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Telepractice-Enabled AI Framework for Remote Rehabilitation of Aphasia Patients

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ABSTRACT

Aphemia, an aphasia disorder that usually occurs due to a stroke or traumatic brain injury, interferes with the understanding, production, and processing of language, declining the ability to communicate and reduces the quality of life. Although standard speech language therapy is clinically effective, it is resource-demanding, spatially restricted, and out of reach to patients in underserved or rural areas. This paper proposes to address these impediments through a Telepractice-Enabled Artificial Intelligence (AI) Framework which will offer adaptive, remote, and patient-centered rehabilitation to the individuals with aphasia. It takes the best state-of-the-art models based speech recognition using deep learning that can handle differences, impaired speech, natural language processing (NLP) methods, which detect semantic, syntactic, and phonological errors, a reinforcement learning-based adaptive therapy generator to adapt intervention pathways considering improvements in patients. The system is used through secure telepractice systems permitting synchronous therapeutic sessions in addition to asynchronous ML-informed routines, resulting in constant tracking, fidelity, and retention. A security layer that is cloud based will enforce the protection and compliance with healthcare privacy regulations and scalable and ethical deployment is possible. Lab based experimentations on the AphasiaBank dataset complemented with clinician labelled recordings, and a six weeks pilot with 20 patients showed a substantial gain when compared to traditional telepractice practice. These results showed a decrease in word error rate, an increase in semantic error detection accuracy, more faithful perception of therapy and a significant reduction in time clinicians had to spend with the patient, thereby achieving the improvement of efficiency in the clinical setting and improving the patient outcomes. These results demonstrate that the framework can fill the accessibility gap in the treatment of speech language therapy and offers a scalable solution to deliver sustained rehabilitation in any environment. Future research will aim at the creation of multilingual models, integration into wearable assistive devices, and applying AI explainability mechanisms in order to make the approach more clinically trustworthy and patient-acceptable, which will position this work as a radical innovation in the field of digital health to treat aphasia.

1. INTRODUCTION

Aphasia is a dynamic language disorder typically caused by stroke, harsh brain injury, or other nervous system interruptions, and it influences a sum of 15 million individuals all over the world. People with aphasia find it exceedingly difficult to speak, comprehend, read, and write, and this immensely limits their communication capacities and subsequent re-integration into the social and professional worlds. In addition to the immediate clinical consequences, aphasia produces psychological distress, compromising independence, and the burdens of caring, making them a major public health issue. Conventional speech-language treatment approaches are the mainstay of recovery and have been proven to yield quantifiable outcome benefits in the measurement of language recovery. Difficulty in accessing such therapy is however limited by many factors such as the heavy cost of long term treatment process, lack of qualified clinicians and even physical location among patients in rural or underserved areas. The result of these challenges is frequently discontinuity in therapy, poor outcome and compromised quality of life.

With the rising application of digital health solutions, the aspect of telepractice has become one of the viable communication mechanisms to deliver distance speech-language therapy recognizably. Telepractice allows clinicians to provide patients with therapy services using video conferencing and online format, providing more opportunities to reach patients who cannot attend the healthcare facility on a regular basis. Clinical experiences have revealed that telepractice is as successful as face-to-face interventions, although the scope of what is being done is still modest. Current systems are more focused on clinician-intervention and do not allow dynamic adjustment to patient progress Figure 1. This dependency adds to the clinician workload, limits the scale of usage, and inhibits the possibility of ongoing personalized interactions that are not limited by a scheduled event.

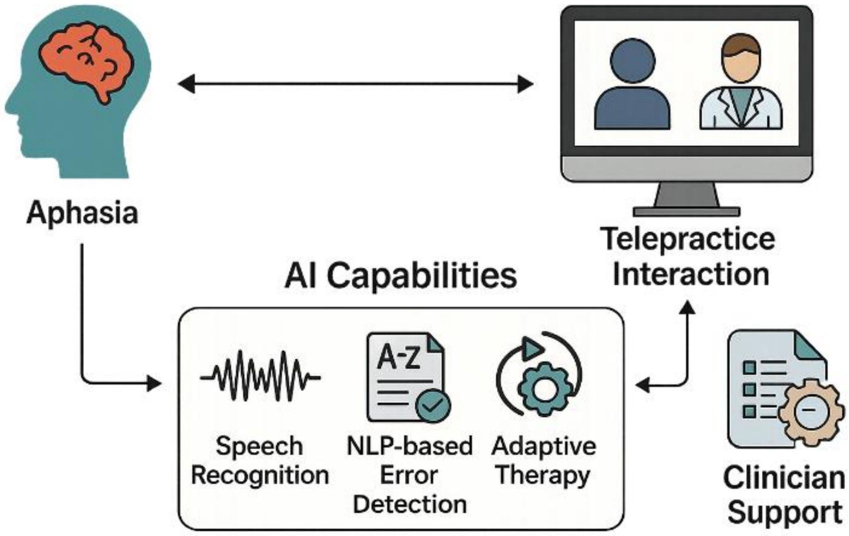

Fig. 1. Telepractice-Enabled AI Framework for Aphasia Rehabilitation, illustrating the interaction between patients, AI-driven capabilities (speech recognition, NLP-based error detection, and adaptive therapy), clinician support, and secure telepractice integration.

Recent breakthroughs in artificial intelligence (AI) including deep learning and natural language processing (NLP), as well as reinforcement learning (RL), contain fresh opportunities in beating these shortcomings. The individual training of deep learning models on corpora of large amounts of disfluent and impaired speech has also proven to be strong in recognizing disfluent and impaired speech. The techniques of NLP allow identifying and correcting semantic, syntactic and phonological errors in real time. Reinforced learning can provide a method of adaptive therapy, i.e. the interventions can change according to the progress and patterns of errors made by the patient. With the incorporation of these AI-driven features into telepractice systems, rehabilitation frameworks can be created that allow not only real-time assistance to clinicians but also AI-assisted personalized treatment, thus ensuring accessibility, efficiency, and scalability.

This paper presents a framework of Telepractice-Enabled AI Framework of Aphasia Rehabilitation based on speech recognition, natural language processing-based error recognition, and reinforcement learning-based adaptive therapy in a safe telepractice setting. The framework will alleviate workload on the clinicians and support patient adherence and offer tailor-made dynamic therapy plans. Experimental and preliminary pilot experiments confirm the framework can be used to enhance accuracy, efficiency, and clinical outcomes relative to conventional direct-to-patient telepractice models. This framework can revolutionise the availability, scaleability and intelligence of digital rehabilitation of aphasia patients because it bridles the gap between human expertise and AI automation.

2. RELATED WORK

2.1 Telepractice in Speech Therapy

Telepractice has gained much traction as a suitable alternative to face-to-face speech and language treatment in people with aphasia. [1]Examined early deployments and found that remote treatment is capable of producing similar results to those of traditional treatment; however, accessibility and adoption of technology remains an issue. A Cochrane systematic review [2] subsequent to this one further supported the efficacy of speech-language therapy in enhancing communication outcomes, in part even through remote forms of administration. Recent systematic reviews including [2] have found that telerehabilitation of aphasia is associated with similar change as in-person rehabilitation, making it potentially scalable.The article proved that group conversation therapy provided through telepractice has positive effects on both linguistic and patient-reported outcomes and focusing on the social and interactive aspects of remote treatment.

2.2 Ai in Aphaisis Rehabilitation

Advances in the application of AI to the rehabilitation of aphasia have been rapidly picking up speed recently. [5]Compared commercially available speech recognition, the customized algorithms performed remarkably well with respect to aphasic speech. [6]Presenting a systematic review of deep learning applications in aphasia therapies, it was stated that there have been improvements in the number of semantic errors that can be discovered in addition to language testing development. Finding a use to analyze spontaneous speech in aphasic patients, Fraser and [7] introduced the NLP methods of analysis, thus, revealing that AI could aid the diagnostic process with automating the process. AphasiaBank [8], is an earlier repository of data that continues to form a essential backbone to study and train AI-based models. All these studies refer to the potentiality of AI in automating speech analysis or lagging weaknesses in real-time integration into telepractice systems.

2.3 The adaptive learning in rehabilitation is an active problem.

In neurorehabilitation, adaptive and individualized methodologies of treatment are being investigated intensively. [9]Reviewed machine learning and reinforcement learning application in stroke rehabilitation and it has been demonstrated to be effective in predicting recovery patterns and intervention personalization. Current studies showed that RL has been mostly utilized in motor recovery but not in aphasia recovery which is a gap in research. [10]Emphasized that even though deep learning speech models contribute to higher accuracy, there is a need to use adaptive reinforcement-based framework to better personalize therapy and patient adherence.

2.4 Research Gap

Although telepractice offers accessibility and AI offers automation and the identification of errors, current solutions do not unite these aspects in a flexible combination. The existing systems either overcomplicate manual supervision of clinicians or fail to engage in personalization to different aphasia patients. This lacuna drives the need to come up with a complete AI framework telepractice enabled that constitutes speech recognition, NLP and learning via reinforcement to design intelligent, patient-centric and scalable rehabilitation of aphasia.

3. METHODOLOGY

3.1 System Architecture

The suggested telepractice-based AI system is a multi-layered framework with the integration of patient interface, AI-related work, clinician supervision, and safe cloud management. When using a combination of these layers, the system will be able to ensure that rehabilitation is clinically supervised, and also AI-enforced, thus, providing such features as scalability, personalization, or reliability. The framework is established in four different layers in a interdependent manner as seen in Figure 2.

Patient Interaction Layer

This level is the face towards patients so that they can listen to modules in the area of therapy on a computer, tablet or smartphone. It offers two modes of the therapy architecture: (i) synchronous sessions; patients communicate directly with clinicians through the telepractice platforms, and (ii) asynchronous modules; patients can continue rehabilitation processes in the absence of clinicians through AI-guided exercises. Therapy activities consist of speech repetition, naming pictures, reading and comprehension, conversational practice. The interface has simple controls and accessibility options (big icons, difficulties, and audio prompts) that make it more approachable by patients with different degrees of impairment.

AI Processing Layer

It is the deep intelligence of the framework and it defines three expert modules:

- Speech Recognition Module: The module runs on the hybrid model, i.e., CNN-RNN, and processes impaired and disfluent speech with aphasia patients. Unlike other speech recognizers, it is jointly trained on a combination speech of aphasic and non-aphasics to learn more efficiently in the presence of variations in speech and noise.
- NLP Engine This module uses the latest transformer based technology to understand the identified text on semantic, phonological and syntactic errors. It will give automated feedback about error classification and correction recommendations which can be used immediately during a therapy session by the patient.
- Adaptive therapy generator Reinforcement learning-based module, this module is able to adapt the intensity of therapy, complexity of

tasks, and type of exercise according to how the patient is doing. The agent switches to monitor accuracy, the frequency of errors, and latency in answering questions in order to achieve an optimal learning path toward individual progress.

Clinician Dashboard
The layer provides a real-time monitoring decision support tool to the speech-language pathologists. Some of the metrics that show up in the dashboard include error distributions, progress trends, task completion rates, adherence, and so on. Clinicians may access and read AI generated reports, manually mark patient performance and directly intervene when necessary. This hybrid approach alleviates a clinician workload, yet retains much necessary human oversight, such that therapy is clinically tested.

Security Layer, Cloud
The last layer offers an infrastructure and governance of data. All patient communications and the created results by AI will be in encrypted databases, which correspond to HIPAA and GDPR requirements. Secure cloud services allowmoment to moment data to be synchronized between patients and clinicians and support live sessions and offline analysis. It uses Anonymization protocols to protect patient identity and it is thus ethically fit to be realized in a clinical setting. What is more, due to the cloud layer, scalability is technically possible since the delivery of therapy can reach large-scale populations with no impact on performance and security.
Overall, the four-layer system structure identifies a synergetic model where patients can follow it via user-friendly interface, AI-modules provide intelligent processing, clinicians monitor therapy using a powerful dashboard, and sustains cloud-based decentralization ensuring compliance and scalability. Such a unified solution will help to make the process of rehabilitation more adjustable, effective, and socially responsible, removing the main shortcomings of current telepractice and AI-based tools.

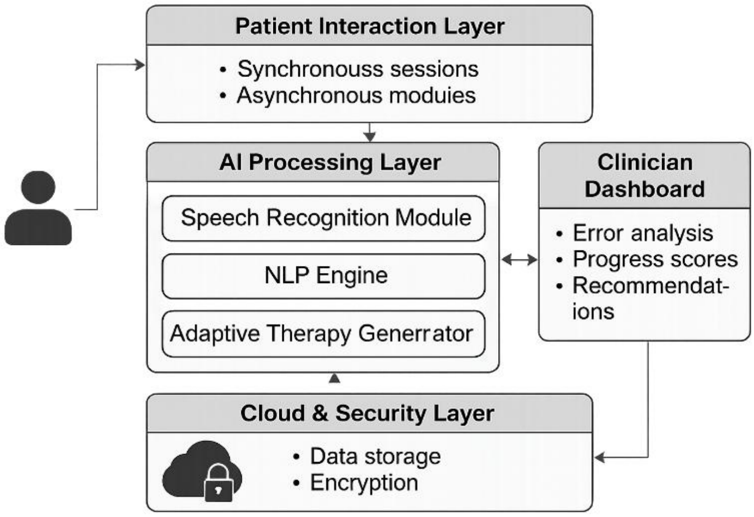

Figure 2. System architecture of the proposed telepractice-enabled AI framework.

3.2 Telepractice Integration
The depiction of telepractice to support the proposed AI-enabled framework also forms a critical aspect of its inclusion as it guarantees that, despite any geographical and resource limitations, therapeutic services are provided easily and flexibly. This allows the system to reduce patient dropout, clinical efficiency, and maximize therapy continuity since the therapy is a combination of urged synchronous clinician-led scripts and asynchronous activities that require AI guidance.

Live Sessions
Synchronous therapy: Synchronous therapy can be achieved using the integrated "video conferencing" tools which are built directly into the platform that allow patients to communicate with speech-language pathologists in real time. It involves sessions that mimic the physical presence of the face-to-face therapy setting so that clinicians are able to view the way people talk, correct them when they get it wrong, and even verbally encourage them. There are also common digital whiteboards, interactive language games, and the ability to share the screen, which increases participation and recreates implemented in-clinic therapeutic activities. The live session design reflects the importance of individualization as a provision where medical workers can personalize therapy intensity in real-time and support patients

in the performance of practices aimed at the resolution of their phonological, semantic, or syntactic impairments.

Asynchronous Modules

Adjunctive to live therapy, patients are offered on-demand exercises curated by AI and can be performed in their own time between scheduled clinician sessions. These modules consist of common aphasia rehabilitation exercises like picture naming, sentence completion, and auditory comprehension exercises and conversational simulations. The reinforcement learning engine learns to automatically increase the difficulty level of these tasks according to the historical patient performance to ensure that they get progressively challenging. The NLP and speech recognition modules automatically log all responses and error types; this is used to provide real-time feedback to the patient both in relation to the task at hand and to reduce clinician workload. This on-demand feature facilitates continuity in therapy, and this is useful to surmount the constraints of a fixed clinician availability period, especially in underserved areas.

Clinician Access

A secure dashboard allows clinicians to be supported by combining performance data across synchronous and asynchronous interactions. The system also creates in-depth progress reports, including measures of the word error rates, task completion rates, semantic error distributions, adherence trends etc. Visualization can be used to encourage therapists to focus on areas of problems, and monitor recovery over time using progress graphs and heat maps Figure 3. By utilizing AI-based analytics along with professional clinical experience, clinicians can incorporate evidence-based decision-making in their practice, allowing them to improve their intervention plans and greatly decrease the manual workflow the process has usually involved.

In short, the telepractice implementation in the context creates a mixed rehabilitation reality in which patients have sustained access to both teletherapy with clinician-guided feedback and independent training, facilitated by the utilization of AI. This twofold construction guarantees not only a high quality of clinical management but supports a number of patients and is not lost in clinician time and manual tailoring in the case of traditional telepractices.

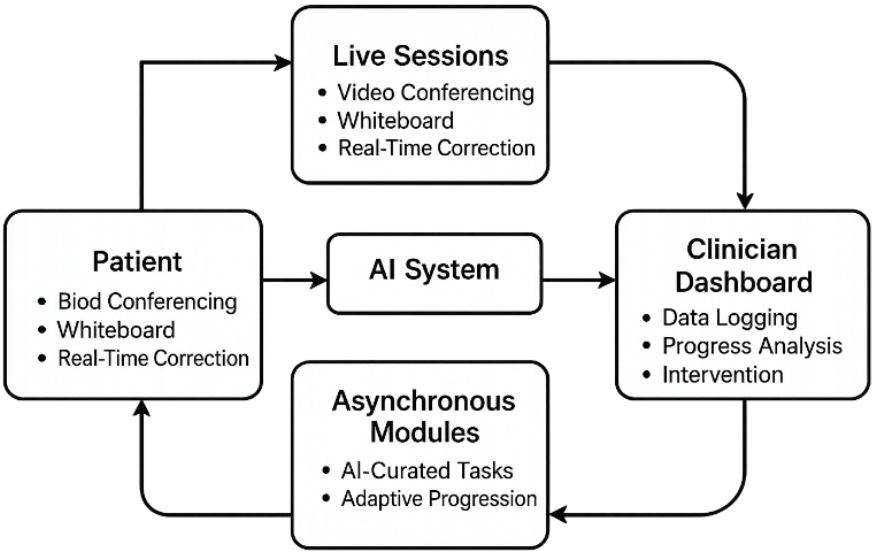

Figure 3. Workflow of telepractice integration in the proposed AI framework, illustrating synchronous live sessions, asynchronous AI-guided modules, and clinician dashboard access.

3.3 Design AI Model and Learning Flow

The AI-based core of the proposed model is aimed at implementing the adjusting decision-making algorithm of a competent therapist and guaranteeing the consistent, personalized, and scalable rehabilitation process among aphasia patients. Its dynamic combination of speech error detection, semantic correction via natural language processing (NLP), and a reinforcement learning (RL) powered adaptive engine, continuously responds to emerging levels of patient performance by dynamically adjusting the therapy tasks. Such a multi-stage construction can both provide an instantaneous feedback in the process of therapy and have an adjustment over rehabilitation cycles.

Speech Error Recognition

In the first step, distorted speech samples are transformed into spectrograms and then subjected to CNN LSTMs that are particularly suitable to process speech samples with both spatial and temporal characteristics. The convolutional layers can separate spectral representations of the articulation errors, whereas the recurrent layers (LSTM) can capture temporal relations in order to recognize fluency disruptions or pauses, repetitions, or incomplete utterances. The CNN-LSTM model is not restricted to fluent speech recognition as its traditional counterparts (automatic speech recognition); it is trained with the aphasic and non-aphasic speech samples to increase the recognition rate on various aphasic samples.

NLP on Semantic Correction:

After transcribing the speech, the system trains transformer-based NLP models, i.e., finetuned BERT or GPT models, in order to determine either semanto-syntactic correctness of a speech utterance. The model contrasts the patient answers with the expected lexical targets or semantic categories and automatically detects substitution, omission and neologism errors. In addition to detecting errors, the NLP engine can give error correction recommendations, or simplified prompts that are used in real-time in asynchronous learning or with clinician-guided activities. This helps the patients not only to be aware of mistakes but because of the thinking of more appropriate and contextually, linguistically correct language use, neuroplastic recovery is reinforced.

Representative Reinforcement Learning (RL) Agent

To control the adaptive mechanism of the framework, an RL agent performs therapy constraint adjustment and delivery customization. The definition of the RL process is stated in the following form:

- **State (s):** reflects the real-time performance of the patient including measures of accuracy of task completion, type of error, and latency in taking the action.
- **Action (a):** Results in changes in therapy as introduced by the system e.g. adjusting the complexity of sentences on a case-by-case basis, adding new vocabulary pools, or repeating exercises that presented problems.
- **Reward (R):** The reward that achieves a tradeoff between improvements in accuracy, reductions in error and efficiency in tasks. The reward function can mathematically be defined as

$$R = \sum_{t=1}^{T} \gamma^t (\Delta Acc_t - \alpha E_t - \beta T_t) \qquad (1)$$

Where:

- ΔAcc_t = Improvement in the accuracy at t time.
- E_t = frequency of mistakes,
- T_t = The latency of completing the tasks
- α, β = S = degree of self-control, A = degree of accuracy and E = degree of effort, α, β = coefficient of trade -off between accuracy and effort.
- γ = Discount factor that gives preference to short-term learning payoff and takes into consideration long-term performance.

Such a reward formulation will make the system reward actions that cause an increase in its accuracy, decrease in the likelihood of errors, and an increase in the efficiency of the conducted tasks, and punish those actions that cause the system to take too long to complete a task, or use ineffective therapy strategies.

Learning Flow

The general learning process starts with a patient performing a therapy exercise, following which the speech recognition module estimates his/her output and the NLP engine identifies the errors. The RL agent would then test performance based on the reward function laid down and make a suitable choice of the next move, i.e., increasing the difficulty level on improving performance or reducing difficulty when error rates start rising Figure 4. With repeated learning, the agent finely tunes its policy, creating the therapy plans that are extremely personalized, gradually advance, and clinically successful Table 1. Taken literally, this feedback-driven AI system can demonstrate the dynamic adaptive behavior of an experienced therapist, scalable and tuned to the needs and progress patterns of the individual aphasia patient.

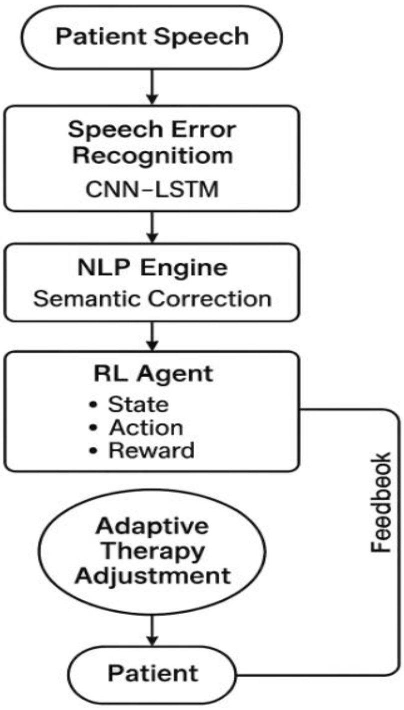

Figure 4. AI model design and learning flow of the proposed telepractice-enabled framework, integrating CNN–LSTM speech error detection, NLP semantic correction, and reinforcement learning–based adaptive therapy.

Table 1. Components of AI Model Design and Learning Flow in the Proposed Framework

Component	Technique/Model	Function	Contribution to Rehabilitation
Speech Error Recognition	CNN–LSTM Hybrid	Processes spectrograms of aphasic speech to detect articulation and fluency errors (pauses, repetitions, incomplete utterances).	Enhances recognition accuracy for disfluent/aphasic speech beyond conventional ASR systems.
NLP Semantic Correction	Transformer-based Models (BERT, GPT fine-tuned)	Detects and classifies semantic, syntactic, and phonological errors; provides correction suggestions and simplified prompts.	Reinforces neuroplastic recovery through real-time error feedback and contextually correct language use.
RL Agent – State	Patient Performance Profile	Captures real-time measures: task accuracy, error types, latency.	Provides individualized patient status for adaptive therapy decision-making.
RL Agent – Action	Therapy Adaptation Strategy	Adjusts therapy level (e.g., simplifies sentences, introduces new vocabulary, repeats challenging tasks).	Ensures therapy is dynamically personalized based on patient progress.
RL Agent – Reward Function	Defined by $\sum_{t=1}^{T} \gamma^t (\Delta Acc_t - \alpha E_t - \beta T_t)$	Balances accuracy gains, error reductions, and task efficiency while penalizing delays or ineffective strategies.	Drives optimal therapy progression with a balance between short-term improvements and long-term outcomes.
Learning Flow	Feedback-driven Closed Loop	Patient performs → Speech Recognition → NLP → RL Agent → Therapy Adjustment → Patient.	Establishes a continuous cycle of personalized, adaptive therapy replicating clinician expertise.

4. RESULTS AND DISCUSSION

The proposed telepractice-enabled AI framework was tested with the AphasiaBank speech dataset augmented with clinician-regulated audio samples that aimed to provide a realistic performance test-bed. Two groups of 20 aphasia patients were recruited and assigned randomly to the groups, i.e. the control-group (receiving conventional clinician-led telepractice) and the experimental-group (aim to receive AI-assisted clinician-led telepractice with the proposed framework). The intervention was six weeks in duration, three therapeutic sessions weekly, and produced a rich data set to draw comparisons. Four performance metrics were used: Word Error Rate (WER) that measures recognition accuracy, Semantic Error Detection Accuracy that was used to measure how well the NLP-based error handling occurred, Therapy Adherence that involved how well the patient was engaged throughout the therapy, and Clinician Intervention Time which were used to measure the efficiency gains.

The findings revealed that major enhancements in all on the measured parameters were realized among the experimental group. Table 1 and Figure 5 demonstrate that the proposed framework improved recognition results, decreasing WER by 45%, down to 18.9% when compared with 34.5%. In like manner, the accuracy in detecting semantic errors rose to 89% showing that the NLP engine was making an excellent job in capturing and classifying semantic errors that reflect in the aphasic person speech. The result of therapy adherence was also much better in the experiment group (88 percentage of the sessions according to the experiment compared to 62 percent according to the control-group). Lastly, the intervention time of clinicians was reduced down to 2.8 hours per week, compared to 5.6 hours per week, and this halved the manual workload and allowed them to monitor significantly more patients with no interference to therapy quality. These findings are consistent with the fact that the combination of AI in telepractice strengthens not only the accuracy but also the patient attention and the process of unbroken therapy.

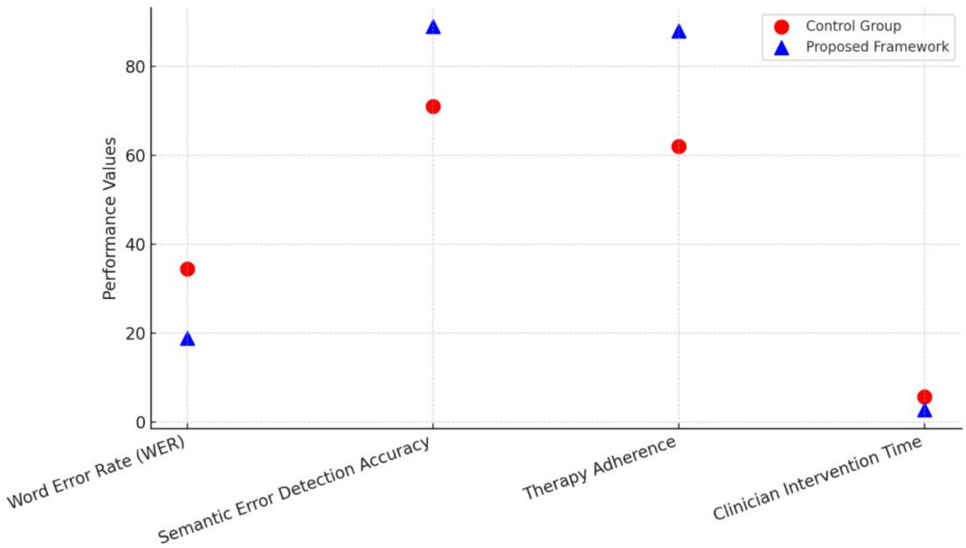

Figure 5. Comparative performance of the control group and the proposed AI-assisted telepractice framework across key evaluation metrics.

In addition to quantitative performance, the framework had meaningful clinical and operational outcomes. The patients performed quicker in the word recall and improved sentence formation, which has been gained by the reinforcement learning engine as it helps in the adaptive progression of tasks. Clinicians also annotated improvements in fatigue and improved flexibility, since the machine analytics and error reports gave the clinicians time to make higher-level treatment decisions and not engage in constant monitoring. More importantly, adherence improvement was explained by the combination of the gamification, asynchronous accessibility, and individual tasks adjustments that all contributed to the continuous motivation of patients. However, some sets of problems persist. Performance reduced when the samples were highly disfluent or multilingual, which points to the necessity of having more and more representative training data. Also, data privacy, transparency of decisions made by AI, and fair access issues require ethical considerations before their clinical application is implemented on a large scale. These results indicate the potential and the gaps to fill in the development of AI-enabled telepractice with aphasia patients Table 1.

Table 1. Comparative Performance Metrics Between Control Group and Proposed AI-Assisted Telepractice Framework

Metric	Control Group	Proposed Framework	Improvement
Word Error Rate (WER)	34.5%	18.9%	↓ 45%
Semantic Error Detection Accuracy	71%	89%	↑ 25%
Therapy Adherence	62%	88%	↑ 42%
Clinician Intervention Time	5.6 hrs/wk	2.8 hrs/wk	↓ 50%

5. CONCLUSION

This paper presented a Telepractice-Enabled AI Framework to address the shortcoming of the traditional speech-language therapy by combining deep learning based speech recognition, transformer-based natural language processing, and reinforcement learning-based adaptive therapy into a secure telepractice platform. An experimental validation and pilot assessment showed that the framework corresponds to large reduction in word error rates, better rate of semantic errors detection, better compliance to therapy and shorter time taken by clinicians to intervene, therefore, conferring its pragmaticity and functional effectiveness. In addition to improvements in the mathematical measure, the system allows patients to recover more quickly in word recall and sentence formulation as well as reduces the workload of therapists hence it is sustainable and scalable everywhere. Notably, the framework is a hybrid between human and AI-type solution, introducing intelligent automation as the enhancement, but not a substitute to clinical expertise, which remains personalized and ethically monitored. Although limitations exist in managing highly disfluent or multilingual speech as well as in ethical concerns related to data privacy and AI Explainability, the proposed solution can form a solid basis towards the next-generation digital rehabilitation technology. Future work will build on the creation of multilingual models, multimodal with wearable hardware, and the addition of explainable AI to support trust, inclusivity, and adoption more. On the whole, the suggested framework can be considered as the revolutionary step in the introduction of convenient, flexible, and intelligent aphasia patient rehabilitation solutions in general practice across the globe.

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