Cross-Domain Speech Synthesis for Personalized Communication Assistance in Patients With Speech Impairments

Ruy Infante
Department of Computer Science, University of Houston, Houston, TX, USA.
ruy.infante@uh.edu

Abstract

Speech impairments alter intelligibility, prosody, voice quality, and communicative timing, and conventional augmentative and alternative communication voices often impose a generic synthetic identity. Cross-domain speech synthesis offers a route to personalized assistance by transferring speaker, style, and prosodic information from limited patient speech and larger typical or atypical corpora. This manuscript develops a methodological framework for such synthesis that treats personalized communication as a constrained cross-domain generation problem rather than a generic text-to-speech task. The framework separates content, speaker identity, prosodic style, and channel factors; aligns source and target domains through adversarial representation learning; adapts prosody and voice quality with reference-based style objectives; and shapes generation with an intelligibility-aware objective and uncertainty-controlled acceptance rule. It specifies the variables, assumptions, loss terms, and decision logic required to synthesize speech that is intelligible, identity preserving, controllable, and safe for assisted communication. Analytical assessment examines trade-offs among disentanglement, naturalness, speaker similarity, latency, and clinical robustness, and identifies failure modes such as content leakage, adversarial instability, over-smoothed prosody, and intelligibility loss under atypical articulation. The framework does not report empirical outcomes; its contribution is a technically coherent design and evaluation logic that links cross-domain representation learning to the communication needs of patients with speech impairments. The resulting perspective supports clinician-supervised personalization, transparent fallback behavior, and reproducible technical evaluation before clinical deployment.

Keywords

cross-domain speech synthesis; personalized voice; dysarthria; voice conversion; intelligibility-aware modeling; uncertainty-aware communication assistance

1. Introduction

Speech synthesis converts text or symbolic input into acoustic speech and has long served as a core technology for accessible communication [1]. Parametric statistical synthesis supplied explicit control over spectral envelopes, excitation, duration, and prosodic parameters, which made voice adaptation and personalization technically tractable [2]. Progress in speech synthesis has also depended on evaluation practices that distinguish naturalness, intelligibility, and speaker similarity, because these dimensions can move in different directions under adaptation [3]. Deep learning changed the design space by replacing hand-engineered acoustic models with learned representations and by allowing acoustic modeling to be optimized jointly with linguistic and prosodic context [4]. Sequence-to-

sequence neural synthesis subsequently reduced reliance on separately engineered front ends by learning alignment and prosody from data [5], while neural waveform generation improved the perceptual quality of synthesized speech [6]. Voice conversion provided a complementary route to personalization by transforming one speaker's voice toward another while preserving linguistic content [7], and zero-shot or one-shot conversion methods showed that speaker and content representations can be partially separated with limited target data [8]. Comprehensive reviews of voice conversion describe the field's central trade-off between parallel and nonparallel data assumptions, speaker modeling, and spectral conversion accuracy [9], and shared evaluation campaigns have made those trade-offs comparable across systems [10].

Patients with speech impairments present a different problem from conventional text-to-speech personalization. Dysarthria, laryngectomy, neurological disease, and structural speech disorders affect phonation, articulation, resonance, prosody, and timing in ways that are speaker specific and often progressive. A patient's residual speech may be highly intelligible in some contexts and nearly unintelligible in others, and the available speech may be limited, variable, fatigued, or recorded under adverse conditions. Communication assistance therefore requires more than a synthetic voice that pronounces text correctly. It requires a voice that preserves enough of the patient's identity for social recognition, supports rapid turn-taking, allows repair when a listener fails to understand, and respects the patient's control over when and how the voice is used.

Most existing synthesis systems remain domain specific. A conventional neural text-to-speech model is trained on healthy read or conversational speech; a voice conversion model typically assumes source and target utterances share linguistic content; and a disorder-specific model may be trained only on speakers with a single diagnosis. Cross-domain synthesis for personalized communication must instead use heterogeneous source data, including healthy speech, speech from other impaired speakers, donor voices, and a small amount of target-speaker residual speech. Direct fine-tuning on the target speaker can overfit to idiosyncratic articulation or to a narrow phrase set. Zero-shot speaker embeddings can fail when pathological voice quality is outside the training distribution. Reference-based style transfer can improve prosodic similarity but may leak content or normalize the very speech characteristics that make the patient recognizable.

The central contribution of this manuscript is a methodological framework for cross-domain speech synthesis that treats personalized communication assistance as a constrained generation problem. The framework factorizes speech into content, speaker identity, prosodic style, and channel factors; aligns source and target domains through adversarial representation learning; adapts prosody and voice quality with reference-based style objectives; and constrains generation with an intelligibility-aware objective and uncertainty-controlled acceptance rule. The framework is analytical and design oriented. It does not report a clinical trial, a benchmark evaluation, or a deployed system. Its purpose is to specify the variables, assumptions, loss terms, failure modes, and evaluation logic that must be made explicit before cross-domain synthesis can be evaluated responsibly with patients who have speech impairments.

2. Clinical and Communication Requirements

Speech impairment is not a single acoustic condition. Dysarthria can arise from amyotrophic lateral sclerosis, stroke, cerebral palsy, Parkinson's disease, traumatic brain injury, or other neurological conditions, and it may affect respiratory support, laryngeal

control, velopharyngeal function, articulatory precision, and prosodic modulation in different combinations. Laryngectomy and other structural interventions alter the excitation source and resonance differently from neurological dysarthria. A synthesis framework that collapses these conditions into a single atypical domain will learn a misleading average. The target domain must therefore be described by clinically meaningful variables, including diagnosis where appropriate, severity, speaking rate, phrase length, fatigue sensitivity, and the patient's residual contrastive inventory. The TORGO database illustrates the value of paired acoustic and articulatory descriptions of dysarthric speech, while also showing the heterogeneity that makes cross-speaker generalization difficult [11].

Personalized synthetic voices can support social participation, self-expression, and communicative efficiency for individuals with severe speech impairment, but personalization is not reducible to speaker similarity [12]. A voice that sounds like the patient but is slow, unstable, or poorly intelligible does not serve assisted communication. A voice that is highly intelligible but sounds like a generic donor may undermine identity and acceptance. The design problem is therefore multi-objective: intelligibility, speaker identity, naturalness, prosodic appropriateness, controllability, latency, and privacy must be considered together. These objectives are not independent. Increasing intelligibility by canonicalizing articulation can reduce identity; increasing identity by preserving atypical formant patterns can reduce intelligibility; increasing naturalness by smoothing prosody can remove communicative cues that listeners rely on.

The operational context of augmentative and alternative communication imposes constraints that laboratory text-to-speech evaluation often ignores. Communication assistance must support phrase selection, prediction, repair, turn-taking, and listener accommodation. It must allow the patient to interrupt, repeat, rephrase, and signal urgency. It must function under background noise and with listeners who are unfamiliar with the patient's speech. It must also provide a transparent fallback when synthesis is uncertain or when the patient chooses not to use a personalized voice. These requirements imply that the synthesis model cannot be evaluated only by word error rate or mean opinion score. It must be evaluated by communicative effectiveness: whether a listener understands the intended message, whether the patient can repair miscommunication, and whether the patient accepts the voice as an acceptable representation of self.

Data constraints further shape the design. Some patients can provide substantial pre-impairment recordings or voice-banked speech; others cannot. Some can provide residual speech with reliable transcripts; others require assisted transcription or cannot provide enough usable material for speaker-dependent training. Cross-domain synthesis must therefore operate under partial supervision. Source-domain speech may supply phoneme coverage, prosodic variation, and stable acoustic modeling, while target-domain speech supplies speaker identity, residual articulation patterns, and communicative preference. The model must distinguish what should transfer from source domains from what must be preserved from the target speaker. That distinction is both statistical and ethical, because it determines which aspects of a patient's speech are treated as signal and which are treated as noise to be removed.

3. Cross-Domain Formulation and Representation Model

Let the observed acoustic representation of an utterance be denoted x. In cross-domain personalized synthesis, the model has access to source domains with utterances drawn from healthy speakers and from other impaired speakers, and to a target domain containing the patient's residual speech and profile. The goal is to generate an acoustic sequence y for new

text that preserves the patient's identity and communicative style while improving intelligibility and stability. The cross-domain gap is not only distributional. It includes anatomical differences, recording conditions, speaking strategies, and the linguistic material available for adaptation. The model therefore needs a representation that separates factors that should be shared across domains from factors that should remain speaker specific.

A useful starting assumption is that an utterance can be represented through factor-specific encoders and a shared decoder:

$$z_x = [z_c; z_s; z_p] = [E_c(x); E_s(x); E_p(x)]$$

Here E_c, E_s, and E_p are encoders for content, speaker identity, and prosodic style, respectively; z_c, z_s, and z_p are the corresponding latent representations; and z_x is their concatenation. The notation is a modeling assumption, not an observed decomposition. Content is intended to capture phonetic and linguistic information that should be shared across speakers. Speaker identity is intended to capture vocal-tract and source characteristics that make the patient recognizable. Prosodic style is intended to capture timing, pitch movement, loudness, and voice quality that vary across utterances and communicative situations. The assumption is only partially identifiable in practice, because pathological articulation can entangle speaker identity with content and because emotional prosody can alter phonetic realization. The framework treats disentanglement as a regularization target rather than a guaranteed property.

Cross-domain style transfer provides evidence that out-of-domain style information can be separated from singer identity and linguistic content, but it also shows that style and identity can leak when the reference is acoustically distant from the target [13]. For personalized communication assistance, this lesson is directly relevant. A reference utterance from the patient may carry both desirable identity cues and undesirable instability. A donor reference may carry stable prosody but foreign identity. The synthesis model must therefore weight style transfer according to the reliability of the reference and the communicative goal. It should not copy all prosodic variation indiscriminately, because some variation is a symptom rather than a communicative intention.

Communication assistance also imposes system-level requirements that go beyond acoustic generation. Augmentative and alternative communication practice emphasizes rapid message construction, partner repair, and support for participation rather than isolated word production [14]. A personalized synthesizer that requires long text entry before speaking will fail in conversation even if its acoustic quality is high. The model must therefore be integrated with phrase prediction, quick repair actions, and patient-controlled prosodic modifiers such as urgency, question intonation, or emphasis. These controls can be represented as conditioning variables on the prosodic style latent, but they must be learned or specified without assuming that the patient can produce them reliably in residual speech.

Intelligibility is a multidimensional endpoint. Phonetic intelligibility testing in dysarthria shows that segmental errors, prosodic disturbances, and listener experience interact, and that word identification alone does not capture communicative success [15]. For synthesis, this means that an intelligibility objective should not simply maximize acoustic similarity to canonical speech. It should reward the preservation of contrastive information that listeners need, while allowing patient-specific variation that does not impair identification. The model must also account for listener adaptation: a listener who knows the patient may understand

atypical speech that an unfamiliar listener cannot. Personalized assistance may need listener-specific or context-specific modes rather than a single fixed voice.

Voice conversion offers a complementary formalization in which source and target spectral trajectories are aligned under a probabilistic criterion [16]. That formulation is valuable for preserving linguistic content while changing speaker characteristics, but it assumes that source and target utterances are comparable in content. Cross-domain synthesis for speech impairment cannot rely on that assumption. The patient's residual speech may be sparse, errorful, or limited to a small phrase set. The system must therefore combine conversion-like speaker adaptation with text-to-speech generation, using source-domain text-speech pairs to supply content and using target-domain speech to supply identity and style. This combination is the central technical challenge of the framework.

4. Methodological Framework

4.1 Factorized Encoding and Reconstruction

The first component of the framework is a factorized encoder-decoder that learns from source and target data simultaneously. A text or phoneme encoder produces the content representation z_c. A speaker encoder produces z_s from an enrollment utterance or a fixed speaker profile. A prosody encoder produces z_p from a reference utterance when one is available; when no reference is available, a prosody predictor generates z_p from text, discourse context, and patient-selected communicative intent. A shared decoder G reconstructs or generates acoustic features from the three latent factors. The reconstruction objective compares the generated acoustic representation with the observed utterance when a paired target is available:

$$\mathcal{L}_rec = E_x[||x - G(z_c, z_s, z_p)||_1]$$

In this expression, E_x denotes expectation over available utterances, x is the observed acoustic representation, G is the decoder, and the latent variables are produced by the encoders defined above. The L1 norm is used as a robust reconstruction criterion because pathological speech and clinical recordings can contain outliers and abrupt acoustic events. A perceptual or spectral loss can be added when differentiable feature extractors are available, but the reconstruction term alone is not sufficient. It can preserve target-domain instability when the target data are noisy, and it can leak source identity when the decoder relies too heavily on z_s.

Adversarial training has been incorporated into parametric speech synthesis to reduce over-smoothing and improve the perceptual realism of generated speech [17], building on the general generative adversarial framework [18]. In the present framework, adversarial terms are not used to maximize realism at any cost. They are used with explicit regularizers on speaker and content factors. The discriminator must not reward the model for producing fluent but speaker-generic speech, and it must not penalize patient-specific variation that does not reduce intelligibility. The reconstruction objective therefore provides stability, while adversarial and domain terms shape the latent space.

The factorized design has a practical advantage under data scarcity. Source-domain data can train the text encoder, decoder, and prosody predictor, while target-domain data fine-tune only the speaker encoder, adapter layers, and selected prosodic parameters. Freezing the shared content path reduces catastrophic forgetting and limits overfitting to a small target corpus. The design also supports fallback: if the target speaker encoder is unreliable, the

system can switch to a donor speaker embedding or to a generic synthetic voice without retraining the entire model. That fallback must be visible to the patient and clinician, because a changed voice changes the communicative and social meaning of the output.

4.2 Cross-Domain Alignment and Adversarial Representation Learning

The second component addresses the mismatch between source and target domains. Let P_S and P_T denote the source and target distributions over acoustic representations. A domain classifier D attempts to distinguish source from target using the content representation. The discriminator objective is:

$$\mathcal{L}_d om = E_{P_S}[\log D(E_c(x))] + E_{P_T}\left[\log\left(1 - D(E_c(x))\right)\right]$$

Here E_{P_S} and E_{P_T} are expectations over source and target utterances, D is the domain classifier, and E_c is the content encoder. The discriminator is trained to maximize this objective, while the content encoder is trained adversarially to make source and target content representations indistinguishable. Domain-adversarial training provides a principled way to reduce source-target shift in learned representations [19]. In this framework, however, the alignment target is deliberately narrow. Content representations should be domain invariant enough to support shared phonetic and linguistic structure, but speaker identity and pathological prosodic cues should not be erased from the speaker and style branches.

This narrow alignment is important because indiscriminate domain confusion can remove clinically meaningful information. If the content encoder is trained to make dysarthric and healthy speech indistinguishable, it may discard articulatory cues that the speaker branch needs to preserve identity. If the speaker encoder is trained adversarially across domains, it may learn a generic speaker representation that fails to capture the patient's vocal quality. The framework therefore applies adversarial alignment primarily to the content path and uses reconstruction, speaker classification, and style consistency losses to prevent collapse in the other branches. The trade-off is controlled by a gradient-reversal schedule and by validation on held-out patient utterances, not by maximizing domain confusion alone.

The cross-domain alignment also needs a mechanism for source selection. Not all source speakers are equally useful. Healthy speech provides broad phoneme coverage and stable prosody, but it may be acoustically distant from the patient. Speech from other impaired speakers provides pathological variability, but it may introduce identity leakage and disorder-specific artifacts. The model can weight source domains according to their relevance to the target speaker's severity, speaking rate, and residual articulation. That weighting is a design choice that must be documented because it affects which voices and which clinical populations are represented in the training signal. A system trained mainly on mild dysarthria may fail for a patient with severe impairment, even if the domain-adversarial loss is low.

4.3 Style and Prosody Adaptation With Reference Constraints

The third component adapts prosody and voice quality to the patient's communicative style. The decoder generates an acoustic representation y_hat from the content, speaker, and style factors. A reference utterance x_ref supplies a target style. A style loss compares intermediate representations of the generated and reference speech:

$$\mathcal{L}_sty = \sum_k ||\varphi_k(y_hat) - \varphi_k(x_ref)||_2^2$$

In this expression, φ_k denotes the k-th layer of a feature extractor, y_hat is the generated acoustic representation, and x_ref is a reference utterance selected by the patient, clinician, or

adaptation procedure. The sum runs over selected feature layers. The loss encourages the generated speech to match the reference in prosodic and voice-quality characteristics without requiring frame-level alignment. It is not a content loss, because content is supplied by the text and the content latent. The reference can be the patient's residual speech, a pre-impairment recording, or a donor voice, but the interpretation of the loss changes with the reference source. A patient reference preserves identity but may import instability; a donor reference imports stability but may reduce identity.

Style adaptation must be conditioned on communicative intent. A patient may need a neutral voice for routine communication, a louder and slower voice for a noisy environment, and a more expressive voice for social interaction. These modes can be represented as discrete style codes or continuous prosodic controls. The style loss can then be computed within each mode, rather than forcing all utterances toward a single average prosody. This design avoids the common failure in which personalized synthesis removes the patient's characteristic rhythm and produces a voice that is intelligible but socially unrecognizable. It also supports repair: if a listener fails to understand, the patient can repeat the message in a slower, more emphatic mode without switching to a different speaker identity.

The reference-based style loss has a leakage risk. If the feature extractor is sensitive to phonetic content, the model may imitate the reference's content rather than its style. This risk is highest when the reference is short and phonetically unbalanced. The framework mitigates leakage by using content-normalized features, by training with content-varying references, and by evaluating style transfer on held-out text that does not appear in the reference. The mitigation is not complete, because content and style are entangled in natural speech. The practical consequence is that style transfer should be treated as a constrained approximation, not as a guaranteed factorization.

4.4 Intelligibility-Aware Synthesis Objective

The fourth component shapes generation toward intelligibility. A purely acoustic objective can produce speech that is close to a reference but still hard for listeners to understand. The framework therefore adds an intelligibility-oriented term based on a differentiable or weakly supervised predictor. One formulation uses an automatic speech recognizer as a surrogate:

$$\mathcal{L}_int = -\sum_t \log P_ASR(w_t \mid y_ < t, x_hat)$$

Here t indexes output tokens, w_t is the target word or phoneme sequence, y_<t is the preceding token history, x_hat is the generated acoustic representation, and P_ASR is the recognizer's posterior. Minimizing the negative log-likelihood encourages the generated speech to be decodable as the intended message. The term is a surrogate, not a clinical measure. Automatic recognizers can be biased against atypical speech and can reward canonical pronunciation in ways that reduce speaker identity. The framework therefore treats the recognizer as one signal among several and requires calibration against listener intelligibility, especially for patients whose residual speech is poorly represented in recognizer training data.

The reconstruction, domain, style, and intelligibility terms are combined into a multi-objective loss:

$$\mathcal{L} = \mathcal{L}_rec + \lambda_dom\mathcal{L}_dom + \lambda_sty\mathcal{L}_sty + \lambda_int\mathcal{L}_int + \lambda_kl\mathcal{L}_kl$$

The coefficients λ_dom, λ_sty, λ_int, and λ_kl control the relative influence of domain alignment, style adaptation, intelligibility shaping, and latent regularization. The term $\mathscr{L}$_kl is a Kullback-Leibler regularization on the latent speaker and style distributions, motivated by variational autoencoding [20]. It discourages the model from assigning excessively specific latent codes to a few target utterances, which is important when the patient provides limited data. The weights are not universal constants. They express clinical and communicative priorities. A high λ_int favors canonical intelligibility; a high λ_sty favors identity and prosodic similarity; a high λ_dom favors domain invariance. The framework requires these weights to be documented and evaluated as design choices rather than hidden tuning parameters.

The multi-objective formulation also exposes a tension between intelligibility and identity. If the recognizer is the dominant signal, the model may flatten atypical articulation until the patient's voice is no longer recognizable. If style and speaker losses dominate, the model may preserve unintelligible residual patterns. The framework does not resolve this tension by a single scalar objective. It treats the weights as a communication policy that should be set with the patient and clinician, and it allows multiple operating modes. A repair mode may prioritize intelligibility; a social mode may prioritize identity and naturalness; a public-address mode may prioritize loudness and clarity. The existence of modes is itself a safeguard, because it prevents one technical objective from silently defining the patient's communicative identity.

4.5 Uncertainty, Risk, and Acceptance Decision

The fifth component addresses uncertainty. Cross-domain synthesis with sparse patient data is inherently uncertain, and a communication aid must know when not to speak or when to request confirmation. In a Bayesian approximation, Monte Carlo dropout can provide predictive uncertainty by sampling multiple stochastic forward passes [21]. The predictive variance is estimated as:

$$\mathrm{Var}(y) \approx \left(\frac{1}{M}\right)\sum_{m}\left(y_m - \bar{y}\right)^2$$

Here M is the number of stochastic forward passes, y_m is the generated acoustic representation from the m-th pass, and ȳ is the sample mean. The variance captures both aleatoric variability and epistemic uncertainty, although the two are not separately identified without additional modeling. The distinction matters for communication assistance. Aleatoric variability may reflect natural prosodic variation or recording noise; epistemic uncertainty may reflect the model's lack of experience with the patient's articulation or the current text. Bayesian deep learning distinguishes these sources conceptually and shows why a single confidence score can be misleading [22]. The framework therefore treats uncertainty as a diagnostic signal, not as a substitute for clinical judgment.

The acceptance decision combines confidence, estimated communication risk, and predicted intelligibility:

$$A(x) = 1[conf(x) \geq \tau_c \wedge risk(x) \leq \tau_r \wedge intel(x) \geq \tau_i]$$

In this expression, A(x) is an acceptance indicator, conf(x) is the model's confidence, risk(x) is an estimated communication risk, intel(x) is a predicted intelligibility score, and τ_c, τ_r, and τ_i are thresholds. The thresholds are policy parameters, not empirical constants. They should be set according to the communication setting, the patient's preference, and the

cost of misunderstanding. If the acceptance condition fails, the system can request confirmation, repeat the message with a slower prosodic mode, switch to a donor voice, or display text. The decision rule makes fallback explicit and auditable. It also prevents the synthesizer from presenting an uncertain output as if it were reliable, which is especially important when the patient cannot easily monitor or correct the generated speech in real time.

5. Analytical Assessment and Design Trade-offs

The framework's central technical trade-off is between disentanglement and reconstruction. Stronger factor separation can improve cross-domain transfer by preventing source identity from leaking into the target voice, but it can also remove acoustic cues that are needed for intelligibility. Pathological speech often violates the clean separation assumed by factorized models: a patient's identity may be expressed through the same atypical formant patterns that reduce intelligibility. A model that removes those patterns to improve intelligibility may also remove the patient's vocal identity. A model that preserves them may fail the communicative goal. The framework's multiple operating modes and weighted objective are designed to make this trade-off visible rather than to hide it behind a single loss value.

The choice of source domains is similarly consequential. Healthy speech provides broad phonetic coverage and stable prosody, but it may be acoustically distant from severe dysarthria. Other impaired speakers provide closer acoustic and articulatory statistics, but they introduce disorder-specific artifacts and identity leakage. A model trained on a small number of impaired speakers may learn a stereotype of the disorder rather than the target patient's residual speech. A model trained only on healthy speech may produce a voice that is intelligible but not recognizable. The framework's source-weighting mechanism is a partial response, but it cannot eliminate the need for careful corpus documentation and clinical validation.

Adversarial alignment introduces instability. If the domain classifier becomes too strong, the content encoder may collapse to a domain-invariant representation that discards phonetic detail. If the classifier is too weak, source and target distributions remain misaligned. Gradient-reversal schedules, feature normalization, and early stopping are engineering responses, but they do not remove the underlying trade-off. The framework therefore treats domain-adversarial training as one component of a constrained objective, not as a standalone solution. The content path is aligned; the speaker and style paths are regularized but not forced into domain invariance. This selective alignment is more defensible for clinical speech than indiscriminate domain confusion.

Intelligibility-aware training has its own failure modes. An automatic recognizer used as a surrogate may reward canonical pronunciation and penalize atypical but understandable speech. It may also perform poorly on the very patients the system is intended to serve. The framework's use of recognizer posteriors should therefore be calibrated against listener studies and clinician judgments. The intelligibility term should not be interpreted as a clinical outcome. It is a training signal that helps the model preserve contrastive information, and it must be validated with human listeners who represent the patient's communication partners.

Latency is a practical constraint that interacts with uncertainty. Monte Carlo sampling improves uncertainty estimation but increases inference cost. A communication aid that requires many stochastic forward passes may be too slow for conversational turn-taking. The framework can use adaptive sampling, in which the number of passes depends on the

communication mode and the estimated risk. In routine phrase-bank use, a fast deterministic path may be sufficient. In novel or high-stakes messages, more sampling and confirmation may be appropriate. This adaptive design reflects a general principle: uncertainty estimation should be allocated according to the cost of error, not applied uniformly.

Baseline comparisons clarify the framework's position. Parametric synthesis offers explicit control and predictable behavior but may sound less natural than neural systems [2]. End-to-end neural synthesis produces natural speech but requires substantial data and may not preserve a target speaker with atypical speech [5], [6]. Voice conversion can personalize a source voice with limited target data but assumes comparable content and may not generate novel text robustly [7], [8], [16]. Style transfer can improve prosodic similarity but may leak content or identity [13]. The proposed framework combines these strengths while making their interactions explicit. It is more complex than any single baseline, and that complexity is justified only if each component addresses a documented failure mode in cross-domain personalized synthesis.

The framework also has boundary conditions. It is intended for patients who can provide at least some usable speech or a pre-impairment recording, or who consent to a donor voice. It is not a substitute for speech-language pathology assessment, and it does not diagnose or treat a speech disorder. It assumes that the patient and clinician can choose among operating modes and that the patient can control when the personalized voice is used. It also assumes that the training data and generated outputs are handled under appropriate privacy and consent protections. These conditions are not peripheral. They define the situations in which the technical framework is ethically and clinically meaningful.

6. Ethical, Clinical, and Deployment Considerations

A personalized synthetic voice is a representation of a person, not merely an acoustic model. Consent must cover the collection of speech, the training of the model, the use of donor voices, the storage of embeddings, and the conditions under which the voice may be shared. Patients should be able to withdraw consent and to delete voice models without losing access to communication assistance. Clinicians should be able to inspect fallback behavior and to document which voice mode was used in a clinical interaction. These requirements are especially important when the patient's speech is deteriorating, because a voice model created at one stage may no longer reflect the patient's current identity or communicative preferences.

Voice ownership and misuse are central risks. A model trained on a patient's speech could be used to generate utterances the patient did not authorize, or to impersonate the patient in social or financial contexts. The framework therefore requires access control, logging, and a clear distinction between assistive use and general-purpose synthesis. Donor voices raise parallel issues. A donor may consent to provide a voice for a specific patient or clinical purpose, but that consent does not automatically extend to other users or applications. The system should preserve the provenance of speaker and style representations so that voice identity can be audited.

Bias is another concern. Speech synthesis and recognition systems are often trained on populations that do not represent the full range of ages, dialects, languages, and disabilities. A cross-domain model trained on healthy read speech may perform poorly for patients with severe dysarthria, and a recognizer used as an intelligibility surrogate may be biased against atypical pronunciation. The framework's emphasis on listener validation, clinician oversight, and multiple operating modes is a partial response, but it does not eliminate the need for

representative data and transparent reporting. Evaluation should include listeners who are familiar with the patient and listeners who are not, because the communicative demands differ.

Clinical deployment should proceed in stages. Offline technical validation can test whether the model preserves content, speaker identity, and prosody under controlled conditions. Listener studies can test intelligibility and naturalness with representative communication partners. Clinical feasibility studies can test whether the system supports actual communication goals, including repair and turn-taking. Longitudinal evaluation can test whether the voice remains acceptable as the patient's speech changes. The framework does not claim that these stages have been completed. It specifies the logic that should guide them: intelligibility is necessary but not sufficient; speaker identity is important but not absolute; and patient control is a design requirement, not an optional feature.

The communication assistance context also requires transparency. The patient and listener should know when the output is synthetic, when a fallback voice is being used, and when the system is uncertain. A synthetic voice that is indistinguishable from the patient's speech may be desirable in some social settings, but it can also create confusion in clinical or emergency contexts. The framework's acceptance rule and mode selection provide a technical basis for this transparency. They allow the system to say, in effect, that it is confident in the message, that it is using a repair mode, or that it recommends confirmation. These signals can be implemented as interface cues rather than as changes to the acoustic voice, but they must be designed with the patient and clinician rather than imposed by the model.

7. Conclusion

Cross-domain speech synthesis for personalized communication assistance is not simply a matter of training a text-to-speech model on a patient's voice. Patients with speech impairments present sparse, heterogeneous, and clinically meaningful data; their residual speech may be both the source of identity and the source of unintelligibility; and their communication needs include repair, timing, and control. This manuscript has developed a methodological framework that treats these conditions as a constrained cross-domain generation problem. The framework factorizes content, speaker identity, and prosodic style; aligns source and target domains selectively through adversarial representation learning; adapts prosody with reference-based style objectives; shapes generation with an intelligibility-aware objective; and uses uncertainty-controlled acceptance to make fallback explicit.

The analytical assessment identified the principal trade-offs. Strong disentanglement can improve transfer but can remove identity-bearing and intelligibility-bearing cues. Source selection can provide phonetic coverage but can introduce stereotypes or leakage. Adversarial alignment can reduce domain shift but can become unstable or over-invariant. Intelligibility surrogates can improve contrastive clarity but can reward canonical speech and punish atypical pronunciation. Uncertainty estimation can support safe fallback but adds latency. These trade-offs are not defects of the framework; they are the substance of personalized communication assistance. A technically responsible system must expose them, document them, and evaluate them with the patients and listeners who will use the technology.

The framework's contribution is a coherent design and evaluation logic that links cross-domain representation learning to clinical communication requirements. It does not replace empirical validation, and it does not claim clinical efficacy. It provides a basis for reproducible implementation, transparent fallback, clinician-supervised personalization, and listener-centered evaluation. If these elements are treated as first-class requirements rather

than post hoc additions, cross-domain speech synthesis can support a form of communication assistance that is intelligible, identity preserving, and accountable to the patient it represents.

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