RESEARCH PAPER

A Comparative Analysis of Virtual Reality and Conventional Therapy: Predicting Rehabilitation Outcomes in Chronic Neck Pain

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ABSTRACT

Chronic neck pain is one of the most common musculoskeletal conditions. Individuals with chronic neck pain often experience pain, stiffness and a restricted range of motion in the cervical spine, which can interfere with daily activities and reduce quality of life. Conventional assessment relies largely on clinical observation, which limits how often progress can be monitored. This study compared virtual reality (VR)-assisted and conventional physiotherapy for chronic neck pain and examined whether machine-learning (ML) models could predict rehabilitation outcomes from clinical and movement data.

Fifty-five participants took part, 27 in the VR group and 28 in the conventional group. Each performed seven cervical exercises, with data recorded in the 2nd, 4th, 6th and 8th weeks, giving exercise-level records. The VR framework used an Azure Kinect DK sensor for markerless body tracking and a Unity 3D avatar that mirrored the user's movements as real-time visual feedback. Pain was measured using the Visual Analogue Scale (VAS). Four classifiers (Decision Tree, Random Forest, Support Vector Machine and XGBoost) were evaluated using participant-level data splitting, accuracy, precision, recall, F1-score, ROC analysis and confusion matrices.

Mean VAS scores fell from 4.667 to 1.704 in the VR group and from 4.000 to 2.321 in the conventional group. All four models performed better on VR data, with accuracy gains of 4.6 to 5.7 percentage points. XGBoost performed best in terms of accuracy in both groups (86.1% for the VR group and 80.4% for the conventional group), followed by the Random Forest, SVM and Decision Tree algorithms. All models performed best at predicting correct movements but found it harder to separate slightly incorrect movements from incorrect ones. These findings suggest that movements captured using VR technology allow for more reliable outcome prediction, though these findings should be confirmed using larger cohorts of participants.

Keywords: Chronic neck pain, virtual reality, machine learning, Azure Kinect, rehabilitation assessment, XGBoost

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I. INTRODUCTION

Artificial intelligence (AI) systems have become smarter because AI based human interaction system can track movements in real-time and recognize gestures while understanding human body language. Users can now interact with digital environments through VR and XR thanks to deep learning progress and body-tracking system enhancements which create natural and intuitive digital space interactions. The combination of upper-limb segmentation with XR gesture recognition and virtual dressing rooms demonstrates how AI systems analyze human body movements together with body measurement data during interactive experiences [1]-[3]. The technological progress in these areas establishes a solid foundation which enables AI-based movement

evaluation to support healthcare services together with physical therapy programs.

In physical rehabilitation, the ability of patients to perform the exercises prescribed for their rehabilitation needs to be assessed on an ongoing basis. The assessments of the patients' ability to perform the exercises accurately and effectively is usually performed by healthcare professionals with the expertise to make such assessments, which makes frequent assessments difficult, especially in the patients' home environment. Computer-aided assessment offers an alternative, in which movement data captured by sensory systems are processed to evaluate how well exercises are performed. Existing approaches, however, can be limited in versatility, robustness and practical implementation. For this reason, deep learning-based frameworks have been explored to automate the assessment of rehabilitation exercises. Liao *et al.* [4], for example, developed such a framework that combines movement-performance metrics, numerical scoring functions and neural network models to estimate the quality of performed movements. The researchers developed deep spatiotemporal neural networks which they combined with autoencoder-based representations to study joint movements and generate exercise-quality ratings for multiple rehabilitation activities. The research demonstrates that exercise performance can be measured through computational methods which eliminate the need for manual assessment. Physiotherapy based on exercise serves as the main treatment method for conservative management which includes rehabilitation programs that teach patients to perform cervical mobility exercises and stretching and strengthening and postural training. Research studies that took place in clinical settings analyzed the impact of cervical exercises on pain levels and disability and cervical movement range which demonstrates the necessity to measure both patient-reported clinical results and actual physical mobility. A randomised clinical trial published in 2024, for instance, reported improvements in pain, disability and cervical range of motion after exercise-based interventions for chronic nonspecific neck pain [5].

Virtual reality, gamification and low-cost sensing technologies have opened new ways to make rehabilitation more engaging and to deliver exercise outside the clinic. Robotic systems and VR-based rehabilitation can provide structured, interactive training, but they still face practical obstacles, including limited accessibility, usability issues and a continued reliance on supervision in a clinical setting. Smartphone-based rehabilitation systems offer another route to affordable home-based exercise, as they use the phone's built-in camera and interactive interface to track movement and support game-based training [6]. Taken together, these developments point to the value of combining AI, movement tracking and interactive technologies to make rehabilitation assessment both more accessible and more objective.

Machine learning (ML) provides a computational means of analysing clinical and movement-related data and identifying patterns linked to rehabilitation outcomes. In a clinical application, Han *et al.* [7] developed and externally validated ML models to predict which patients with neck pain were more likely to benefit from spinal manipulation. Although their aim differs from assessing movement during cervical rehabilitation, the study shows how ML can support the prediction of treatment response.

Building on this work, the present study proposes an ML-based framework for analysing cervical rehabilitation outcomes in patients receiving VR-assisted or conventional physiotherapy. The framework draws on the available clinical variables, including pain scores measured on the Visual Analogue Scale (VAS), together with cervical movement measures recorded during the prescribed exercises. Four classification algorithms, namely Random Forest, Support Vector Machine (SVM), Decision Tree and XGBoost, are evaluated for their ability to classify a clearly defined rehabilitation-related outcome. Model performance is assessed using suitable classification metrics, confusion matrices and Receiver Operating Characteristic (ROC) curves.

The main contribution of this study lies in bringing together ML-based classification, clinical pain assessment and cervical movement analysis within a comparative rehabilitation setting. By evaluating clinical outcomes separately from model performance, the study examines whether movement and clinical features can support the assessment of rehabilitation progress, and lays a foundation for future intelligent, sensor-assisted cervical rehabilitation systems.

II. RELATED WORK

A. VR-Based Cervical Rehabilitation

The reviewed studies demonstrate the application of VR technology in cervical pain management, the assessment of chronic neck conditions through sensorimotor evaluation, and rehabilitation. Úbeda-D'Ocasar et al. [8] conducted a single-blind Randomised Controlled Trial (RCT) of 56 women with fibromyalgia and chronic cervical pain, divided into three groups: one group performed VR combined with cervical mobility exercises, another group performed only the cervical mobility exercises, and the final group acted as a control. The group of women who performed the VR combined with cervical mobility exercises were the only group to maintain significant improvements across all outcome measures at follow-up, including a marked reduction in kinesiophobia. This suggests that VR can serve as an effective adjunct therapy for women with fibromyalgia and chronic cervical pain. In a study by Paul et al. [9], it was found that while at-home exercise therapy is recommended for women with chronic neck pain, many women do not perform the exercises correctly or follow the prescribed routines. To encourage regular and accurate exercise, the authors developed the "HeadTurner VR" exergame, and the neck-rotation data it collected were compared with values reported for the

Spine Motion Analyser, inclinometer, universal goniometer and a cervical range-of-motion device.

In contrast to these positive findings, Cetin *et al.* [10] evaluated immersive VR and cervical mobilisation (CM) by assigning 45 patients to VR plus traditional exercise, CM plus traditional exercise, or traditional exercise alone over 10 treatment sessions. Adding VR or CM to traditional exercise did not produce significant additional improvements in Joint Position Sense (JPS) or pain ($p > 0.05$), and no significant between-group differences were found in balance, disability or global perceived effect. The practical side of VR-based rehabilitation was explored further by Luc *et al.* [11], whose qualitative study described participants' experiences in terms of the home setting, interaction with VR technology and the performance of therapeutic exercises in the virtual environment. Most participants found the system comfortable and easy to operate, and the interactive nature of VR made the exercises more enjoyable and motivating than traditional exercises. Although home-based use was generally viewed positively, participants raised concerns about using the system independently and having less direct contact with healthcare professionals. The study therefore emphasised that physiotherapists remain essential for giving individualised instructions, monitoring progress remotely and ensuring exercises are performed correctly.

VR has also been applied to the assessment of cervical function. Development of an immersive VR system for the multidimensional assessment of cervical sensorimotor control in 30 healthy adults and reported good-to-excellent test–retest reliability, with strong correlations against reference methods [12]. Another implantation used a VR apple-harvesting task with 30 patients with neck pain and 30 asymptomatic participants and found that patients rotated their heads more slowly and needed more time to complete the task [13]. In terms of treatment, author reported that combining VR therapy with conventional rehabilitation reduced pain and disability and improved kinematic function in 64 patients with chronic neck pain, while found VR exercises to be more effective than motor control exercises for improving joint position sense and pressure pain thresholds [14]-[15]. Exercise application showed that a head-controlled serious game was well accepted by older adults with chronic neck pain and found that internet-based telerehabilitation was as effective as in-person exercise for young women with chronic neck pain and forward head posture [16]-[17]. Overall, these findings suggest that immersive VR and remote approaches offer promising and engaging options for neck rehabilitation, provided that adequate professional support is built into the programme.

B. Machine Learning in Neck Pain and Cervical Spine Assessment

Machine-learning methods have been used for several related tasks, including treatment-response prediction, posture analysis and the diagnosis of cervical conditions. Table 1 summarises the studies most relevant to the present work [7], [18]-[22].

TABLE 1. MACHINE-LEARNING APPROACHES IN NECK PAIN AND CERVICAL SPINE ASSESSMENT

Author and Year	Research Objective	Dataset and Input Features	ML Technique	Main Findings	Relevance to the Present Study
Han *et al.* [7] (2025)	To identify which patients with neck pain are likely to respond to spinal manipulation.	Retrospective cohort of 623 patients, with an external validation cohort of 319; 40 candidate variables.	Nine algorithms compared; Boruta and LASSO for feature selection; MLP performed best; SHAP for interpretation.	MLP reached an AUC of 0.823 (test) and 0.824 (external validation) and was deployed as a web-based tool.	Shows ML can predict treatment response; focuses on spinal manipulation rather than VR-assisted exercise.
Hwang *et al.* [18] (2024)	To explore craniocervical alignment patterns and their relation to nonspecific neck pain.	Craniocervical angles at rest, in protraction and retraction, with pain and disability scores.	Unsupervised clustering of movement patterns.	Three clusters with different links between posture, age and disability; some near-normal angles still had high disability.	Supports analysing cervical angles together with clinical outcomes.

Author and Year	Research Objective	Dataset and Input Features	ML Technique	Main Findings	Relevance to the Present Study
Xie *et al.* [19] (2024)	To diagnose cervical spondylosis from X-ray images.	1,371 X-ray images from 595 patients (1,235 for training and validation, 136 for testing).	ResNet-34 convolutional neural network (CNN).	89.7% classification accuracy on the test set.	Shows the value of deep learning for diagnosis; image-based rather than exercise tracking.
Ji *et al.* [20] (2023)	To detect cervical spondylotic myelopathy (CSM) from gait.	Gait data from 45 patients with CSM and 45 healthy controls.	RBF neural networks based on deterministic learning; leave-one-out cross-validation.	95.56% detection accuracy.	Shows movement-derived features can support automated classification.
Sreeraj *et al.* [21] (2022)	To estimate cervical spondylosis severity or risk from posture.	60 training and 12 testing videos across four posture classes.	CNN-based classification with six-fold cross-validation.	83.33% training vs 16.66% testing accuracy, indicating poor generalisation.	Highlights the risk of small video datasets and the need for patient-level validation.
Kumar and Elias [22] (2020)	To classify neck postures using kinematic and kinetic data.	Neck kinematics combined with kinetic data generated in OpenSim with a musculoskeletal neck model.	Machine-learning posture classification.	100% accuracy in the experimental setting.	Basis for posture analysis from sensor-derived features.

III. METHODOLOGY

A. VR Framework Design

The proposed VR framework spans low-level sensor integration through to the patient-facing exercise experience. The components of the system, including the hardware, game engine, avatar, exercise modules, and feedback and storage systems, are connected in a single pipeline in Fig. 1. A generic humanoid character represents the avatar in the system and is rigged to Unity's Humanoid avatar standard [23]. This character is used both as the avatar that demonstrates the exercise and as the real-time mirror of the movements of the patient themselves.

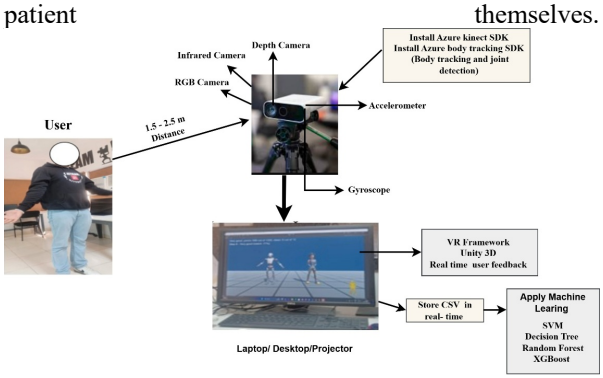


Fig. 1. System architecture of the proposed VR rehabilitation framework.

1) User Positioning and Capture Volume: The participant is positioned at 1.5-2.5 m from the sensor unit. This distance is selected as it corresponds to the operating distance of the depth sensor in the Azure Kinect DK, where the depth-sensing accuracy remains stable. Furthermore, this distance ensures that the participant's full upper body remains within the field of view of the sensor during the exercises [24].

2) Multi-Modal Sensing Hardware: The sensor unit (Azure Kinect DK, mounted on a tripod) integrates complementary sensing modalities that together enable

markerless motion capture: (a) a depth camera, which captures 3D spatial data of the user's body for skeletal reconstruction, with infrared sensing supporting operation under variable lighting conditions [25]; (b) an RGB camera, which captures colour video for visual reference and recording; and (c) an accelerometer and gyroscope, whose onboard inertial measurement unit (IMU) provides orientation and motion-stability data for the sensor's spatial calibration [26].

3) Software Integration: Once the hardware is positioned, the Azure Kinect SDK and the Azure Body Tracking SDK are installed on the host machine. This software layer converts the raw depth, infrared and RGB streams into a skeletal representation and performs the body tracking and joint detection on which the rest of the framework depends [27].

4) Display Unit: The processed skeletal and sensor data are streamed to a laptop, desktop or projector, which hosts the real-time visualisation and processing environment. This marks the transition from raw sensor acquisition to the application layer of the framework [28].

5) Biofeedback: The VR framework, built in Unity 3D, receives the tracked joint data and renders them as an interactive on-screen avatar that mirrors the user's movements in real time. The user's movement is captured by the sensor, processed by the SDK and reflected as real-time visual feedback, forming the core interaction mechanism of the rehabilitation system [29]. Joint data are also stored in CSV format in real time for subsequent machine-learning analysis.

B. Study Design and Dataset

A supervised machine-learning framework was developed to evaluate and compare several classification algorithms, using clinical and cervical movement features recorded from participants who received either VR-assisted or conventional physiotherapy. The study included 55 participants, of whom 27 were in the VR group and 28 were in the conventional physiotherapy group. Each participant performed seven cervical exercises, and data for every exercise were collected at four points during the intervention period: the 2nd, 4th, 6th and 8th weeks. This produced a longitudinal dataset of 1,540 exercise-level records (55 participants × 7 exercises × 4 time points). The analysis had two objectives. The first objective was to compare the clinical outcomes between the VR and conventional rehabilitation groups. The clinical outcome examined in this study was pain reduction, and changes in pain scores between baseline and Week 8 of rehabilitation were compared between the two groups. The second objective was to assess the performance of various machine-learning models in predicting rehabilitation outcomes. Random Forest, SVM, Decision Tree and XGBoost models were trained to predict exercise performance, which was classified as correct, slightly incorrect, or incorrect. The study aimed to see whether the models could reliably assess rehabilitation performance, rather than the treatment group to which participants belonged. Because each participant contributed multiple records across exercises and time points, the data were divided at the participant level rather than the record level. All records belonging to a given individual were placed in only one subset, which prevented the models from being tested on data from participants they had already seen during training. The data were split into training (80%), validation (10%) and independent testing (10%) subsets, with stratification by the target class where the class distribution allowed. ROC curves were generated from predicted probabilities obtained through 5-fold cross-validation.

IV. RESULTS

A. Pain Outcomes

Table II shows the descriptive statistics for pain intensity, measured on the VAS, in the VR and conventional physiotherapy groups at baseline and in Week 8. At the start of the treatment period, the VR group had a mean VAS score of 4.667 (SD = 0.620) and the conventional group had a mean score of 4.000 (SD = 0.816). These scores placed both groups in the mild-to-moderate pain category. By Week 8 of the treatment period, the VR group had a mean VAS score of 1.704 (SD = 0.542) while the conventional group had a mean score of 2.321 (SD = 0.476). Thus, both groups saw a decrease in pain over the treatment period, with the VR group experiencing a descriptively larger decrease in pain. This pattern of pain reduction suggests that the VR-assisted rehabilitation may produce better pain outcomes for patients with ankle sprains compared to conventional rehabilitation. However, inferential statistical tests are needed to confirm this hypothesis.

TABLE 2. DESCRIPTIVE STATISTICS OF VAS SCORES AT BASELINE AND WEEK 8

Group	Time Point	N	Mean	SD	Variance	Skewness	Kurtosis
VR	Baseline (Week 0)	27	4.667	0.620	0.385	−1.741	2.080
VR	Week 8	27	1.704	0.542	0.293	−0.135	−0.475
Conventional	Baseline (Week 0)	28	4.000	0.816	0.667	0.000	−1.491
Conventional	Week 8	28	2.321	0.476	0.226	0.809	−1.456

B. Classification Performance

Table 3 displays the classification performance of the four models trained separately on the data from the two groups (conventional therapy and VR therapy). The four models evaluated are XGBoost, Random Forest, Support Vector Machine (SVM), and Decision Tree. The evaluation metrics used are precision, recall, F1-

score and accuracy. XGBoost model achieved the best results among the models. For the data from the VR therapy group, it achieved an accuracy of 86.1%, a precision of 0.878, a recall of 0.861 and F1-score of 0.866. For the data from the conventional therapy group, it achieved an accuracy of 80.4%, a precision of 0.823, a recall of 0.804 and F1-score of 0.811. Random Forest was the second-best performing model with accuracies of 83.1% and 78.1% for the VR and conventional groups respectively. The SVM model performed slightly worse with accuracies of 81.8% and 76.5%. Finally, the Decision Tree model had the lowest accuracy.

TABLE 3. PERFORMANCE COMPARISON OF ML CLASSIFICATION MODELS

Model	Therapy	Precision	Recall	F1-Score	Accuracy
Decision Tree	Conventional	0.764	0.748	0.752	74.8%
Decision Tree	VR	0.812	0.794	0.801	79.4%
Random Forest	Conventional	0.793	0.781	0.785	78.1%
Random Forest	VR	0.847	0.831	0.836	83.1%
SVM	Conventional	0.781	0.765	0.771	76.5%
SVM	VR	0.836	0.818	0.824	81.8%
XGBoost	Conventional	0.823	0.804	0.811	80.4%
XGBoost	VR	0.878	0.861	0.866	86.1%

In Fig 2, all the models performed better with VR data compared to their performance with conventional therapy data. The improvements in accuracy were between 4.6 and 5.7 percentage points across the different models. Additionally, the improvements were observed across all the evaluation metrics, not just one measure. This indicates that the features derived from the VR framework provided more reliable and rich features for predicting rehabilitation outcomes compared to conventional therapy data.

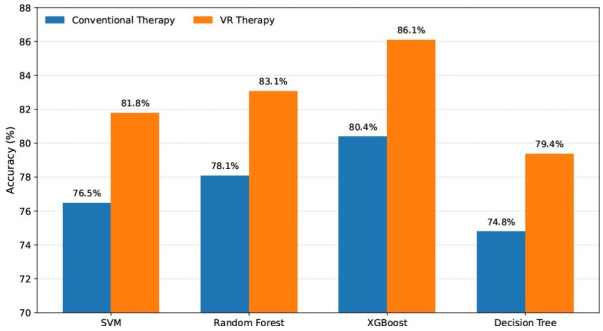


Fig. 2. Classification accuracy of the four ML models for the conventional and VR therapy groups.

C. ROC Analysis

Receiver operating characteristic (ROC) analysis was performed to evaluate the model's discriminative ability. A ROC curve plots the true positive rate against the false positive rate at different classification thresholds. The area under the curve (AUC) summarizes the curve as a single value between 0.5 and 1.0. A value of 0.5 signifies that the model performs no better than random classification, while values closer to 1.0 indicate stronger discriminative ability in the model. Fig. 3 shows the ROC curves of the four models for the VR therapy group. XGBoost achieved the highest AUC (0.940), followed by Random Forest (0.900), SVM (0.880) and Decision Tree (0.860). All models performed well above the random classifier, indicating that the features captured by the VR framework carry meaningful information for predicting rehabilitation outcomes, and the higher AUC values of the ensemble methods are consistent with their accuracy results.

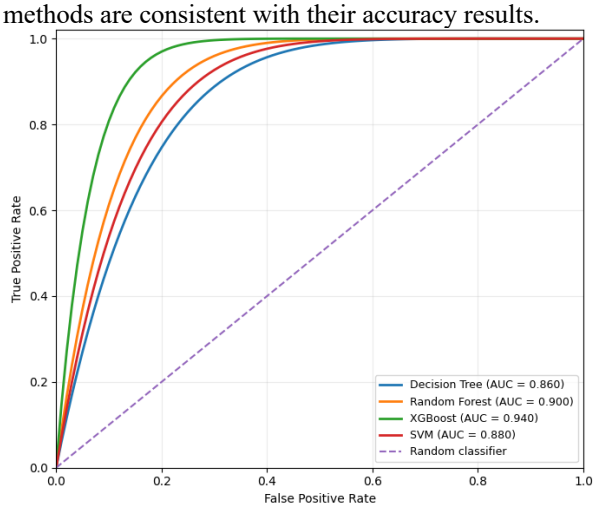


Fig. 3. ROC curves of the four ML models for the VR therapy group.

D. Confusion Matrix Analysis

Fig. 4 shows the confusion matrices of the four classifiers used to classify exercise performance as correct, slightly incorrect or incorrect. Rows give the actual class and columns the predicted class; values on the diagonal are correct classifications, and values off the diagonal are errors. XGBoost gave the highest accuracy, classifying 804 of 1,000 instances correctly (80.4%), followed by Random Forest (78.1%), SVM (76.5%) and Decision Tree (74.8%). All four models recognised correct movements most reliably, with recall

between 80.0% and 86.0% for this class. Most errors occurred in the incorrect class, where 21–30% of instances were labelled as slightly incorrect. The models therefore separated correct from incorrect performance well but had more difficulty distinguishing the two error categories, which may partly reflect the smaller number of incorrect samples in the dataset.

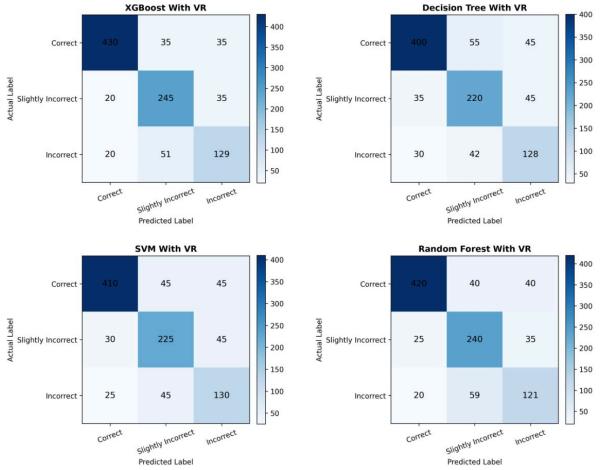


Fig. 4. Confusion matrices of XGBoost, Decision Tree, SVM and Random Forest for exercise-performance classification.

V. CONCLUSION

This study compared VR-assisted and conventional physiotherapy for chronic neck pain and examined whether machine-learning models could predict rehabilitation outcomes from clinical and cervical movement data. Pain decreased in both groups over eight weeks, with mean VAS scores falling from 4.667 to 1.704 in the VR group and from 4.000 to 2.321 in the conventional group The four classifiers showed improved performance with VR data because their accuracy percentages score between 4.6 and 5.7 points. XGBoost generated the best accuracy results for both sets at 86.1% and 80.4% and achieved the top AUC score of 0.940. The VR framework provides complete information for predicting results because it records joint angles together with movement range and exercise performance scores. The confusion matrices showed that correct movements were recognised most reliably, whereas slightly incorrect and incorrect performance were more often confused. The study shows various weaknesses which affect its overall strength. The research groups displayed different starting pain levels while machine-learning analysis worked with too few participants because it had only 55 subjects which makes the results preliminary. The framework requires future testing with a bigger group of independent participants to prove its effectiveness for supporting remote cervical rehabilitation at home.

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