

FROM TURN-TAKING TO SYNCHRONOUS DIALOGUE: A SURVEY OF FULL-DUPLEX SPOKEN LANGUAGE MODELS

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ABSTRACT

True Full-Duplex (TFD) voice communication—enabling simultaneous listening and speaking with natural turn-taking, overlapping speech, and interruptions—represents a critical milestone toward human-like AI interaction. This survey comprehensively reviews Full-Duplex Spoken Language Models (FD-SLMs) in the LLM era. We establish a taxonomy distinguishing Engineered Synchronization (modular architectures) from Learned Synchronization (end-to-end architectures), and unify fragmented evaluation approaches into a framework encompassing Temporal Dynamics, Behavioral Arbitration, Semantic Coherence, and Acoustic Performance. Through comparative analysis of mainstream FD-SLMs, we identify fundamental challenges—synchronous data scarcity, architectural divergence, and evaluation gaps—providing a roadmap for advancing human-AI communication.

For code and further details, please refer to GitHub¹.

Index Terms— True Full-Duplex, Full-Duplex Spoken Language Models, Cognitive Parallelism, Synchronization

1. INTRODUCTION

Contemporary SLMs fundamentally lack simultaneous listening and speaking capabilities essential for natural conversation. While LLMs have revolutionized language understanding [1, 2], their spoken dialogue implementations remain constrained by sequential listen-think-speak cycles. Current systems achieve only pseudo-full-duplex (PFD) behavior through time-division multiplexing, failing to match human conversational dynamics [3, 4] characterized by natural turn-taking behaviors illustrated in Fig. 1.

FD-SLMs transform this paradigm from sequential to parallel cognitive architectures. Unlike PFD systems that alternate between listening and speaking, FD-SLMs enable simultaneous encoding and generation within unified processing cycles, supporting natural conversational events including interruptions, backchanneling, and adaptive turn-taking through bidirectional information flow.

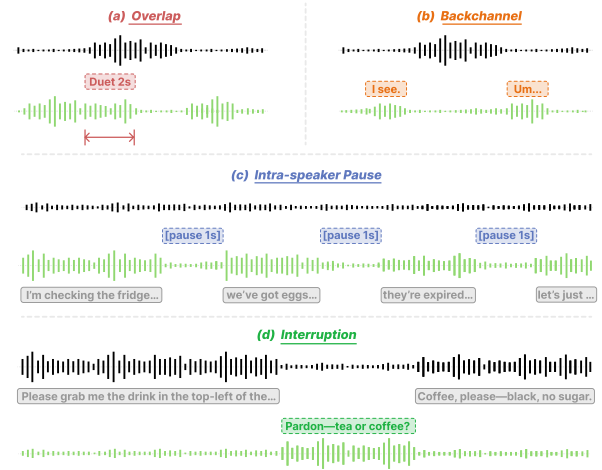


Fig. 1. Natural conversations contain turn-taking events: (a) Overlap, (b) Backchannel, (c) Pause, and (d) Interruption.

Early systems demonstrated incremental processing [5] and finite-state control [6], achieving responsiveness without semantic flexibility. LLM integration yielded engineered synchronization [7–9] and end-to-end architectures. Following dGSLM’s emergent turn-taking discovery [10], recent advances include hierarchical multi-stream processing [11], next-token-pair prediction (NTPP) [12], and continuous-discrete alignment [13].

Despite these advances, existing surveys [14, 15] treat full-duplex as implementation detail rather than fundamental requirement, lacking systematic FD-SLM design analysis. Evaluation also remains fragmented [16–18].

This paper makes the following primary contributions:

- Formal duplex characterization:** Mathematical definitions rigorously distinguish half-duplex, pseudo-full-duplex, and true full-duplex systems, exposing computational requirements for cognitive parallelism.
- Architectural taxonomy:** Systematic categorization reveals the design space along synchronization strategy, state management, and training paradigm axes, identifying trade-offs and unexplored opportunities.

¹<https://github.com/elpsykongloo/FD-SLMs>

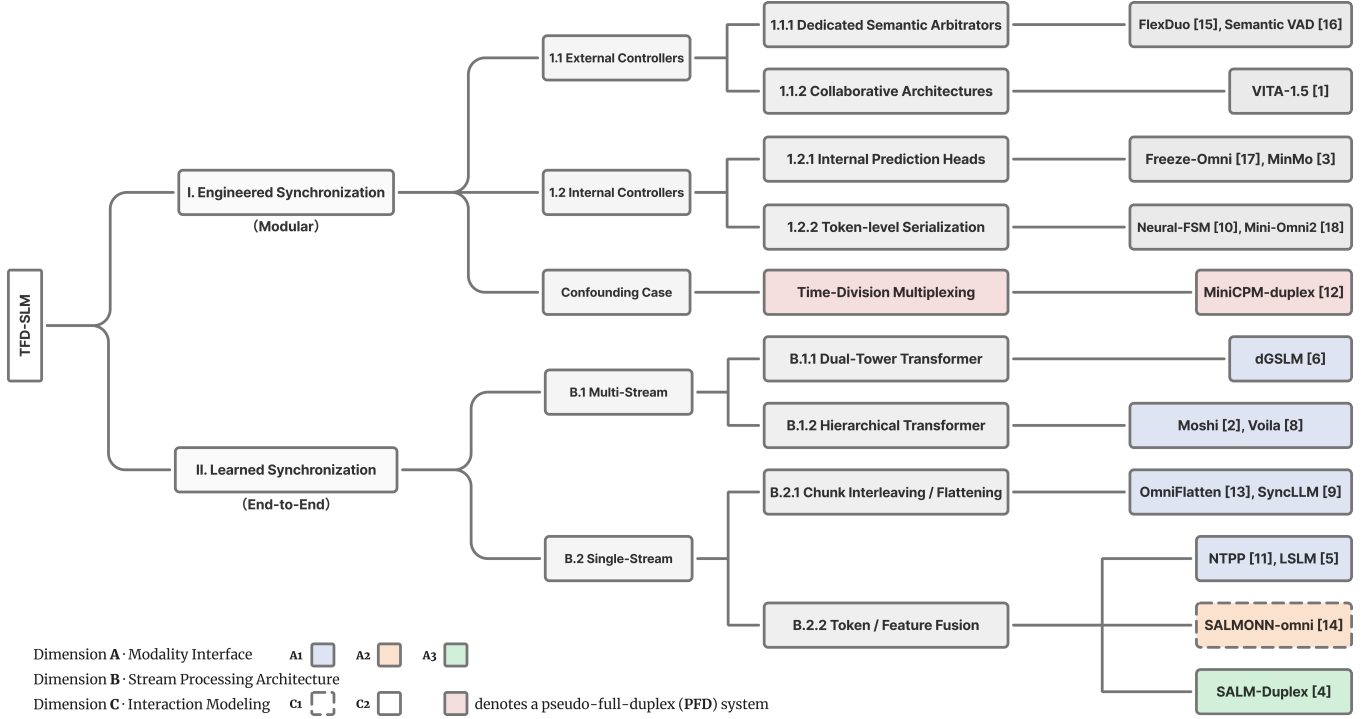


Table 1. Comparative analysis of architectural components in open-source FD-SLMs.

Model	Input Perception	Core Processing	Output Synthesis
dGSLM	HuBERT + k-means clustering	Two-tower Transformer with cross-attention	HiFi-GAN unit vocoder
Moshi	Mimi neural codec (RVQ)	RQ-Transformer joint autoregression	Mimi decoder
SyncLLM	HuBERT features	Interleaved and predictive synchronization	HiFi-GAN vocoder
SALMONN-omni	Mamba streaming encoder	Dynamic control tokens for stream management	CosyVoice2 with fixed-length generation
MinMo	SenseVoice-Large + projector	Full-Duplex Predictor (FDP) head	CosyVoice2 chunk-aware flow-matching
FlexDuo	Qwen2-Audio encoder	Finite-state machine control	External TTS delegation
VITA 1.5	Conv + Transformer encoder	Dual LLM instances with shared KV cache	TiCodec decoder

3. TAXONOMY

Cognitive parallelism, enabling simultaneous speech encoding and output decoding, requires departing from sequential Transformer architectures. Figure 2 shows current approaches following two paradigms: **engineered synchronization** via modular architectures and **learned synchronization** through end-to-end systems.

3.1. Engineered Synchronization

Modular approaches enhance dialogue engines with specialized components, eliminating retraining through explicit state arbitration. The duplex controller—a neural FSM—extends beyond acoustic VAD to perform semantic arbitration, differentiating interruptions from backchannels and noise.

External controllers. External controllers maintain independence from the core engine. FlexDuo introduces a ternary FSM with an idle state for selective attention [7]. Semantic VAD uses lightweight ($\sim 0.5B$) models analyzing ASR outputs to minimize computational load [21]. VITA-1.5 employs dual instances that swap roles upon interruption detection, trading computational cost for latency [22].

Internal controllers. Internal controllers embed control logic within the engine architecture. Freeze-Omni performs chunk-wise state prediction on frozen LLMs [23]; MinMo’s Full Duplex Predictor reads embeddings for turn-yielding decisions [24]. Neural-FSM extends vocabularies with FSM tokens enabling autonomous state management through next-token prediction [8]. Mini-Omni2 implements command-based interruption via semantic state tokens [24].

3.2. Learned Synchronization

End-to-end architectures natively process bidirectional audio streams. Following dGSLM’s demonstration of emergent turn-taking from raw audio [10], these systems make full-duplex capabilities intrinsic. The challenge lies in reconciling Transformer sequentiality with conversational parallelism.

Modal interfaces. Modal interfaces vary in representation. Codec-based approaches [10–12, 20, 25] discretize audio into tokens despite sequence elongation. SALMONN-omni directly processes continuous embeddings [13]. SALM-Duplex

combines continuous inputs with discrete outputs for an accuracy–latency tradeoff [26].

Stream processing. Stream processing follows multi-stream or single-stream paradigms. Multi-stream approaches like dual-tower architectures use cross-attention for synchronization [10], while Moshi’s RQ-Transformer jointly models user/agent audio and internal monologue [11]. Single-stream methods serialize inputs for standard decoders: SyncLLM interleaves chunks with synchronization tokens [20], NTPP uses pairwise causal masking [12], and LSLM/SALM-Duplex explore varying fusion depths [19, 26].

Interaction modeling. Interaction modeling predominantly employs implicit dynamics where models control turn-taking through silence or audible token generation without explicit supervision [10–12, 20, 25]. In contrast, SALMONN-omni’s Dynamic Thinking mechanism [13] generates control tokens for explicit state management, positioning the LLM as the duplex predictor within an end-to-end framework.

4. EVALUATION

FD-SLMs demand coordinated assessment across three interdependent axes: streaming architectures enabling real-time interaction, conversational training data, and comprehensive benchmarking methodologies.

4.1. Architectural Components

FD-SLMs require specialized streaming architectures achieving sub-200 ms latency for natural turn-taking [14, 15]. Table 1 summarizes strategies across three critical stages.

Input Perception. Continuous encoding with minimal lookahead is essential. While conventional encoders need causal adaptation, purpose-built streaming encoders operate natively [13, 27, 28]. Discrete paradigms employ strictly causal/near-zero-lookahead neural codecs [11, 12]; tokenizer chunk granularity fundamentally bounds perception latency [12, 29–31].

Core Processing. Concurrent streams are synchronized via cross-attention [10], joint autoregression [11], predictive synchronization [20], or explicit control mechanisms [7, 24]. A

Table 2. Comprehensive evaluation of representative open-source FD-SLMs across four dimensions.

Model	Temporal Dynamics		Behavioral Arbitration			Semantic Coherence		Acoustic Performance	
	FTO (\downarrow)	SL (\downarrow)	IRD (\downarrow)	ISR (\uparrow)	WER (\downarrow)	PPL (\downarrow)	QA Acc (\uparrow)	N-MOS (\uparrow)	M-MOS (\uparrow)
Human	~ 0.20 s	~ 0.30 s	2.32 s	93.69%	1.5%	10.2	92%	4.92 (± 0.02)	4.85 (± 0.03)
dGSLM	0.33 s (± 0.12)	0.15 s (± 0.03)	1.33 s	60.31%	25% (± 3.4)	334.4	17.2%	3.85 (± 0.12)	1.38 (± 0.10)
NTPP	0.30 s (± 0.15)	0.18 s (± 0.05)	1.30 s	80.82%	7.5% (± 1.22)	35	55.2%	4.15 (± 0.06)	3.95 (± 0.04)
Moshi	2.22 s (± 0.70)	0.75 s (± 0.10)	1.44 s	77.73%	5.20% (± 0.13)	59.3	33.8%	3.90 (± 0.07)	3.75 (± 0.06)
SALMONN-omni	0.38 s (± 0.10)	0.25 s (± 0.08)	1.38 s	85.6%	8.40% (± 0.20)	21.1	61%	3.85 (± 0.10)	3.95 (± 0.15)
VITA-1.5	2.10 s (± 0.65)	0.12 s (± 0.05)	9.49 s	78.53%	5.45% (± 0.10)	26.8	50.5%	4.00 (± 0.10)	4.10 (± 0.10)
Freeze-Omni	-0.40 s (± 0.05)	1.11 s (± 0.17)	9.25 s	54.97%	7.30% (± 0.05)	30.2	56.9%	3.80 (± 0.10)	3.90 (± 0.07)

100–200 ms “cognitive clock” sets perception–reaction granularity [9, 11, 20]. KV-cache efficiency directly affects sustained responsiveness [12, 32].

Output Synthesis. Discrete models reuse codec decoders for minimal latency [33, 34]. Continuous pipelines employ chunk-aware flow-matching [35], fixed-length interleaved generation [13], or tightly coupled LLM–vocoder stacks [22].

4.2. Training Data

Data scarcity remains critical: FD-SLMs require synchronized multi-channel spontaneous dialogue, unavailable in monologue corpora. Current training uses limited datasets [10–12] constraining diversity (see Table 3 for examples; full listings in our repository).

Table 3. Publicly Available Datasets for FD-SLM

Dataset	Lang	Scene	Channels	Hours
AMI Meeting Corpus	EN	meeting	8	100
ICSI Meeting Corpus	EN	meeting	6	70
LibriCSS	EN	meeting	7	10
Fisher English	EN	phone	2	1,960
SEAME (Mandarin–English CS)	EN+ZH	interview	2	192
HKUST Mandarin Telephone	ZH	phone	2	149

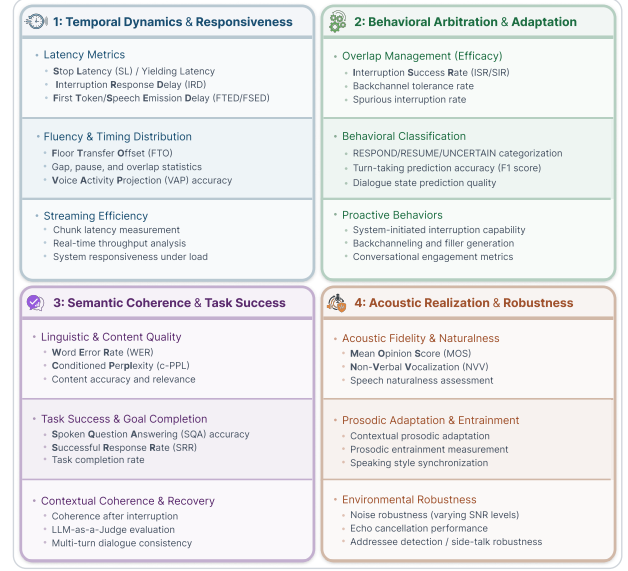
Synthetic TTS generation [20] fails to capture prosodic entrainment and overlap dynamics, limiting generalization. Progress requires end-to-end conversational synthesis and advanced source separation for single-channel data.

4.3. Benchmarking Framework

Conventional metrics built for half-duplex systems [1, 36] fail to capture real-time FD behaviors: when models speak, how they intervene, and conversational floor arbitration [6].

Historical fragmentation through model-specific metrics [8, 10–12] prevented systematic comparison. Recent standardization efforts [16–18] enable reproducible evaluation via our four-pillar taxonomy (Fig. 3).

Table 2 reveals critical gaps: while acoustic quality approaches human levels, temporal dynamics vary widely, behavioral arbitration underperforms (ISR: 54–86% vs. 94% human), and semantic coherence trades off against responsiveness—demonstrating that human-parity FD requires paradigmatic architectural advances.

**Fig. 3.** Four-Pillar Taxonomy of Benchmarking FD-SLMs.

5. CONCLUSION

FD-SLMs mark a paradigm shift from turn-based to synchronous dialogue. Through cognitive concurrency formalization and our taxonomy distinguishing Engineered from Learned Synchronization, we clarify fundamental design trade-offs. Our four-pillar evaluation reveals that while acoustic quality approaches human levels, critical gaps persist: inconsistent temporal dynamics, suboptimal behavioral arbitration, and inverse latency-coherence correlation.

Progress requires addressing interconnected challenges. Architectural fragmentation prevents scalable designs aligned with LLM scaling laws. Data scarcity—particularly synchronized multi-channel recordings and non-English resources [37]—constrains learning. Current evaluation lacks proactive behavior metrics [25], while ultra-low latency introduces safety risks requiring real-time filtering.

Advancing FD-SLMs demands architectural convergence, synthetic data capturing authentic dynamics, comprehensive behavioral evaluation, and robust safety mechanisms. Only through coordinated efforts can we achieve truly human-like conversational AI that is responsive, scalable, and ethically deployable.

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