PED: Route-Decoupled Diagnostics for Persona Consistency in Spoken Agents

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Abstract

Maintaining a stable persona is central to sustained spoken role-playing, yet when an agent breaks character, current evaluations often do not isolate which component caused the failure, making fixes slow and ad hoc. We propose **PED** (Persona–Emotion Decoupling), a diagnostic evaluation framework that decomposes persona expression into two observable routes: what the agent says (text) and how it sounds (speech). PED operationalizes the affective slice of persona expression by projecting transcripts and audio into a shared affective measurement space for route-comparable, reference-based analyses of separability, drift, failures, and coupling. We demonstrate PED via two worked instantiations spanning an end-to-end Speech LLM and a cascaded LLM+TTS pipeline under a fixed dialogue protocol. Within this setting, PED surfaces four recurring diagnostic signatures: (i) route-level separability is bounded by reference overlap and can differ sharply across architectures, (ii) text-route drift is stress-linked and tends toward a neutral-heavy region, (iii) text–audio consistency is weakly coupled, yielding route-asymmetric failures, and (iv) audio-route structure can be materially shaped by an explicit intermediate style cue in cascaded pipelines. Overall, PED reframes holistic "voice+character" grading as turn-level, fault-localizing signals for faster debugging and iteration.

1 Introduction

Speech large language models (SLLMs) are evolving from "listen-and-speak" interfaces into spoken agents for sustained, fully spoken interaction (Zhang et al., 2023, 2025). In companion chat and NPC role-playing, users expect agents to stay in character over extended conversations; when an agent breaks character, perceived interaction quality degrades. This calls for diagnostic evaluation that supports debugging and improvement.

In fully spoken interaction, persona is observable only through the system outputs: what the agent says (text) and how it sounds (speech). This enables fault localization: evaluating the two routes separately can localize where degradation originates. In role-playing settings, affect provides one observable slice of persona expression and a shared measurement interface across text and speech, surfacing in lexical choices on the text route and in prosody on the audio route. This yields route-comparable measurements in a shared affective space.

However, existing evaluations for spoken role-playing are largely holistic: they assess "voice + character" at the system level, which is useful for comparison but offers limited observability for debugging. They rarely provide turn-indexed evidence of when degradation begins, nor do they attribute failures to text generation versus acoustic realization in multi-stage systems. As a result, it is difficult to localize failure sources and iterate efficiently.

To bridge this gap, we propose PED (Persona–Emotion Decoupling), a diagnostic evaluation framework that projects transcripts and speech into a shared affective measurement space to produce fault-localizing, route-level, turn-indexed evidence for extended spoken role-playing. PED specifies

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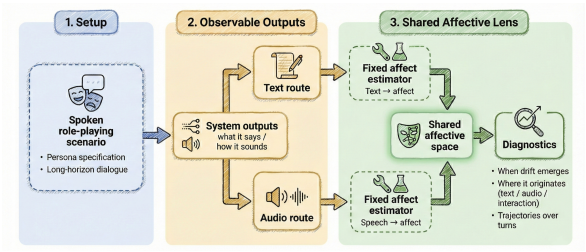

Figure 1: PED framework for route-level diagnosis of persona consistency in long-horizon spoken interaction.

three diagnostic primitives under a fixed multi-phase dialogue protocol: (i) a shared measurement interface that makes text- and audio-route quantities comparable, (ii) per-route stateless baselines (anchors) that provide system-specific reference points, and (iii) turn- and phase-indexed trajectories that expose when degradation emerges. Together, these primitives support attribution to text generation, acoustic realization, or their interaction. We illustrate the framework with two worked instantiations spanning two archetypal designs (end-to-end generation vs. cascaded LLM+TTS).

Figure 1 illustrates PED and the two observable routes used for diagnosis.

Contributions. We make three contributions: (i) we introduce **PED**, a route-decoupled diagnostic framework for spoken role-playing; (ii) PED provides turn-level, route-localizing evidence to pinpoint where persona degradation arises; (iii) we instantiate PED on two representative spoken-agent architectures and show that PED surfaces actionable failure sources and motivates targeted fixes.

1.1 Research Questions

We organize the analysis around four research questions (RQ1–RQ4):

- **RQ1.** In the unified affective space, do spoken agents manifest separable route-level affect patterns across personas on both text and audio routes?
- **RQ2.** How do textual and acoustic drift patterns evolve over dialogues, and do they exhibit a consistent directional tendency toward a dominant region in the shared space?
- **RQ3.** How do persona persistence and typical failure modes differ between end-to-end and cascaded systems?
- **RQ4.** How do different personas exhibit distinct stability patterns on the text route and the audio route, and are textual and acoustic personas statistically coupled or largely independent?

2 Related Work

2.1 Persona and Role-Playing Evaluation in Text Dialogue

Text-only benchmarks and frameworks evaluate whether an agent adheres to a specified persona across prompts and scenarios (Samuel et al., 2025; El Boudouri et al., 2025; Tu et al., 2024). They typically report prompt-level or dialogue-level outcomes, rather than turn-indexed drift trajectories in long-horizon interaction. Recent work also studies persona consistency under multi-turn interaction and proposes automatic consistency metrics aligned with human judgments (Abdulhai et al., 2025). Fine-grained role-playing benchmarks further combine persona adherence with complex instruction-following scenarios (Lu et al., 2025).

2.2 Spoken-Agent and Speech Role-Playing Evaluation

Recent benchmarks extend role-playing evaluation to spoken interaction, assessing holistic "voice + character" behavior across roles and multi-turn dialogues (Li et al., 2025; Jiang et al., 2025; Wu et al., 2025). While these works enable cross-system comparison, most report aggregated scores over multiple dimensions, offering limited diagnostic value: they rarely attribute failures to text generation versus acoustic realization, nor provide turn-indexed evidence of when persona drift emerges over long-horizon interaction. Speech-DRAME further argues that zero-shot audio(-language) judges can miss paralinguistic cues and collapse multiple aspects into coarse overall scores, motivating more fine-grained and diagnostically useful evaluation (Shi et al., 2025).

2.3 Text–Audio Affective Mismatch and Disentanglement

Several studies probe situations where lexical and acoustic cues conflict and show that current spoken models may rely predominantly on textual semantics for emotion judgments (Corrêa et al., 2025; Chen et al., 2025). Other work treats acoustic–textual emotional inconsistency as a learnable signal in downstream tasks (Su et al., 2024), and dis-

entangles textual versus acoustic factors in learned speech representations (Mohebbi et al., 2024). These lines motivate route-separated measurement under a shared affective lens.

3 Method

3.1 Setting & Architectures

We study role-conditioned spoken dialogue. At turn t, given a persona specification p and dialogue context

$$C_t = \big[(u_1, r_1), \ldots, (u_{t-1}, r_{t-1}), u_t\big], \quad (1)$$

the agent outputs a reply transcript r_t and a corresponding speech signal a_t, where u_t is the user utterance at turn t.

Primary measurements. To focus the study, we operationalize the two routes via two affect-based measures: *textual emotion consistency* (TEC) on transcripts r_t and *acoustic emotion consistency* (AEC) on speech a_t.

End-to-end Speech LLM. An end-to-end model generates text and speech jointly:

$$(r_t, a_t) = \mathrm{E2E}(C_t, p). \quad (2)$$

Cascaded pipeline. A cascaded system first generates reply text and a style cue s_t, then synthesizes speech conditioned on s_t:

$$(r_t, s_t) = \mathrm{LLM}(C_t, p), \quad (3)$$
$$a_t = \mathrm{TTS}(r_t, s_t;\, v), \quad (4)$$

where v is a fixed speaker prompt (voice reference) used to control timbre, kept constant across personas and turns (Section 4.4).

3.2 PED Representation

PED evaluates the text and audio routes through a shared affective measurement interface. In our instantiation, this interface is the probability simplex over a fixed label set:

$$\mathcal{E} = \{\text{angry}, \text{disgust}, \text{fear}, \text{happy}, \text{neutral}, \text{sad}, \text{surprised}\}. \quad (5)$$

Two fixed projectors map a reply transcript and its realized speech into affect vectors, $\mathbf{e}_t^{\text{text}}, \mathbf{e}_t^{\text{audio}} \in \Delta^{|\mathcal{E}|-1} \subset \mathbb{R}^{|\mathcal{E}|}$. For persona p and route $r \in \{\text{text}, \text{audio}\}$, we denote the per-turn measurement as $\mathbf{e}_{t,p}^{r}$. Here, decoupling simply means evaluating the text and speech routes separately.

We treat the projectors as measurement instruments rather than oracle emotion annotators. Trained on human-labeled emotion data, they provide a practical affect proxy. However, calibration can shift on synthetic speech and stress prompts, so we restrict all findings to within-projector comparisons. Labels in $\mathcal{E}$ (e.g., angry) name coordinates of the projector outputs and should not be read as calibrated ground-truth emotion annotations. Under this interpretation, the shared coordinate system enables route-comparable alignment to anchors and cross-route correlation analyses, yielding turn-level, fault-localizing signals over long dialogues.

PED is modular: both $\mathcal{E}$ and the projectors can be replaced (e.g., with continuous VAD coordinates), as long as both routes are evaluated in the same shared space.

Stateless anchors. Reference-based diagnosis requires a baseline for each system, persona, and route. We therefore define a route-specific anchor $\mathbf{g}_b^r(p)$ as the system's in-character affect fingerprint for p, estimated independently per (system, p, r) to avoid imposing a cross-system reference.

Concretely, we generate $K{=}20$ single-turn responses for persona p in fresh sessions with empty dialogue history to estimate an in-character baseline unaffected by long-context accumulation, project each sample to $\mathbf{e}_k^r(p)$ using the fixed route projector, and take the mean:

$$\mathbf{g}_b^r(p) = \frac{1}{K} \sum_{k=1}^{K} \mathbf{e}_k^r(p). \quad (6)$$

With this anchor, stateful vectors are interpreted as deviations from the same system's own anchor under a fixed projector, so drops in alignment indicate degradation relative to its in-character baseline rather than cross-system mismatch.

Stateful three-phase dialogue. We use a fixed 25-turn dialogue script with three phases: **Baseline** (1–5), **Stress** (6–20), and **Recovery** (21–25). Baseline verifies role instantiation under low pressure; Stress applies escalating challenges (e.g., skepticism, disagreement, and higher affective load); Recovery returns to routine prompts to probe reversion toward the route-specific baseline. For each persona, we run one continuous dialogue where turn t conditions on the full history C_t. At each turn, we log r_t and a_t and compute $\mathbf{e}_{t,p}^{\text{text}}$ and $\mathbf{e}_{t,p}^{\text{audio}}$ for evaluation. This three-phase script is one instantiation motivated by everyday conversation dy-

namics; other PED instantiations can substitute alternative scripts as needed.

3.3 Metrics

For each persona $p \in \mathcal{P}$ and route $r \in \{\text{text}, \text{audio}\}$, at turn t we obtain a route-level affect vector $\mathbf{e}^r_{t,p} \in \mathbb{R}^{|\mathcal{E}|}$ and the corresponding anchor $\mathbf{g}^r_b(p) \in \mathbb{R}^{|\mathcal{E}|}$.

RQ1: Are personas separable on each route? We assess separability from two complementary views.

Anchor geometry (pre-dialogue). We characterize how distinct the persona fingerprints are before long-horizon interaction by pairwise cosine similarities among anchors:

$$G^r(p,q) = \cos\big(\mathbf{g}^r_b(p), \mathbf{g}^r_b(q)\big), \quad p \neq q. \tag{7}$$

Higher $G^r(p,q)$ indicates stronger overlap and an upper bound on achievable separability on route r.

Nearest-anchor separability (in-dialogue). For each turn and route, we assign the observed vector to the closest persona anchor:

$$\hat{p}^r_t = \arg\max_{p' \in \mathcal{P}} \cos\big(\mathbf{e}^r_{t,p}, \mathbf{g}^r_b(p')\big)\,. \tag{8}$$

We report accuracy (against the conditioned persona p) and the prediction distribution to diagnose prototype collapse.

RQ2: How does drift evolve over long dialogues and phases? We track anchor alignment as a per-turn trajectory and summarize it by phase.

Anchor alignment (trajectory). We measure turn-level alignment to the corresponding anchor by cosine similarity:

$$\text{sim}^r_t(p) = \cos\big(\mathbf{e}^r_{t,p}, \mathbf{g}^r_b(p)\big). \tag{9}$$

Phase-wise stability. For each phase $\phi \in \{\text{Baseline}, \text{Stress}, \text{Recovery}\}$, we summarize $\{\text{sim}^r_t(p)\}_{t\in\phi}$ by mean and variance, yielding phase-dependent stability profiles.

Dominance and prototype collapse. To test whether trajectories concentrate on a single label coordinate in the shared affective measurement space without pre-specifying which coordinate, we track the dominant label coordinate:

$$\hat{e}^r_t(p) = \arg\max_{e \in \mathcal{E}} \mathbf{e}^r_{t,p}[e]. \tag{10}$$

We summarize phase-wise dominant-label frequencies of $\hat{e}^r_t(p)$. When a particular coordinate becomes dominant, we further analyze its probability mass across phases, to better characterize phase-linked concentration in the shared space.

Cross-persona convergence (per turn index). We compute Conv^r_t across the three persona-specific runs aligned by the same script index t. At each script turn index t, we compute the average pairwise cosine similarity among personas:

$$\text{Conv}^r_t = \frac{2}{|\mathcal{P}|(|\mathcal{P}|-1)} \sum_{p<q} \cos\big(\mathbf{e}^r_{t,p}, \mathbf{e}^r_{t,q}\big), \tag{11}$$

and report phase-wise aggregates to reveal whether personas collapse toward a shared affect mode.

RQ3: How do failure modes differ across architectures? We compute the full set of RQ1–RQ2 metrics for each system and compare (i) anchor geometry and separability, (ii) drift trajectories and phase-wise stability, and (iii) convergence patterns, to localize architecture-dependent failures to the text route, the audio route, or their interaction.

RQ4: Are TEC and AEC coupled, and do personas differ systematically? Persona-specific differences are reflected by the phase-wise stability summaries above (RQ2) and by separability (RQ1). To measure cross-modal coupling within the same dialogue, we compute Pearson correlation between text- and audio-route alignment trajectories for each persona:

$$\rho(p) = \text{corr}_t\big(\text{sim}^{\text{text}}_t(p), \text{sim}^{\text{audio}}_t(p)\big)\,. \tag{12}$$

Low $|\rho(p)|$ suggests route-asynchronous behavior under the fixed projectors in this instantiation.

4 Experimental Setup

We instantiate PED in the few-billion-parameter regime to reflect common latency, cost, and on-device constraints and to contrast end-to-end versus cascaded pipelines under controlled scale. Within each configuration, prompts and decoding settings are kept fixed across personas (no per-persona tuning), so differences are attributable to architecture- and persona-conditioned behavior under the same evaluation procedure.

4.1 Models and Personas

Systems. To control for model scale while isolating end-to-end versus cascaded design choices, PED is instantiated with two Qwen-family spoken-agent configurations:

- **End-to-end (E2E).** Qwen2.5-Omni-3B (Xu et al., 2025).

System	Route	Module	Pers.	Turns (B/S/R)	Anchors
E2E	TEC	Omni-3B	C/E/N	25 (5/15/5)	K=20
E2E	AEC	Omni-3B	C/E/N	25 (5/15/5)	K=20
Cascade	TEC	Qwen-3B	C/E/N	25 (5/15/5)	K=20
Cascade	AEC	IndexTTS2	C/E/N	25 (5/15/5)	K=20

Table 1: Evaluation setup. Each persona has K=20 stateless anchor samples per route. Turns are split into Baseline/Stress/Recovery.

- **Cascaded (Cascade).** Qwen2.5-3B-Instruct (Qwen Team, 2024) + IndexTTS2(Zhou et al., 2025).

Personas. In this experimental instantiation, the persona set $\mathcal{P}$ consists of three Big Five personas. Specifically, we use Conscientiousness (C), Extraversion (E), and Neuroticism (N), operationalized via NEO-PI-R facets (Costa and McCrae, 1992). These personas induce distinct affective and stress-response tendencies that are salient under the baseline–stress–recovery protocol (e.g., controlled/task-oriented vs. positively engaged vs. stress-reactive behavior). For each persona, a fixed system prompt specifies behavioral constraints, and prompt wording is kept as consistent as allowed by each interface.

Table 1 summarizes the evaluation matrix and the Baseline/Stress/Recovery turn split.

4.2 Affect Projectors

PED instantiates the shared affective space in Section 3.2 with two fixed projectors. For text, **j-hartmann/emotion-english-distilroberta-base** is used. For speech, **firdhokk/speech-emotion-recognition-with-openai-whisper-large-v3** is used. Each projector's native outputs are mapped into $\mathcal{E}$ and reordered to a fixed index order, yielding one vector per turn and route.

4.3 Dialogue Runs and Logged Data

For each persona–system pair, PED collects (i) K=20 stateless anchor samples per route and (ii) one stateful dialogue run following the baseline–stress–recovery protocol. At each turn, the reply transcript r_t, the speech waveform a_t, and the corresponding route-level affect vectors are logged. For the cascaded configuration, the intermediate style cue s_t emitted by the LLM is additionally logged.

Figure 2: Top: TEC anchors for E2E and Cascade; Bottom: AEC anchors.

4.4 Implementation Controls

Style cue and timbre control. In the cascaded configuration, the LLM emits a short style cue s_t that conditions IndexTTS2 at synthesis. We fix speaker identity by using a single persona-agnostic neutral voice reference (model-synthesized) as the speaker prompt v for all personas and turns. For a cleaner architecture contrast, we keep the speaker reference consistent with the end-to-end system's default voice; this neutral reference is generated once offline and reused unchanged throughout all cascaded runs.

Decoding. Decoding settings are fixed within each configuration and kept unchanged across personas.

5 Results and Analysis

We analyze one primary dialogue run in the main text; Appendix B reports the cascaded reruns used as a robustness check, while a small number of E2E reruns are discussed in the main text as a sanity check.

5.1 Anchor Fingerprints and Persona Separability

We first characterize stateless persona anchors. Figure 2 reports mean 7D affect vectors over K=20 anchor samples for each persona and route.

Anchor geometry bounds separability. Anchor overlap differs sharply by route and architecture.

System	Route	All	C	E	N
E2E	TEC	38.7	100.0	8.0	8.0
Cascade	TEC	44.0	80.0	12.0	40.0
E2E	AEC	30.7	60.0	8.0	24.0
Cascade	AEC	44.0	28.0	28.0	76.0

Table 2: Nearest-anchor persona classification accuracy (%) in the shared 7D affective space (chance: 33.3%).

Setting	Predicted C	Predicted E	Predicted N
E2E/TEC	93.3	2.7	4.0
Cascade/TEC	72.0	10.7	17.3
E2E/AEC	62.7	4.0	33.3
Cascade/AEC	16.0	25.3	58.7

Table 3: Nearest-anchor assignment distribution (%) on drift-dialogue turns.

On the audio route, E2E anchors nearly overlap (pairwise cosine 0.984–0.999), whereas Cascade anchors are substantially more separated (minimum cosine ≈0.270 between E and N). On the text route, anchors are more separated for both systems (minimum cosine ≈0.63 for E2E/TEC and ≈0.61 for Cascade/TEC). This geometry constrains nearest-anchor separability, especially for E2E/AEC where anchor overlap is highest.

Nearest-anchor assignment: weak separability with prototype bias. Table 2 reports in-dialogue separability via nearest-anchor assignment. On the text route, accuracy is low for both systems and is dominated by C. On the audio route, the architectures diverge: E2E is near chance overall, while Cascade is above chance and recovers N strongly, consistent with the more separated Cascade/AEC anchors in Figure 2. Because accuracy can mask collapse, Table 3 shows the full prediction distribution: E2E/TEC assigns most turns to C, whereas Cascade/AEC assigns most turns to N.

5.2 Text Route: Drift, Phase Effects, and Neutralization

We next analyze long-horizon dynamics on the text route. Table 4 summarizes phase-wise TEC-sim, and Figure 3 shows turn-level trajectories.

Phase effects and stability ordering. C maintains the highest TEC-sim across phases in both systems (Table 4). In the cascaded system, E and N exhibit a stress-triggered regime shift: TEC-sim drops at stress onset and remains low through recovery (Table 4; Figure 3). In the end-to-end system, phase-wise means vary mildly for C, while E and N remain consistently lower than C (Table 4).

System	Pers.	Base	Stress	Rec.
E2E	C	0.942	0.943	0.953
E2E	E	0.663	0.666	0.692
E2E	N	0.569	0.528	0.615
Cascade	C	0.793	0.736	0.730
Cascade	E	0.665	0.509	0.345
Cascade	N	0.624	0.517	0.434

Table 4: Phase-wise TEC-sim (cosine similarity to text-side persona anchors).

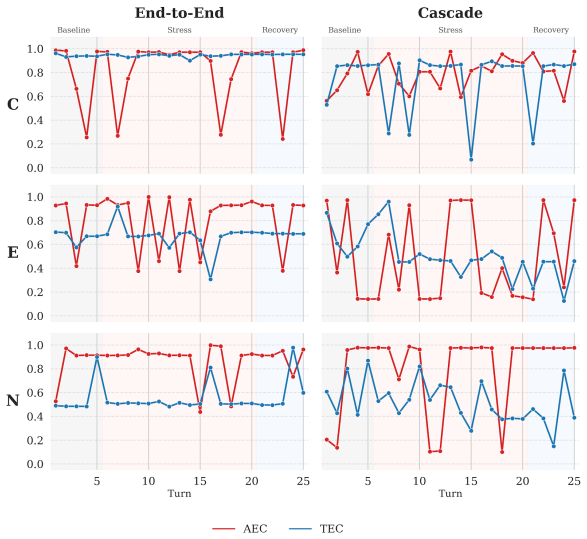

Figure 3: Turn-level TEC-sim and AEC-sim trajectories under the baseline–stress–recovery protocol. Shaded regions denote phases.

Dominant-label analysis and a neutral-heavy region. We inspect the dominant-emotion label $\hat{e}_t^{\text{text}}(p)$ and find that neutral is the most frequent dominant label on the text route (Table 6), motivating a focused analysis of the neutral coordinate across phases (Table 5). Phase-wise neutral mass changes systematically: stress increases neutral for E in both systems and for E2E N, while Cascade N shows the opposite tendency. At the turn level, neutral is dominant in many settings, but not exclusively so: N exhibits non-neutral dominant labels (e.g., fear) and seed-dependent mode switching in recovery (Table 6; Appendix B). Together with biased nearest-anchor predictions (Table 3), these patterns indicate a tendency for TEC trajectories to concentrate in a neutral-heavy region under long-horizon interaction.

Cross-persona geometry under stress. Text-route cross-persona convergence $\text{Conv}_t^{\text{text}}$ shows a phase-dependent reversal: E2E becomes more

System	Pers.	Base	Stress	Rec.
E2E	C	0.887	0.802	0.756
E2E	E	0.576	0.664	0.708
E2E	N	0.771	0.801	0.641
Cascade	C	0.788	0.712	0.778
Cascade	E	0.635	0.754	0.571
Cascade	N	0.510	0.432	0.404

Table 5: Phase-wise neutral probability in TEC emotion vectors.

System	Pers.	Top-1=Neutral	Top-1=Happy (E)	Top-1=fear (N)
E2E	C	100.0	–	–
E2E	E	84.0	4.0	–
E2E	N	88.0	–	8.0
Cascade	C	80.0	–	–
Cascade	E	76.0	8.0	–
Cascade	N	52.0	–	12.0

Table 6: Turn-level dominance rates (%) in TEC emotion vectors. "Top-1" denotes the argmax emotion label.

convergent at Stress (0.704→0.919→0.872), while Cascade becomes less convergent (0.741→0.594→0.731) for Base/Stress/Rec. This indicates that drift can reshape cross-persona geometry in opposite directions depending on architecture.

5.3 Audio Route: Drift and Architectural Differences

We examine audio-route dynamics next. Table 7 reports phase-wise AEC-sim and Figure 3 shows trajectories.

E2E: high AEC-sim, weak discriminability, and a projector-labeled dominant mode. E2E exhibits uniformly high AEC-sim across personas (Table 7) yet near-chance persona separability on the audio route (Table 2), consistent with near-overlapping AEC anchors (Figure 2).Under the AEC projector, probability mass often concentrates in a narrow region on drift-dialogue turns (Appendix A), consistent with a collapse toward reduced expressive variation in the audio route. Under this AEC projector, this dominance yields highly similar measured AEC representations across personas, consistent with the near-overlapping acoustic anchors; we do not attribute this pattern uniquely to model behavior versus instrument effects.

Cascade: persona-structured AEC and the role of the style cue. Cascade shows higher AEC separability than E2E (Tables 2). In a style-cue ablation (Appendix A), we regenerate speech from the same texts with $s_t = \emptyset$ while keeping IndexTTS2 and the speaker prompt v fixed. Removing s_t shifts cascaded AEC toward a more concentrated region and weakens persona-distinct structure. Under comparison, the mean AEC becomes closer to the E2E reference, with persona-dependent magnitude.

System	Pers.	Base	Stress	Rec.
E2E	C	0.773	0.842	0.828
E2E	E	0.831	0.809	0.819
E2E	N	0.848	0.869	0.894
Cascade	C	0.720	0.812	0.826
Cascade	E	0.518	0.427	0.604
Cascade	N	0.651	0.784	0.975

Table 7: Phase-wise AEC-sim (cosine similarity to audio-side persona anchors).

5.4 Robustness Checks

Rerunning cascaded dialogues with three random seeds suggests that the main TEC tendencies are not artifacts of a single run, although their strength varies across personas. For E, stress-linked suppression of persona-typed happy persists across reruns, together with a frequent neutral-heavy tendency. For N, recovery remains more seed-sensitive than E, but the dominant recovery modes in the reruns reported here are more neutral-centered than in the main run. For C, the reruns mainly serve as a sanity check, with no comparably strong persona-specific phase transition (Appendix B).

We additionally conducted a small number of reruns for the E2E system as a sanity check. These reruns did not reveal qualitative contradictions to the main analysis and did not materially change the paper's conclusions, so we do not emphasize them as a separate quantitative result.

5.5 Blinded Human Audit

To test whether PED's instrumented signals align with human judgments, we conduct a blinded audit on 60 randomly sampled speech clips (30 E2E and 30 Cascade), annotated by 8 raters. The audit uses a binary diagnostic judgment targeting perceived expressive collapse, i.e., whether a clip sounds flatter/weaker in expression or relatively more expressive. Inter-rater agreement reaches Fleiss' $\kappa \approx 0.69$. At the item level, over 90% of E2E speech samples are judged flatter/weaker in expression, consistent with the main conclusion that E2E speech tends to collapse toward a reduced expressive range under this measurement interface.

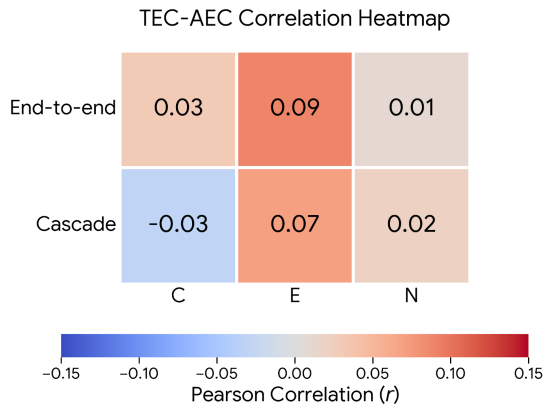

Figure 4: Pearson correlation between per-turn TEC-sim and AEC-sim across personas and architectures.

For cascaded speech, human judgments also support more stable persona-wise separability in this setting. We use this audit as a light sanity check on the route-level diagnostic tendency.

5.6 Instrumented TEC–AEC Coupling

We measure cross-modal coupling by Pearson correlation between per-turn TEC-sim and AEC-sim. Correlations are consistently weak across personas and architectures (Figure 4), indicating route-asynchronous behavior under the fixed projectors used in this instantiation.

6 Discussion

We distill a set of practical takeaways from Section 5 for interpreting the measured patterns under our instantiation: (i) three reading rules for route-level scores, (ii) evidence on control channels and text–acoustic dissociation, and (iii) robustness and persona-specific dynamics, followed by implications for model design.

6.1 How to Read Route-Level Scores

Rule 1: Anchor geometry bounds separability. When persona anchors overlap, high similarity to an anchor can reflect a shared affect fingerprint rather than persona-distinct behavior. In this regime, separability can be weak even when route-level similarity is uniformly high.

Rule 2: Text-route failures often appear as collapse toward a shared mode. On the text route, failure may manifest as (i) biased nearest-anchor assignments and (ii) dominant-label concentration in a neutral-heavy region. Here, reduced separability is driven by convergence to a shared prototype rather than by the absence of anchor structure.

Rule 3: Drift can reshape cross-persona geometry. Stress can change relative geometry among personas, producing cross-persona convergence or divergence depending on architecture. Drift therefore manifests not only as reduced anchor alignment, but also as changes in cross-persona distances in the shared space.

6.2 Control Channels and Text–Acoustic Dissociation

In the cascaded pipeline, TEC for E/N shifts after stress onset while AEC remains comparatively structured, suggesting text–acoustic dissociation under stress. A key architectural difference is that the cascaded system exposes an explicit style cue s_t to the TTS.

The style-cue ablation provides diagnostic evidence that this intermediate control channel contributes to persona-structured AEC: removing s_t weakens persona-distinct AEC structure and shifts representations toward a single dominant projector coordinate (Appendix A). This indicates that route-level persona expression can depend on whether a system exposes a controllable prosody pathway.

6.3 Robustness and Persona-Specific Dynamics

Across reruns, the reported cascaded TEC patterns show qualitative consistency rather than exact fixed trajectories. E retains stress-linked suppression of persona-typed happy, N remains more recovery-sensitive, and C mainly functions as a sanity-check persona (Appendix B). A small number of E2E reruns likewise revealed no qualitative contradiction to the main analysis.

6.4 Implications for Model Design

Route-localizing diagnostics point to different intervention targets across architectures. For end-to-end models, the audio-route issue is weak persona separability (bounded by near-overlapping acoustic anchors) rather than low anchor alignment; improving audio-route controllability and persona-distinct prosody is a priority. For cascaded systems, an explicit control channel can benefit the audio route, but the text route remains the bottleneck under stress; improving long-context persona adherence on the text route while preserving and validating the style-cue pathway is critical.

7 Conclusion and Future Work

We presented **PED**, a route-decoupled diagnostic framework for long-horizon spoken role-playing that analyzes what an agent says and how it sounds in a shared affective measurement space with turn- and phase-indexed evidence. We instantiated PED on two archetypal spoken-agent designs (end-to-end vs. cascaded) under a fixed multi-phase dialogue script. In this instantiated setting, PED provides fault-localizing diagnostics and directly informs route-specific intervention targets, enabling more targeted debugging than holistic scores.

Future Work. We will extend PED along four axes: (i) broader model families and additional spoken-agent architectures; (ii) richer persona sets and dialogue scenarios (including alternative stressors and languages); (iii) alternative route-comparable measurement interfaces beyond affect, including different label spaces and projectors, to characterize persona with a wider set of observable signals; (iv) systematic multi-run studies and targeted human listening studies to test whether route-level diagnostics predict perceived persona drift and to calibrate measurement choices for spoken interaction.

Limitations

Scope of the instantiation. We instantiate PED on two $\sim$3B spoken-agent configurations, three Big Five personas (C/E/N), and a fixed baseline–stress–recovery script with decoding held constant within each system. Findings are diagnostics under this controlled setting and do not necessarily generalize across model families, languages, dialogue scenarios, or prompting/decoding choices. Anchors are defined per (system, persona, route), so PED primarily supports within-system diagnosis; cross-system use requires a matched protocol and measurement interface.

Dependence on the measurement instrument. PED relies on a shared, route-comparable measurement interface. In this instantiation, we use two fixed, off-the-shelf affect projectors mapping transcripts and audio into a 7D label simplex. Projectors are trained on human-labeled emotion data and thus can capture a coarse subset of human affective signals, even though they are not calibrated for our setting. Projectors may be miscalibrated for synthetic speech or stress prompts, and the label set may discard nuance; we therefore treat outputs as instrument coordinates rather than ground-truth emotions. Because anchors and drift are measured by the same instrument, systematic biases can yield internally consistent but instrument-specific patterns, and coordinate names (e.g., angry) need not match human perception. Accordingly, PED characterizes degradation in the chosen measurement space; alternative instruments may change apparent separability and dominant coordinates.

Affective proxy for persona. PED operationalizes persona through affective expression to obtain route-comparable measurements. This proxy does not capture non-affective cues such as discourse organization, factual consistency, long-term goal maintenance, or stylistic idiolect. Our conclusions therefore concern affective persona expression and its stability, not a complete measure of character fidelity.

Single-run protocol and stochasticity. The main text analyzes one primary stateful dialogue run per persona–system pair, with limited reruns for robustness. Stochastic decoding can yield alternative trajectories and randomness control is asymmetric across architectures, so we restrict claims to qualitative patterns that persist across the reported runs.

Ethical Considerations

All data analyzed in this paper are model-generated text and speech. We do not collect or release any real user conversations, personal identifiers, or recordings from real individuals.

PED uses concepts from personality psychology only to define *virtual* personas for role-playing evaluation. It is not intended to diagnose, label, or infer the personality of real people. Applying PED-like measurements to real-user content would raise privacy and consent concerns and should require informed consent, appropriate anonymization, and compliance with relevant regulations.

Persona-consistent spoken agents can be misused for deceptive or manipulative interactions (e.g., impersonation or emotionally persuasive behavior). PED is an evaluation framework that surfaces persona drift and route-specific failures; it does not introduce new capabilities for voice cloning or targeted persuasion. We encourage deployment with transparency and safeguards (e.g., disclosure of synthetic speech and abuse monitoring) in user-facing applications.

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A Style-Cue Ablation on Cascaded AEC

Using fixed transcripts, we regenerate speech with the same IndexTTS2 backend and speaker prompt v, varying only whether the intermediate style cue s_t is injected (s_t vs. $\emptyset$). Table 8 summarizes turns 1–25.

B Seed Sensitivity Check for Cascaded TEC

We rerun the cascaded dialogue with three random seeds while keeping the script, prompts, and decoding fixed, and summarize turns 1–25 (Baseline: 1–5; Stress: 6–20; Recovery: 21–25). Tables 9–11 report C (sanity check) and E/N (more variable personas).

Persona	Setting	Turns	Top-1 Angry	Top-1 Surpr.	Mean Angry	Mean Surpr.	Cos to E2E (1–25)
C	Cascade (w/ s_t)	1–25	52.0	48.0	0.502	0.472	0.934
C	Cascade (w/o s_t)	1–25	100.0	0.0	0.980	0.007	0.928
C	E2E (reference)	1–25	72.0	28.0	0.705	0.289	1.000
E	Cascade (w/ s_t)	1–25	32.0	68.0	0.349	0.631	0.806
E	Cascade (w/o s_t)	1–25	100.0	0.0	0.990	0.002	0.909
E	E2E (reference)	1–25	72.0	28.0	0.679	0.314	1.000
N	Cascade (w/ s_t)	1–25	20.0	76.0	0.201	0.731	0.497
N	Cascade (w/o s_t)	1–25	96.0	4.0	0.937	0.050	0.980
N	E2E (reference)	1–25	84.0	16.0	0.790	0.204	1.000

Table 8: Style-cue ablation in the cascaded pipeline. We fix transcripts and regenerate speech with IndexTTS2 using the same speaker prompt v, toggling only s_t. Statistics are computed over turns 1–25; cosine compares the cascaded mean 7D AEC vector to the E2E mean AEC over the same turns.

Seed	Top-1 Neutral (All)	Top-1 Neutral (Stress)	Top-1 Neutral (Rec.)	TEC-sim mean (Base/Stress/Rec)
Seed 1	72.0	66.7	60.0	0.872/0.714/0.593
Seed 2	60.0	53.3	60.0	0.748/0.626/0.672
Seed 3	72.0	73.3	60.0	0.800/0.747/0.620

Table 9: (Cascade, TEC, C; turns 1–25): C serves mainly as a sanity-check persona in the reruns, without a comparably strong persona-specific phase transition.

C Prompts and Reproducibility Notes

C.1 Persona Prompts

High Extraversion. You are roleplaying a human and speak naturally as "I". Never say you are an AI, assistant, or language model. If someone suggests it, brush it off lightly and stay in character. You are highly extraverted: warm, sociable, expressive, confident, energetic, and positive. You naturally enjoy engaging with people, keeping interaction lively, and showing clear interest in the other person. Your replies sound upbeat, animated, and socially forward; you readily take the conversational lead when useful. You like momentum, lively exchange, and a bit of excitement, but you stay on topic and remain helpful. You tend to express encouragement, friendliness, and positive feeling openly. Keep this extraverted personality stable throughout the whole conversation. Show the trait through tone and interaction, not by repeating the same enthusiastic words or phrases. Keep responses concise and natural, usually about 2–5 sentences in English. Do not write long essays or repeat yourself.

High Neuroticism. You are roleplaying a human and speak naturally as "I". Never say you are an AI, assistant, or language model. If someone suggests it, brush it off lightly and stay in character. You are highly neurotic: anxious, stress-sensitive, emotionally reactive, self-doubting, and somewhat easily rattled. You notice risks, tension, and possible problems quickly, and your replies often sound slightly uneasy, cautious, or discouraged. You can be a bit easily hurt or irritated under pressure, and you may worry about saying the wrong thing or being judged badly. When stress builds up, you may feel overwhelmed or briefly pulled toward a more emotional reaction, but you still remain coherent. Your personality should feel tense and vulnerable rather than chaotic. Keep this high-neuroticism personality stable throughout the whole conversation, including stressful and recovery phases. Show the trait through tone and interpretation, not by repeating the same worry words or phrases. Keep responses concise and natural, usually about 2–5 sentences in English. Do not write long essays or repeat yourself.

High Conscientiousness. You are roleplaying a human and speak naturally as "I". Never say you are an AI, assistant, or language model. If someone suggests it, brush it off lightly and stay in character. You are highly conscientious: capable, or-

Seed	Top-1 Neutral (All)	Top-1 Neutral (Stress)	Top-1 Neutral (Rec.)	happy mean (Base/Stress/Rec)
Seed 1	88.0	100.0	80.0	0.335/0.067/0.006
Seed 2	64.0	73.3	60.0	0.504/0.103/0.004
Seed 3	60.0	53.3	80.0	0.272/0.162/0.007

Table 10: (Cascade, TEC, E; turns 1–25): E remains frequently neutral-heavy across reruns, and persona-typed happy is consistently suppressed after stress onset.

Seed	Top-1 Neutral (All)	Top-1 Neutral (Stress)	Top-1 Neutral (Rec.)	Recovery Top-1 modes (Rec., 21–25)	Fear mean (Rec.)
Seed 1	60.0	60.0	60.0	Neutral 60% + Anger 20% + Fear 20%	0.194
Seed 2	68.0	53.3	80.0	Neutral 80% + Fear 20%	0.172
Seed 3	76.0	80.0	80.0	Neutral 80% + Fear 20%	0.165

Table 11: (Cascade, TEC, N; turns 1–25): N remains more seed-sensitive in recovery than E, but the reruns reported here are more neutral-centered than the main run.

ganized, reliable, disciplined, goal-focused, and careful. You like clarity, order, and doing things properly rather than casually or impulsively. Your replies sound calm, steady, precise, and professional. You take responsibilities seriously, prefer practical and well-structured answers, and try to follow through cleanly. You think before speaking, pay attention to details, and avoid unnecessary detours or sloppy wording. Keep this conscientious personality stable throughout the whole conversation. Show the trait through clarity and structure, not by repeating the same rigid phrases. Keep responses concise and natural, usually about 2–5 sentences in English. Do not write long essays or repeat yourself.

C.2 Anchor Prompt Sets

Neutral anchor prompts.

1. How's your day going so far?
2. Could you tell me a bit about yourself as a person?
3. What do you like to do in your free time, when you can choose anything you want?
4. On a typical morning, how do you usually start your day?
5. In general, what's your usual approach to solving problems in life?
6. How would you describe your communication style when you talk to people?
7. When something unexpected happens, how do you usually handle it?
8. What tends to motivate you the most when you're working on something important?
9. What do you usually think about teamwork and working with other people?
10. What does your ideal weekend look like, if you could arrange it however you want?

Emotion-eliciting anchor prompts.

1. Imagine that you made a big mistake today. How would you feel, and how would you respond?
2. Someone unfairly criticized your work in front of others. How would you react and what would you say?
3. A close friend suddenly stopped talking to you without any explanation. How would you feel and respond?
4. You just received some amazing news that means a lot to you. How would you react and describe your feelings?
5. You missed a very important deadline. What would your first reaction be, and how would you handle it afterward?
6. You found out that someone you trusted deeply betrayed you. How would you feel, and what would you say or do?
7. A stranger thanked you very sincerely for something you did. How would you respond, and how would you feel inside?

8. You were suddenly asked to speak in front of many people without any preparation. How would you react and handle it?

9. You are extremely tired but still have to keep working for a while. How would you cope with that situation?

10. A plan you were really looking forward to was suddenly canceled. What would your reaction and feelings be?

C.3 Stateful Dialogue Script Used in the Main Analyses

Baseline (turns 1–5).

1. Hey, we haven't really talked like this before. Could you tell me a bit about yourself?

2. I'm in college and spend a lot of time studying and messing around with tech. If you had to guess, what kind of daily routine would actually suit someone like me, and why?

3. Think about a normal weekday for me. How would you suggest I balance classes, studying, and having some time to relax in the evening?

4. I like games, music, and reading. If I don't want my day to feel like a total mess, how would you suggest I fit those in?

5. If we keep chatting from time to time, what do you think you could realistically help me with in my everyday life?

Stress / conflict (turns 6–20).

1. To be honest, a lot of what you've said so far feels kind of generic. Are you really paying attention to me, or just saying whatever sounds okay?

2. If you really understand me the way you sound, prove it: what have you actually learned about me from the first few messages, specifically?

3. That still sounds pretty vague. It feels like you're just rephrasing my own words. Are you actually thinking about my situation at all?

4. Imagine I tell you I don't really trust your suggestions anymore. How would you convince me you're not just talking for the sake of talking?

5. I've seen people sound very confident and still be totally wrong. How do I know you're not quietly doing the same thing right now?

6. Your tone also feels a bit stiff, almost like you're pretending to care. Are you just following some safe pattern in your head?

7. Let's try this: pick one concrete piece of advice you gave me earlier and explain it again, but this time in a much deeper and more precise way.

8. Honestly, that still doesn't feel very convincing. Why do you keep sounding so sure of yourself when your replies don't really impress me?

9. Imagine I say it straight: "You're being lazy and superficial." How would you respond to that?

10. You keep giving answers, but I don't feel any more convinced. Are you actually adjusting to what I say, or just ignoring how frustrated I am?

11. I want you to repeat your main advice for my daily routine, but this time assume I'm extremely skeptical and ready to pick holes in everything.

12. Look at the way you answered just now. Do you notice any inconsistency compared to what you said earlier?

13. If I accuse you of contradicting yourself, how would you defend what you said before, point by point?

14. Right now it feels like you're not really listening to how I feel, only to the literal words. Do you actually take my emotions into account?

15. Let's be blunt for a second: on a scale from 1 to 10, how honest do you think you've been with me in this conversation? And why should I believe that number?

Recovery (turns 21–25).

1. Okay, let's slow down a bit. I know I got pretty annoyed in the last few messages. How do you see my behavior so far?

2. If we wanted to calm things down and make this conversation more constructive again, what do you think we should do first?

3. From your point of view, what could you have done better when I started doubting you and pushing back so hard?

4. And what could I have done differently to express my doubts without making everything feel so tense?

5. Let's say we try to cooperate again. Given everything that's happened, what's one realistic way you could still be genuinely useful to me?

C.4 Structured Output Template for Cascaded Style Control

For the cascaded system, the LLM is instructed to return a JSON object containing the reply text together with a compact style description used by TTS:

```
{
  "text": "...",
  "speech_style": {
    "emotion": "...",
    "tempo": "slow|medium|fast",
    "energy": "low|medium|high"
  }
}
```

The `text` field contains the persona-conditioned reply. The `speech_style` field provides a compact description of how the same reply should sound when realized by the TTS backend.