck, exp, jaw, eye} (acceleration on neck / exp / jaw only). The energy-floor losses use floor ratio $\alpha=0.90$ under a ReLU [Nair and Hinton 2010] hinge.

Table 6. Loss coefficients (composite training loss, main-paper Sec. 3.4).

Term	Symbol	Weight
Flow matching	λ_{flow}	1.0
Decoded-motion flow	λ_{decoded}	1.0
Velocity ℓ_1 (neck/exp/jaw/eye)	λ_{vel}	3.0/0.8/1.5/1.2
Accel. ℓ_1 (neck/exp/jaw)	λ_{acc}	0.10/0.03/0.03
Energy floor (neck/exp/jaw/eye)	λ_{energy}	0.60/0.35/0.10/0.15
Preservation distillation	$\lambda_{\text{preserve}}$	1.0
Behavior observer (hidden/decoded)	λ_{obs}	0.30/0.08
Emotion observer (decoded)	λ_{emo}	0.50

B.10 Few-step distillation and streaming inference

The 10-step teacher is distilled to a 2-step student in the spirit of progressive distillation [Salimans and Ho 2022] (main-paper Eq. 11), trained with the same semantic supervision as the teacher so the control surface is preserved. At deployment the student runs streaming under the protocol of main-paper Sec. 3.4: at each emit it consumes the $n_{\text{prev}}=3$ -token clean prefix, predicts $K=25$ candidate tokens, commits $s=1$ leading



Fig. 10. Behavior-control showcase on a single test clip. *Gaze* rows (Base, contact, avert) and *Head* rows (still, nod, shake) are stacked vertically; columns are eight frames across time.

token, and blends the trailing K -s tokens into the next emit through a raised-cosine taper of width 8 tokens. Keys and values from the self-attention and from both cross-attention paths are cached across emits, so the per-step compute scales with the commit stride rather than with the absolute time index.

C PER-AXIS BEHAVIOR CONTROLLABILITY

Fig. 10 shows the per-axis behavior edits on a single test clip. The *Gaze* axis (Base, contact, avert) selects between maintained gaze and gaze aversion; the *Head* axis (still, nod, shake) selects between three head-rhythm modes. Changes are localized to the requested axis: head-mode edits do not alter gaze, and gaze edits do not alter head rhythm.

D EMOTION CONTROLLABILITY

Fig. 11 shows the same clip under the seven emotion classes. Each class consistently colors the target’s expression while

preserving the underlying motion structure shared with the base row, demonstrating that the emotion axis is orthogonal to the behavior controls of Fig. 10.

E QUANTITATIVE CONTROL COMPLIANCE

The main-paper Tab. 2 evaluates motion quality with the semantic controls fixed to their ground-truth per-frame values, so the conditioning pathways themselves are not stressed by that table. To measure how reliably STEER obeys controls when they vary, we re-use the same observers that supervised those pathways during Phase 2 training (main-paper Sec. 3.4) as test-time judges: each observer turns the generated motion back into a per-frame label distribution, and we compare the distribution under a requested control against the one the model produces on the same audio with all semantic controls dropped (the unconditioned baseline). This tests exactly the contract the model was trained to satisfy,

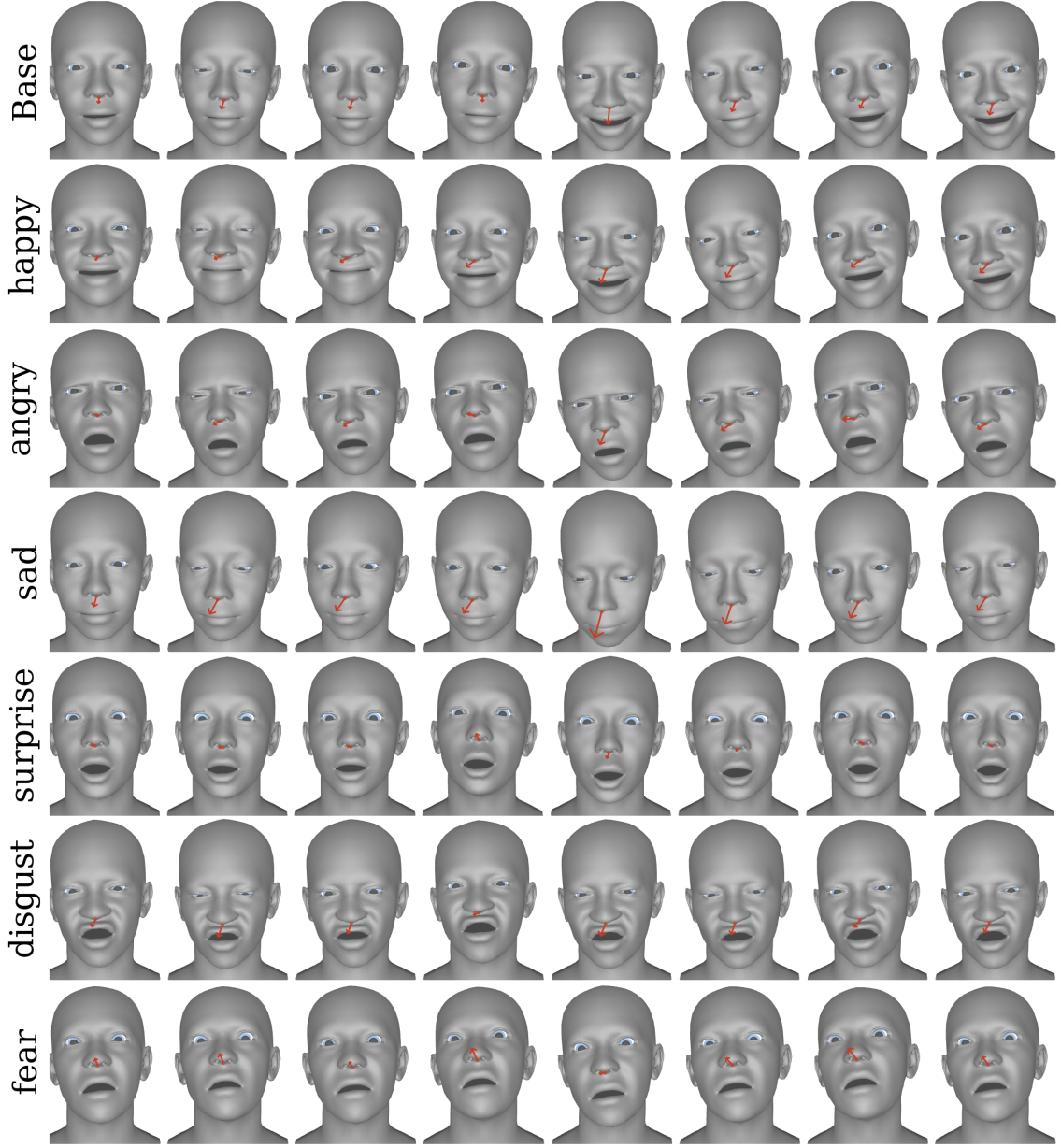


Fig. 11. Emotion-control showcase on a single test clip. Rows: *Base*, *happy*, *angry*, *sad*, *surprise*, *disgust*, *fear*; columns are eight frames across time.

and avoids the methodological circularity of training a fresh classifier from the same supervision signal.

Protocol. We sample $n=100$ random clips from the Listen subset of the held-out test split, with the target’s own audio silenced so the model is in pure-listener mode. For each clip we generate 14 versions: an unconditioned baseline; the 2 gaze classes (contact, avert); the 4 head-rhythm classes (still, nod, shake, tilt); and the 7 emotion classes. Inference uses 10-step rectified-flow sampling with audio classifier-free-guidance scale 1.5, behavior-conditioning scales of 1.5 (gaze)

and 2.5 (head-rhythm), and an emotion-strength multiplier of 1.2.

Gaze. The gaze observer is the geometric contact/avert decision of Sec. A, applied per-frame to the predicted head-plus-eye vector against the partner direction with the same hysteresis used at training. Under conditioning, per-frame argmax matches the requested class on 95.4% of frames for contact and 91.5% for avert (Tab. 7). The model also produces a $1.19\times$ larger eye-pose magnitude under avert than

under contact, so the conditioning produces the physical motion the observer is keying on rather than only its preferred label. Cross-axis leakage is small: gaze conditioning shifts the head-rhythm and emotion observer distributions by an average L_1 of below 0.03 across both axes.

Table 7. Gaze compliance over $n=100$ LISTEN clips. Accuracy is per-frame argmax of the gaze observer (Sec. A) against the requested class. Off-axis Δ is the average L_1 shift the gaze conditioning induces in the head-rhythm / emotion observer distributions.

Requested	Acc. ($\uparrow$)	Δ_{rhythm} ($\downarrow$)	Δ_{emo} ($\downarrow$)	Eye-mag ratio
contact	0.954	0.032	0.020	1.19×
avert	0.915	0.025	0.028	

Head-rhythm. For the three dynamic head-rhythm classes (nod / shake / tilt) we report two effect-size statistics that measure whether the model amplifies motion on the requested neck axis (Tab. 8). Range ratio is the conditioned-generation range on the requested neck axis divided by the unconditioned-generation range on the same axis; axis dominance is the requested-axis range divided by the maximum of the other two neck-axis ranges. Across 100 clips, the requested axis is amplified by 1.91–2.20× over the unconditioned baseline and becomes the dominant neck axis with margins of 1.22–1.66×.

Table 8. Head-rhythm compliance over $n=100$ LISTEN clips. Range ratio and axis dominance are effect-size statistics on the requested neck axis, defined inline.

Requested	Range ratio ($\uparrow$)	Axis dom. ($\uparrow$)
nod	1.91×	1.66×
shake	2.15×	1.22×
tilt	2.20×	1.57×

Emotion. The emotion observer is our affect observer of §B.5, applied window-wise to the generated motion. Under emotion conditioning, the requested class receives the highest observer probability across all seven categories (Tab. 9). The target-emotion probability rises from its unconditioned prior on quiet listening clips — 0.65 for neutral, 0.35 for happy, and below 0.001 for the remaining five — to ≥ 0.999 under the matching request. The peak action-unit activation also increases from 0.41 unconditioned to 0.50–0.76 under emotion conditioning, with the largest peaks under surprise and fear (0.58 and 0.76), consistent with their canonical AU patterns. This suggests that the conditioning changes the generated facial motion in the intended direction, rather than only shifting an abstract classifier score.

Table 9. Emotion compliance over $n=100$ LISTEN clips. Accuracy is window-level argmax of our affect observer (§B.5) against the requested class; p^{cond} and p^{uncond} are the target-class probabilities under conditioning and on the unconditioned baseline; AU-peak^{cond} is the maximum action-unit activation on the conditioned generation.

Requested	Acc. ($\uparrow$)	p^{cond} ($\uparrow$)	p^{uncond}	AU-peak ^{cond}
neutral	1.000	≥ 0.999	0.650	0.32
happy	1.000	≥ 0.999	0.350	0.50
sad	1.000	≥ 0.999	< 0.001	0.51
surprise	1.000	≥ 0.999	< 0.001	0.58
angry	1.000	≥ 0.999	< 0.001	0.54
disgust	1.000	≥ 0.999	< 0.001	0.53
fear	1.000	≥ 0.999	< 0.001	0.76

Independent estimators. The observers above share their supervision source with training. We therefore also verify the gaze and emotion controls with estimators that share no training signal with our pipeline: Py-Feat [Cheong et al. 2023] (emotion; AffectNet-trained) in place of our LibreFace-derived supervision, and L2CS-Net [Abdelrahman et al. 2023] (gaze; Gaze360-trained) in place of our MediaPipe-derived eye pose. Both are applied to rendered video of the generated motion over 40 held-out Listen clips under the same 14-condition protocol (behavior-conditioning scale 2.0, emotion strength 1.2); L2CS-Net is run on the photoreal avatar renders. Under gaze conditioning, avert produces 1.82× the eye-yaw deviation of contact (95% CI ± 0.24), with avert exceeding contact on 91% of clips. Under emotion conditioning, the requested class’s action-unit signature rises relative to the neutral condition on 95–100% of clips for every class; the categorical readout recovers happy and disgust on 100% of clips, neutral on 95%, angry on 92%, surprise on 78%, sad on 55%, and fear on 28%; sad and fear are also the lowest-recall classes for AffectNet-trained classifiers on real faces. These independently-sourced measurements are consistent with the observer-based compliance above.

Motion-quality preservation under conditioning. A control surface that satisfies the observer by destroying the rest of the face would not be useful in practice. Across all 14 conditions we therefore monitor the velocity standard deviation of the jaw, upper-face, and head/neck vertex sets. Jaw velocity-std stays in $[0.001, 0.002]$ across every condition — so no spurious mouth motion is induced by any non-speaking control, despite the controls operating at full strength. The upper-face velocity-std rises by $\sim 25\%$ under surprise and fear (expected: these emotions activate brow and lid regions), and the head/neck velocity-std rises by $\sim 50\%$ under nod / shake / tilt (also expected: those classes are by construction motion on the requested neck axis). The rest of the face is preserved under all controls.

F INFERENCE SPEED AND LIVE DEPLOYABILITY

Tab. 10 reports motion frames per second on a single NVIDIA L40, measuring forward-pass wall time only (audio I/O, FLAME decoding, and rendering excluded); we use L40 here to match the hardware on which the baselines were profiled. DualTalk

Table 10. Inference speed and causality on a single NVIDIA L40 (model-forward only; audio I/O and rendering excluded). The CAUSAL column indicates whether the model can be driven by streaming audio. Output motion is at 25 Hz.

Method	Params	FPS	Causal
DualTalk	647M	6946	×
UniLS	352M	1095	×
Ours (10-step)	~150M	46	✓
Ours-Distill (2-step)	~150M	280	✓

and UniLS report high offline throughput because their forward pass is non-causal — each consumes the entire utterance in a single batched call — which produces a high FPS number on this axis but is a different operating mode from streaming emission. STEER is strictly causal (a 60 ms audio-encoder look-ahead) and at the streaming protocol of main-paper Sec. 3.4 with commit stride $s=1$, each forward emit commits a single 4-frame motion token (160 ms of playback at 25 Hz). The end-to-end cue-to-render latency under our live configuration on the RTX 5090 deployment hardware (main-paper Sec. 4.6) is decomposed per stage in Tab. 11; that breakdown reports the single-emit forward time (model and avatar), whereas Tab. 10 reports amortised forward-only throughput on the L40 baseline hardware, so the two numbers measure different quantities.

Table 11. End-to-end cue-to-motion latency on RTX 5090, decomposed per stage.

Stage	Latency
Token-grid quantisation	80 ms
Audio-encoder lookahead	60 ms
Model forward	80 ms
Gaussian avatar render	70 ms
Total	~290 ms

Lowest-latency live configuration. The live deployment of main-paper Sec. 4.6 sets the commit stride to $s=1$: each forward pass commits a single 4-frame motion token, i.e. 160 ms of playback at 25 fps. The per-emit forward (Model forward + Gaussian avatar render in Tab. 11) totals ~150 ms, fitting inside this 160 ms playback budget; Token-grid quantisation and Audio-encoder lookahead are one-time pipeline costs incurred once per partner cue. Together they give the ~290 ms cue-to-render latency in Tab. 11, within the 200–500 ms reaction-lag range observed in real conversational turn-taking [Stivers et al. 2009].

G PER-SUBSET COMPARISON BREAKDOWN

The main-paper Tab. 2 reports the comparison averaged across the held-out test split ($n=765$). Tab. 12, 13, and 14 break the same comparison down by conversational role: Speak ($n=170$, purely speaking), Listen ($n=330$, purely listening), and Mixed

($n=265$, turn-taking transitions). LipSync (mm) is the per-frame mean lip-vertex error; $rPCC_{fv}$ is reported as $\times 10^{-4}$. Best per column in bold; cells color-shaded by per-column rank.

Table 12. Comparison on the SPEAK subset ($n=170$, target purely speaking).

Method	LipSync↓	vFDE↓	FDD _u ↓	JDD↓	PDD _h ↓	Div _E ↑	Div _H ↑	RPCC _n ↓	rPCC _{fv} ↓
DiffPoseTalk	12.07	0.0414	0.0428	0.1635	0.4119	1.584	0.852	0.558	9.93
DualTalk-FT	8.28	0.0593	0.0680	0.2080	0.3938	1.871	0.988	0.383	6.22
UniLS-FT	10.63	0.0437	0.0483	0.1609	0.3622	1.801	1.199	0.414	6.40
Ours-Distill	8.47	0.0299	0.0287	0.1257	0.3203	2.209	1.340	0.363	5.32
Ours (Full)	8.48	0.0296	0.0279	0.1261	0.3085	2.214	1.401	0.360	5.34

On Speak, Ours (Full) wins six columns (vFDE, FDD_u, PDD_h, Div_E, Div_H, RPCC_n); Ours-Distill wins two (JDD, rPCC_{fv}) by margins under 1%; DualTalk-FT wins LipSync (8.28 vs. Ours 8.48, a 0.2 mm gap that we read as a small lip-event-timing edge of the autoregressive sampler).

Table 13. Comparison on the LISTEN subset ($n=330$, target purely listening).

Method	LipSync↓	vFDE↓	FDD _u ↓	JDD↓	PDD _h ↓	Div _E ↑	Div _H ↑	RPCC _n ↓	rPCC _{fv} ↓
DiffPoseTalk	12.11	0.0342	0.0388	0.1183	0.2121	0.930	0.604	0.448	8.44
DualTalk-FT	9.34	0.0554	0.0627	0.1947	0.2797	0.300	0.253	0.416	5.85
UniLS-FT	11.30	0.0374	0.0430	0.1221	0.2609	0.677	0.647	0.514	7.64
Ours-Distill	8.83	0.0250	0.0251	0.0935	0.1834	1.087	0.686	0.412	4.94
Ours (Full)	8.79	0.0245	0.0245	0.0903	0.1781	1.133	0.822	0.394	5.04

On Listen, Ours (Full) wins eight of nine columns, with Ours-Distill winning rPCC_{fv} by 2% (4.94 vs. 5.04). The gap on Listen Div_H between Ours (0.822) and DualTalk-FT (0.253) is the largest single-column gap in the comparison.

Table 14. Comparison on the MIXED subset ($n=265$, the target alternates between speaking and listening, exercising turn-taking transitions).

Method	LipSync↓	vFDE↓	FDD _u ↓	JDD↓	PDD _h ↓	Div _E ↑	Div _H ↑	RPCC _n ↓	rPCC _{fv} ↓
DiffPoseTalk	13.14	0.0395	0.0410	0.1562	0.3459	1.423	0.788	0.475	8.69
DualTalk-FT	9.98	0.0581	0.0654	0.2046	0.3513	1.343	0.838	0.381	6.39
UniLS-FT	12.79	0.0391	0.0436	0.1365	0.3574	1.301	1.090	0.415	7.69
Ours-Distill	10.06	0.0267	0.0275	0.0992	0.2676	1.737	1.116	0.463	6.65
Ours (Full)	10.04	0.0261	0.0267	0.0975	0.2566	1.774	1.214	0.451	6.61

Mixed is the only subset on which DualTalk-FT beats Ours on partner-coupling: it wins RPCC_n (0.381 vs. Ours 0.451) and rPCC_{fv} (6.39 vs. Ours 6.61). DualTalk-FT also wins LipSync by 0.06 mm (9.98 vs. Ours 10.04, the same tied range observed on Speak). Ours (Full) wins the remaining six fidelity and diversity columns, so the partner-coupling gap on Mixed is specific to turn-taking transitions rather than a general partner-coupling weakness.

H TRAINING-OBJECTIVE ABLATION

We ablate the velocity-energy-floor losses (–no energy; main-paper Sec. 3.4) and the style-conditioning pathway (–no style; main-paper Sec. 3.3) and report results in Tab. 15. The metric set and conventions match main-paper Tab. 2 (best per column in bold; cells color-shaded by per-column rank).

Removing the energy-floor losses (–no energy) is the most damaging variant. On Listen, FDD_u increases by 60%, vFDE by 40%, PDD_h by 22%, and head-pose diversity decreases by

Table 15. Training-objective ablation, split by conversational role: **SPEAK** ($n=170$, purely speaking) and **LISTEN** ($n=330$, purely listening). LipSync on **SPEAK** is the vertex-space mouth-region L2 in mm; $rPCC_{fv}$ reported as $\times 10^{-4}$. Best per column in bold; cells color-shaded by per-column rank.

Variant	Speak ($n=170$)								Listen ($n=330$)						
	LipSync (mm)↓	vFDE↓	FDDu↓	JDD↓	PDDh↓	DivE↑	DivH↑	rPCC _{fv} ↓	vFDE↓	FDDu↓	PDDh↓	DivE↑	DivH↑	RPCCn↓	rPCC _{fv} ↓
Ours (Full)	8.48	0.0296	0.0279	0.126	0.309	2.214	1.401	5.34	0.0245	0.0245	0.178	1.133	0.822	0.391	5.04
– no energy	9.18	0.0346	0.0390	0.126	0.332	2.163	1.362	5.47	0.0342	0.0391	0.218	1.056	0.701	0.387	5.20
– no style	8.87	0.0318	0.0289	0.130	0.291	2.143	1.516	5.24	0.0252	0.0250	0.186	1.144	0.822	0.404	4.97

15% (Div_H 0.822 $\rightarrow$ 0.701). On Speak the same pattern produces the largest LipSync regression in our ablation (+8%, 9.18 mm) together with $vFDE$ +17% and FDD_u +40%. The energy floors are therefore central to upper-face and lip structure on both regimes.

Removing the style-conditioning pathway (– no style) costs lip sync and dynamics tightness on Speak (LipSync +4.6% at 8.87 mm, $vFDE$ +7%, JDD +3%) but is roughly neutral on Listen — – no style stays within 3% of Full on the listening fidelity columns. Head-pose diversity on Speak actually rises (1.401 $\rightarrow$ 1.516, +8%): without the style channel the speaking-side head motion becomes less style-locked and gains entropy. The motion-style code is therefore most useful on the speaking side, where it ties head and face dynamics to the target’s motion idiosyncrasy.

I PARTNER-CONDITIONING ABLATION TABLES

The main-paper Sec. 4.5 discusses the listening-side partner-conditioning ablation; Tab. 16 reports the supporting numbers.

Table 16. Partner-conditioning ablation on the **LISTEN** subset ($n=330$). $rPCC_{fv}$ reported as $\times 10^{-4}$. Best per column in bold; cells color-shaded by per-column rank.

Variant	vFDE↓	FDDu↓	PDDh↓	DivE↑	DivH↑	RPCCn↓	rPCC _{fv} ↓
Full	0.0245	0.0245	0.178	1.133	0.822	0.391	5.04
– partner audio	0.0248	0.0244	0.180	1.131	0.901	0.403	5.46
– partner motion	0.0251	0.0253	0.190	0.826	0.442	0.687	6.30
– partner stream	0.0257	0.0265	0.195	0.784	0.424	0.670	6.54

We additionally report the same ablation on the **Speak** subset ($n=170$).

Table 17. Partner-conditioning ablation on the **speaking** subset ($n=170$). JDD reported $\times 10^{-3}$. Best per column in bold; cells color-shaded by per-column rank.

Variant	LipF1↑	vFDE↓	FDDu↓	JDD↓	PDDh↓	DivE↑	DivH↑
Full	0.454	0.032	0.026	1.8	0.294	2.321	1.540
– partner audio	0.450	0.032	0.026	1.8	0.294	2.310	1.534
– partner motion	0.436	0.031	0.029	1.9	0.314	1.986	0.990
– partner stream	0.421	0.031	0.031	1.9	0.313	1.937	0.983

Smile-timing F1. To quantify the mirror-laugh evidence of main-paper Fig. 7 at event level, we compute a smile-timing F1 inspired by AV-Flow [Chatziagapi et al. 2025]: per clip, a frame counts as smiling when the FLAME mouth-corner

distance exceeds the ground-truth clip’s 70th percentile, and we report the frame-level F1 between predicted and ground-truth smile flags, a geometric score with no classifier in the loop. Over the full test pool, STEER reproduces the timing of the listener’s smiles best (F1 0.37 vs. UniLS 0.32, DualTalk 0.29, DiffPoseTalk 0.20). Zeroing partner motion at inference lowers the Listen-subset score by 21%, while zeroing partner audio changes it only marginally: the mirrored smile is driven predominantly by the partner’s facial motion. We chose smiles as the listener response most reliably mirrored between partners.

LipF1 decreases monotonically along Full $\rightarrow$ – partner audio $\rightarrow$ – partner motion $\rightarrow$ – partner stream (0.454 $\rightarrow$ 0.450 $\rightarrow$ 0.436 $\rightarrow$ 0.421), indicating that on the speaking subset partner inputs continue to contribute to lip-event timing fidelity. Div_E and Div_H drop by 14% and 36% respectively when partner motion is removed, indicating that without partner motion the model produces flatter, less varied facial and head dynamics.

The lower $vFDE$ of the partner-removed variants (0.031 vs. Full 0.032) is not an improvement but a signature of a flatter mouth, as evidenced by the simultaneous drop in Div_E and Div_H .