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DEVELOPMENT OF A LOW-COST AND ACCESSIBLE HAND TREMOR REHABILITATION GAME FOR UNHEALTHY PATIENTS

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Abstract— Hand tremor rehabilitation for unhealthy patients is often hindered by the high costs and limited accessibility of traditional methods. This study addresses these challenges by developing "Fidgy," an affordable and engaging game-based rehabilitation system designed for Android tablets. The game was created using FIGMA for design and Flutter with Dart for coding, focusing on improving hand-eye coordination and muscle control through interactive gameplay with varying difficulty levels. The game was deployed on Android Tablet with graphical user interface to access audio and video settings, start the game, select difficulty, select level, Display the scoreboard and exit the game options. This study was evaluated using Thirteen participants (seven males and five females). Testing revealed that healthy patients achieved near-maximum taps with minimal time (average 31.2 seconds per level in easy mode), while unhealthy patients faced significant delays (average 45.4 seconds per level) and lower tap counts, reflecting their motor impairments. The results indicate that "Fidgy" can effectively support rehabilitation by offering a cost-effective and adaptable solution, potentially enhancing accessibility and patient outcomes in hand tremor therapy.

I. Introduction

Hand tremors, which manifest as involuntary and rhythmic muscle contractions, often severely impair individuals suffering from various neurological conditions, including Parkinson's disease, multiple sclerosis, and post-stroke recovery. Such impairments can drastically reduce the quality of life, making everyday tasks difficult and burdensome. Post-stroke patients, in particular, may experience flexor hypertonia and finger extensor weakness, which hinder their ability to perform functional grasps [1]. Consequently, restoring hand function through effective rehabilitation is of paramount importance. Physical therapy has been well-established as a beneficial approach for rehabilitation, aiding in the improvement of motor functions through repetitive training of the affected limb [2]. Despite the proven efficacy of these methods, there is a significant shortage of rehabilitation therapists relative to the growing number of patients requiring such services [3]. This discrepancy underscores the need for innovative solutions to supplement traditional rehabilitation practices.

Robotic assistance in hand rehabilitation has emerged as a promising avenue, with exoskeleton-based devices demonstrating considerable effectiveness [4]. Traditional exoskeletons, which utilize rigid linkages to transmit force, have been successful in facilitating hand rehabilitation training [5-7]. These devices are capable of providing substantial force and precise control over hand movements. However, their design typically involves placing motors and control systems directly on the patient's hand, resulting in increased weight and reduced ease of use. To address these limitations, cable-driven hand rehabilitation exoskeletons have been developed. These systems separate the motors and control mechanisms from the hand, thereby reducing the weight and enhancing the portability of the exoskeleton [8-12]. Additionally, soft exoskeletons have been introduced, offering further improvements in comfort, safety, and lightweight design [13-15]. Despite these advancements, the dynamic analysis and control of soft exoskeletons present significant challenges due to their complex behavior.

In the literature, control methods for soft hand exoskeletons are generally categorized into two types: open-loop and closed-loop. The open-loop control method is frequently used due to its straightforward structure and ease of implementation. For example, Yun et al. developed a pneumatically-driven glove, Exo-Glove PM, using an open-loop control system [16], and Feng et al. utilized an open-loop controller for a soft robotic hand to assist with grip motion [17]. However, the absence of a feedback mechanism in open-loop control results in low control accuracy and poor anti-disturbance capability, limiting its practical applications.

Closed-loop control methods, particularly those based on the proportional-integral-derivative (PID) scheme, are more suitable for soft hand rehabilitation exoskeletons due to their feedback mechanisms. PID controllers are favored for their simple structure and model-free control algorithm. For instance, Yap et al. developed a fully fabric-based bidirectional soft robotic glove employing a PID control algorithm to regulate valve duty cycles based on pressure feedback [18]. Similarly, Jones et al. implemented a PI controller in a cable-actuated finger exoskeleton to achieve torque control for single joints [19], and Fischer et al. used a PID controller in a portable assistive glove [20]. Ang et al. also utilized a PID controller for valve control in a soft robotic glove [21]. Beyond PID controllers, other closed-loop control algorithms have been applied to soft hand exoskeletons. Zhao et al. designed a state-machine controller for a soft assistive hand [14], and Polygerinos et al. employed a sliding-mode controller (SMC) for a soft robotic glove to facilitate at-home rehabilitation [22]. However, the presence of unconscious tremors during hand rehabilitation introduces disturbances that affect the control system, necessitating a model-free controller with superior disturbance rejection capabilities.

Active Disturbance Rejection Control (ADRC), proposed by Han in 1998, is a promising candidate for these applications [23]. ADRC has been applied across various platforms within the control community. For example, Ma et al. implemented the ADRC control algorithm for a quadrotor helicopter [24], Alonge et al. used ADRC for controlling linear induction motors [25], Sariyildiz et al. applied ADRC to series elastic actuators [26], Ahi et al. utilized ADRC for a one-axis gimbal mechanism [27], and Tao et al. employed ADRC for tracking control of parafoil systems in wind environments [28]. The core concept of ADRC is to aggregate internal uncertainties (including time-variant, time-invariant, linear, and nonlinear dynamics) and external disturbances into a "total disturbance," which is then estimated and compensated in real-time using an extended state observer (ESO) [29]. Additionally, as a model-free controller, ADRC is well-suited for soft hand rehabilitation robots, whose dynamic models are challenging to analytically determine.

In response to the need for more accessible and cost-effective rehabilitation tools, this study introduces "Fidgy," a game designed to aid in hand tremor rehabilitation. Fidgy aims to be a low-cost, engaging, and user-friendly system that enhances hand-eye coordination and muscle control through interactive gameplay. The game features various difficulty levels tailored to the severity of the patient's tremors, providing adaptive and personalized rehabilitation experiences. By tracking performance metrics such as scores and levels, Fidgy offers valuable feedback to both patients and healthcare providers, fostering continuous improvement in motor function.

II. Materials and Method

To develop our rehabilitation game, we utilized several tools and platforms:

Design Environment: FIGMA

Coding Environment: Visual Studio

Hardware: Laptop and Android Tablet.

The software application is deployed on an Android Tablet running the rehabilitation application. This choice ensures cost-effectiveness while maintaining accessibility. processor.

A. Development Phases

The development process was structured into three main phases as shown in Figure 1.

B. Design and Coding

User Interface Design: The initial design was created using FIGMA, a powerful UI/UX design tool. In FIGMA, each page of our application was designed using various tools like the vector editing tool, the app library tool, and the widget library. These tools allowed for detailed and precise design of the application's user interface.

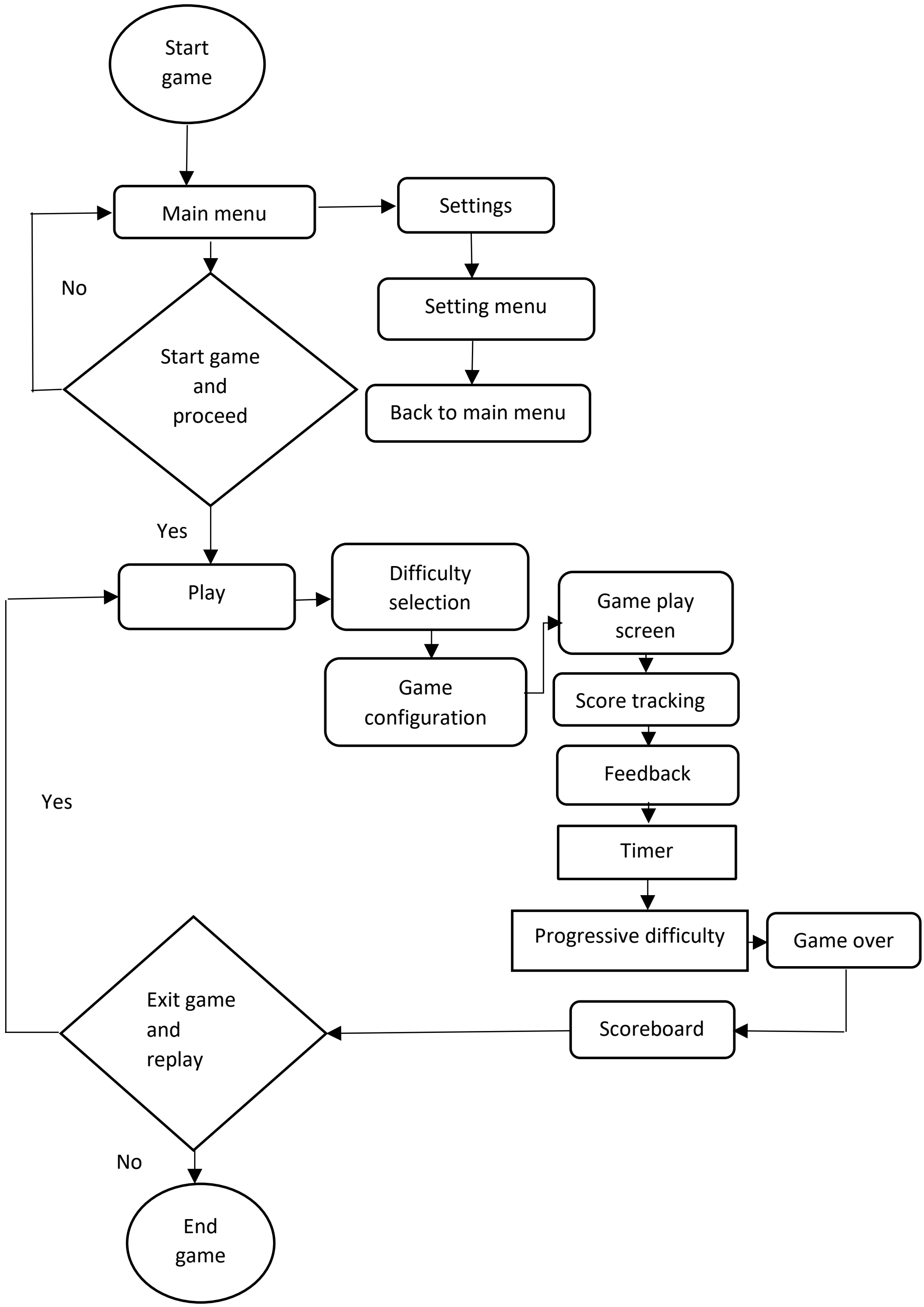

Figure 1: Technical Work flow of the software's operation

Programming: We utilized Flutter, a UI toolkit for building natively compiled applications. The coding was done in Visual Studio. The codebase was organized into folders, with the main Dart code contained in the lib folder. Three types of code were written: Dart code for application logic, Widget code for UI elements, and Layout code for arranging these elements. Dart code defined the behavior and data handling, while Widget and Layout codes brought the UI designs to life, ensuring proper positioning and functionality of buttons, texts, icons, and images.

C. Deployment and Testing

The application was tested extensively on an Android Tablet to ensure functionality and user-friendliness. This phase involved running the application, identifying any issues, and refining the code to address these issues. Testing on an actual device helped in validating the user interface and the performance of the application under real-world conditions.

D. Reviews and Feedback

After initial testing, the application was reviewed by potential users and experts in the field. Feedback was collected to identify areas of improvement. This iterative process ensured that the final product was both effective and user-friendly.

E. Database and Storage

The application's data storage relies on the Android device itself, utilizing a shared preference system for data management. This approach ensures that all scores and progress data are collected and stored locally on the device. This data can be retrieved and displayed on the scoreboard within the application.

F. Deployment Platform

Android Tablet was chosen and deployed due to its widespread availability, affordability, and powerful capabilities. Android devices offer a compact, compatible platform with a robust processor, advanced operating system, and a large touch screen suitable for our graphical user interface.

Additionally, the audio system can provide feedback to the patient, and the internal and external memories support computational processing and data storage as shown in Figure 2.

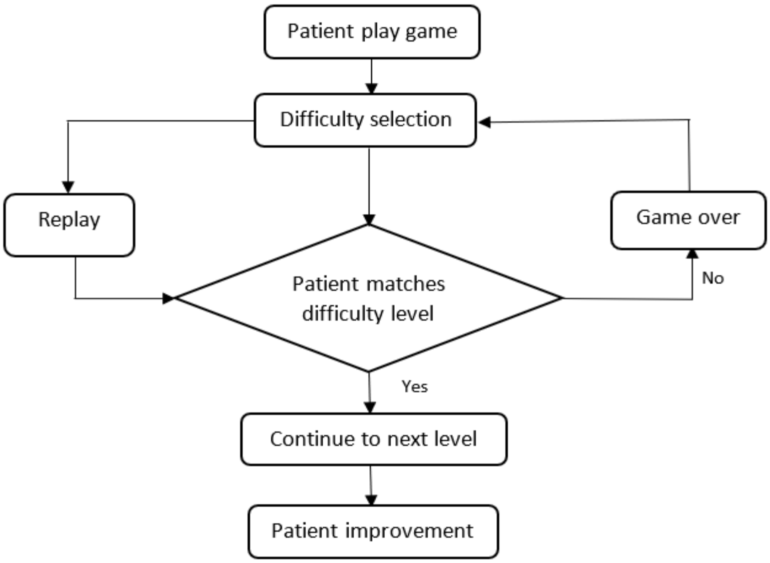

Figure 2: Patient rehabilitation Workflow

The Android Application performs the following operations:

- Start the rehabilitation exercise and instruct the patient through graphical instructions.
- Access settings to adjust audio and video preferences.
- Start the game, select difficulty, and configure game options such as choosing a level and selecting the hand (right or left) for gameplay.
- Progress through the game, where correct gameplay increases difficulty and incorrect gameplay results in game over.
- Display the scoreboard and exit the game.
- Navigate back to the start menu.

The pictorial illustration of the fidgy rehabilitation game

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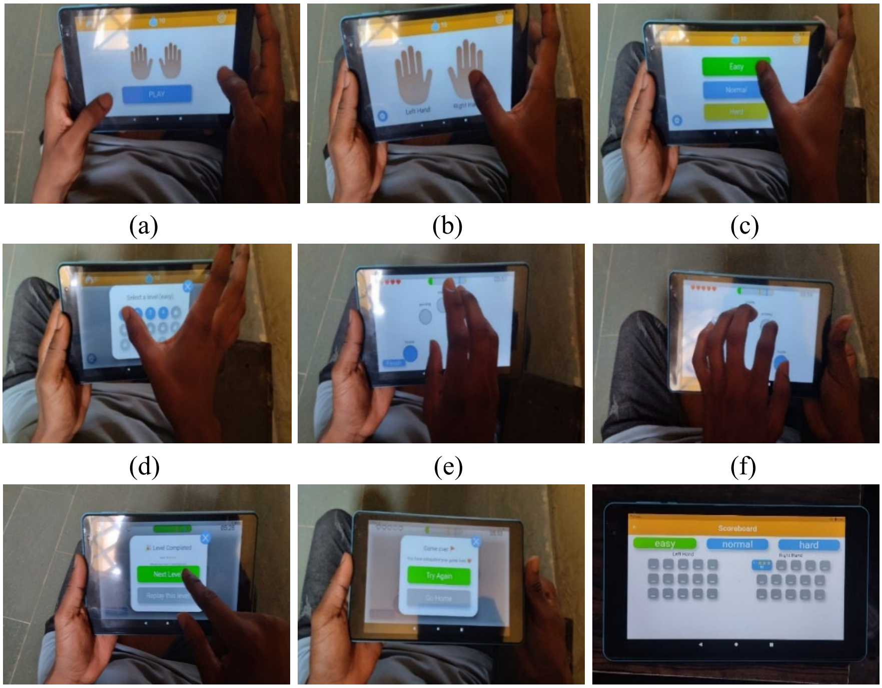
workflow and sequential operations is shown in Figure 3.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Figure 3: Pictorial illustrations of the fidgy rehabilitation game workflow and sequential operations (a) Start game (b) select left or right (c) Select difficulty (d) select level (e) Play game with right hand (f) Play game with left hand (g) Level passed, move to next level or replay (h) Level failed, replay level (i) Scoreboard

G. Gaming Logic

The game logic encompasses several elements, including game settings, number of taps, difficulty levels, and scoring format. The game features three difficulty levels: Easy, Normal, and Hard, each with 15 levels. These difficulties differ by the time allotted for gameplay: 6 minutes for Easy, 4 minutes for Normal, and 2 minutes for Hard. Scoring is based on the number of taps, with each tap equivalent to 2 points. The progression through levels is defined by Equations (1) and (2).

- For the number of taps required to pass:

$$15 + (\text{level} - 1) * 2 \qquad (1)$$

- For the number of maximum possible taps:
  $25 + (\text{level} - 1) * 3$ (2)

These equations apply to all the difficulties i.e. Easy, Normal, and Hard.

For example;

- Equation (1),
  15 + (1-1) *2 = 15 + 0 = 15 taps for the number of taps required to pass.
- Equation (2),
  25 + (level – 1) * 3 = 25 + 0 = 25 taps for the number of maximum possible taps.

There are 2 variables in the game logic, the time taken to play each difficulty and the number of taps for each level.

III. Result and Discussion

The developed low-cost figgy game was tested on both healthy and unhealthy people in each level of the game.

A. Participant

A total of 13 healthy and apparently unhealthy young participants with 7 males and 5 females voluntarily participated in this study.

Participants were recruited from the student's population of University of Ilorin, Ilorin, Nigeria. The recruitment is by means of consultation, social network advertisement, and word-of-mouth.

This study used the existing available literature to determine the inclusion or exclusion of the participants. The work reported in [30] examined the influence of aging on the physiological hand tremor which this work tends to avoid by inclusion only the participants in the range of 20 to 28 years of age. Participants that are diagnosed with some preexisting conditions such as metabolic diseases, cardiovascular, hypertension, neurological conditions, lower extremities or musculoskeletal injury of the back that occurred recently, used of drugs and other related disorders that could influence the tremor characteristics were also excluded [30].

B. Result Gotten from Testing Game by a Healthy Patient

A healthy patient completed all stages in the simple setting with the fewest taps possible,

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demonstrating flawless accuracy and performance as depicted in Table 1. Level 1 takes 25 seconds, while level 5 takes 37 seconds. This is a progressive rise in time. The patient's ability to adjust to rising demands without experiencing a drop in performance is demonstrated by this evolution, which shows an average rise of 3 seconds per level. The amount of consistency in performance indicates that the easy mode is appropriate for sustaining engagement with a gradual increase in challenge.

Table 1: Healthy Easy Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	25	25	25
2	28	28	29
3	31	31	32
4	34	34	33
5	37	37	37

Table 2 shows the result of the healthy patient's performance in the normal mode which was, on average, 0.4 taps less than the maximum number of taps feasible in certain situations. There is a trend to how long it takes to finish each level: level 1 takes 25 seconds, while level 5 takes 36 seconds. This suggests that the normal mode offers healthy patients a well-balanced challenge that pushes their abilities while keeping the degree of difficulty bearable.

Table 2: Healthy Normal Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	23	25	45
2	26	28	47
3	29	31	43
4	32	34	44
5	35	37	48

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The healthy patient continued to do well in the hard mode, with an average deficiency of 0.6 taps per level, or about the maximum number of taps as highlighted in Table 3. Level 1 takes 25 seconds, whereas level 5 takes 36 seconds, indicating a modest rise in difficulty in the amount of time required. The patient's steady performance suggests that the hard mode is appropriate for advanced rehabilitation exercises because it is demanding but doable.

Table 3: Healthy Hard Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	24	25	25
2	27	28	26
3	30	31	29
4	33	34	30
5	36	37	36

C. Result Gotten from Testing Game by Unhealthy Patient

In the easy mode, the unhealthy patient took significantly longer to complete each level compared to the healthy patient, with times ranging from 43 to 48 seconds per level, averaging around 45.4 seconds as Table 4 underscores. The number of taps is slightly below the maximum possible taps (average shortfall of 0.4 taps per level), indicating some difficulty in achieving perfect performance. The extended time taken reflects the patient's challenges with motor control and response time, emphasizing the need for a more gradual difficulty curve in the rehabilitation game for unhealthy patients.

In the normal mode, the unhealthy patient again shows a slower response time, with times ranging from 40 to 46 seconds per level, averaging 43.6 seconds as shown in Table 5. The number of taps is slightly lower than the maximum possible taps (average shortfall of 0.6 taps per level). The time taken to complete each level decreases slightly as the patient progresses, suggesting a learning effect or adaptation to the game mechanics. However, the performance gap compared to the healthy patient remains noticeable, indicating that normal mode still presents a significant challenge for unhealthy patients.

Table 4: Unhealthy Easy Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	23	25	45
2	26	28	47
3	29	31	43
4	32	34	44
5	35	37	48

Table 5: Unhealthy Normal Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	22	25	45
2	25	28	46
3	28	31	40
4	31	34	42
5	34	37	45

Table 6: Unhealthy Hard Mode

Level	Number of Taps	Maximum Possible Taps	Time Taken (sec.)
1	21	25	46
2	24	28	47
3	27	31	42
4	30	34	43
5	33	37	44

In the hard mode, the unhealthy patient struggled more compared to the easier modes as depicted in Table 6. The number of taps remains lower than the maximum possible taps (average shortfall of 0.8 taps per level), and the

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time taken to complete each level is consistently high, ranging from 42 to 47 seconds per level, averaging 44.4 seconds. This mode is particularly challenging for unhealthy patients, highlighting the need for personalized difficulty adjustments in rehabilitation games to ensure they are both challenging and achievable.

D. Discussion of Results

The study's findings show that, when utilizing the rehabilitation game at different difficulty levels, healthy and sick individuals perform very differently from one another. In good health, the patients performed consistently, reaching almost maximal taps and gradually finishing levels in the allotted time. In the easy mode, for example, healthy patients required 31.2 seconds on average for each level, progressively rising in complexity without a discernible performance decline. This shows that they can adjust and retain control precision under a range of demands. This shows that the game is appropriate for preserving motor skills since it effectively challenges and engages healthy individuals. On the other hand, individuals who were unwell had significant challenges, particularly in terms of the amount of time required to do tasks; in easy mode, averages reached 45.4 seconds per level. The significance of motor control issues is shown by this delay, which highlights the necessity for more progressive difficulty escalation and longer time allowances for these individuals. The constant difficulty in all modes, especially in the hard mode, where levels take an average of 44.4 seconds to complete indicates the need for specialized rehabilitation techniques. These results highlight how crucial it is to have modifiable difficulty settings and customized feedback systems so that the game continues to be both demanding and accessible, facilitating successful rehabilitation for patients with different degrees of motor impairment.

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IV. Conclusion

This study demonstrates that "Fidgy," a game-based rehabilitation tool designed for Android tablets, effectively addresses the challenges associated with unhealthy patients. By providing a cost-effective and accessible solution, the game offers a practical alternative to traditional, expensive rehabilitation methods. The testing results reveal that healthy individuals perform well, showing consistent improvement in hand-eye coordination and muscle control across various difficulty levels. In contrast, unhealthy patients exhibit longer completion times and reduced tap counts, highlighting the game's potential to accommodate varying levels of motor impairment. The findings suggest that "Fidgy" is a valuable tool for enhancing home-based rehabilitation, offering an engaging and adjustable platform that can contribute to improved patient outcomes and alleviate the burden on healthcare systems. Future research should explore further customization and integration of adaptive features to better support diverse patient needs and optimize the rehabilitation process.

Departmental Ethical Review Board Statement: This study was approved by the Biomedical Engineering Departmental ethical review board.

Informed Consent Statement: consent of all the participants were duly obtained prior to their participation.

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