Palm Gripper Measurement Device for Post-Stroke Rehabilitation Progressive Tracking

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ABSTRACT

Various devices are used in the medical world to measure grip force. However, there is no well-defined method being used to quantify the distribution of grip forces applied by post-stroke patients. It is important to track the patient's progress in neurofeedback training throughout rehabilitation with quantitative evaluation. A palm gripper measurement device is being developed, equipped with Force Sensing Resistors (FSRs) (RP-S40-ST model) to capture grip force. The device provides valuable insights into rehabilitation progress by assessing the grip force. The analogue value from FSRs is linearly interpolated from the input range to the output range using the map function; 'map(avg_force, 0, 1023, 0, 15)' to scale the 'fsrReading' from the input range of 0 to 1023. The input range is converted into a score 0 to 15 scale of a bar graph to indicate the amount of force measured. The accuracy showed by Pearson's r shows a correlation trend between the analogue value and length of the bar graph with 0.97651 and 0.98083, respectively. A matrix was plotted for three subjects with different object sizes for device testing which shows the adjusted R^2 is 0.955 highest for big objects and the lowest adjusted R^2 is 0.63672 for small objects.

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Introduction

In conventional practice, rehabilitation physicians and therapists employ dynamometric devices as a supported method for evaluating grip strength progress, in tandem with the utilization of the Medical Research Council (MRC) scores depicted in Figure 1 for muscle strength grading. The strength testing is categorized into levels zero (0) until five (5). The assessment of the MRC scale requires the expertise of trained medical and therapist professionals, and currently, there are no available devices capable of measuring it. The MRC scale serves as a tool for medical evaluation rather than a motivational aid for patients. It quantifies distinct movements like elbow flexion and wrist extension, while grip activity involves a complex combination of these specific motions. For example, gripping a cylindrical object involves 2 to 5-finger flexion plus thumb abduction and flexion. Altogether 6 trick movements. All these movements are measured as a sum score in the MRC scale as shown in Figure 1. Consequently, grasping the nuances of the MRC scale exceeds the capacity of most patients.

Visual indicators used to monitor the rehabilitation progress are potentially more efficient for a post-stroke patient [1]. A good example would be having a device that can indicate the progress of the post-stroke patient during rehabilitation training with a Graphical User Interphase (GUI) to monitor their progress. The basis theory for conventional and modern practices for post-stroke rehabilitation is neuro feedback training which requires constant repetitive movement to build muscle memory which will improve neuroplasticity. The motivation behind repetitive movements can be heightened when patients can monitor their progress through a straightforward interactive system or devices.

Many researchers have studied the constraints of conventional assisted measurement devices utilized for muscle grade measurement, as outlined in Table 1. Most of these devices lack the capability for progress monitoring to effectively support patients' motivation.

Table 1

The (standard) MRC-scale of muscle strength/weakness

Grade	Description
0	No contraction
1	Flicker or trace of contraction
2	Full range of active movement, with gravity eliminated
3	Active movement against gravity
4	Active movement against gravity and resistance
5	Normal power

Figure 1: Table of MRC assessment score muscle strength grading [2]

Table 1: Devices used in measuring muscle strength together with the MRC scale

Title	Device	Research work	Limitation
Linking prioritized occupational performance in patients [3].	Hand-dynamometer	A hand dynamometer was used to test the maximum handgrip strength. The maximum value of three tries.	Cannot be used by therapist to check progress of patients from home. Not IOT-based.
Recovered grasp performance after stroke depends on interhemispheric frontoparietal connectivity [4].	Martin-vigorimeter	A rubber ball vigorimeter measured maximal grip strength from medical records within the first four days after stroke.	Not IOT-based. Suitable to focus on Ball grip
Customized manual muscle testing for post-stroke upper extremity assessment [5]	Electronic handheld Manual Muscle Tester (MMT)	Modified electronic manual muscle tester for CFA analysis with structural equation modelling of UE manual muscle testing.	Expensive Possible use of IOT

A regular dynamometer is a cheap option for measuring the amount of force for a palm grip during the rehabilitation process. However, it lacks the capability to measure objects with different shapes such as cylindrical, rectangles etc. The methodology used was suitable for the device data validation. Another optional device is the Martin Vigorimeter which also be used to identify the rehabilitation progress of post-stroke patients. However, it is an analogue device and absences the potential of having IoT features.

Moreover, the Vigorimeter focuses more on one type of grip known as the ball grip. A more advanced option is the electronic handheld Manual Muscle Tester (MMT) to measure grip force, usually used by therapists to measure passive grip. With additional cost, the device could accommodate IoT features if needed. The MMT is versatile in representing rehabilitation results for various upper spasticity movements for post-stroke patients. A more targeted approach was to conduct rehabilitation using MMT by creating or adding a scoring system for an added value in post-stroke rehabilitation [6].

Additionally, dynamometric testing is also found ineffective for weak muscles when movement against resistance is impossible, frequently related to the case of peripheral nerve injuries [7]. This period is important to identify nerve regeneration for rehabilitation purposes. Few researchers have also discussed the dependability and validity of the MRC grading scale regarding peripheral nerve disorders [7]-[8]. In addition, the MRC scale does not consider the Range of Motion (ROM) for which a movement may be performed, nor does it describe the level of resistance against which a movement can be performed [7], [9].

This paper explores the potential enhancement of the MRC scale through the integration of a supplementary device alongside traditional measurement tools. The device aims to motivate patients by enabling them to monitor their rehabilitation progress. It is achieved through IoT features that measure muscle strength focusing on gripping activity applying 15 unitless scale using embedded programming. The 15-unitless scale design of the device is not related to the MRC scale as it measures trick measurement, a combination of a few specific movements, rather than MRC-specific movements.

The measurement device implements a distributed force application between two sensors for better gripping surfaces and different shapes. The muscle strength grading is displayed on the LCD panel and quantitatively measured. The sensitivity of the FSR is set to 10K Ω resistance for a more controlled sensitivity[10]-[11].

System Fabrication

The measurement device is built with a force resistive resistor, and a pressure film sensor RP-S40-ST models and both sensors are configured using Arduino embedded programming. The force sensor was built in a parallel circuit to read the applied force (or grip) while simultaneously integrating the readings. Figures 2 and 3 show the schematic diagram and the prototype.

The device is built with a Velcro strap to be attached to the object of interest as shown in Figure 4. Patients are required to grip and lift the object and the force applied to grip the object is mapped to 15 scale and represented in a bar graph at LCD panel.

The objective of the rehabilitation session is to be able to grip and lift the object. The 15 scale is not related to any mass unit. It is a utility function that enables scaling or mapping a number from one range to another. It accepts an input value, maps it to a new range, and returns the mapped value. The function interpolates the input value from the input range to the output range in a linear fashion. A combined method of mapping both sensors helps to integrate sensors in the system. Therefore, to achieve linearity in readings, the device calibrates the sensitivity of the sensor's analogue value and scale as an output of increasing and decreasing value on the 16 x 2 LCD panel display.

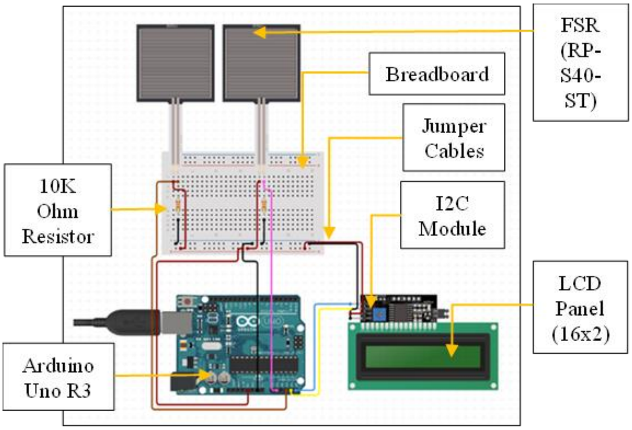

Figure 2: Schematic diagram drawn using circuito.io

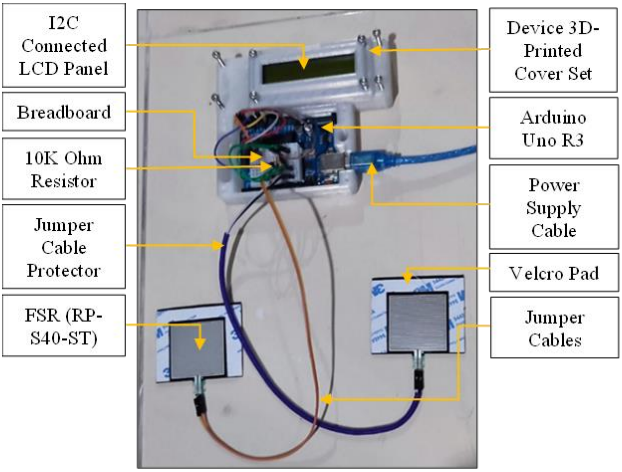

Figure 3: Device anatomy for palm gripper device

It adjusts the analogue value by averaging the input data from both sensors to enable values that span from 0 to 1023 (the analogue input range), to a number that corresponds to the length of the force bar on the LCD, which varies from 0 to 15. Figure 5 shows how to use the measurement device.

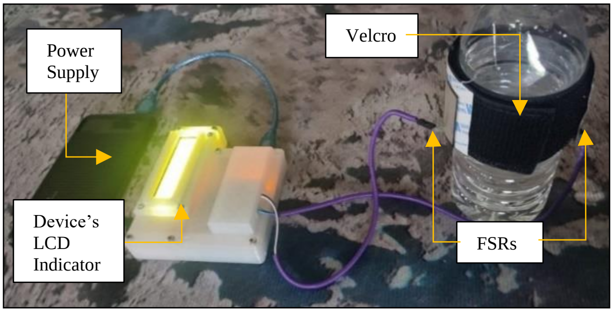

Figure 4: Full device layout for experimentation

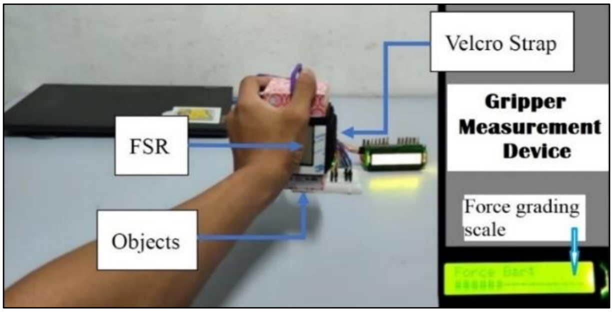

Figure 5: Experimentation for subject's grip force

System Evaluation

FSR coefficient and reliability

The altering and aligning process of the device's output to match a recognised standard or reference was conducted. The FSR sensors had a logarithmic growth relation between the mass and the amount of force exerted during gripping on the surface of the FSRs. From the device, the average analogue value between the two FSR sensors was considered to map into 15 scales in linear relation. The analogue reading was compared to the length of the bar graph over a mass increment of 10 g.

The programming aims to create a scale to represent the amount of force applied to the FSR in a definitive way. Although the analogue value may vary with the repeatability of the experiment, the variations are not significant. Figure 6 illustrates the programming flow with a map function to measure the linear correlation between increasing weight (g) with the analogue reading and unitless 15 scale of the LCD bar. The maximum analogue value for a 5V Arduino Uno-R3 is 0 – 1023 and the maximum length of bar score using a 16 x 2 LCD Panel is programmed for a 15 scale.

Table 2 shows the results between the mass of 10 g to 80 g with the average analogue value and bar length score. Both analogue reading and bar score show high correlation with the increasing weights and Table 3 shows Pearson correlation coefficient r was 0.97 and 0.98, respectively.

However, using the independent variables, the model is unable to reliably predict or estimate the values of the dependent variable [12]. To put it another way, the model is incapable of accurately capturing or accounting for the linear relations between the variables. Therefore, the results suggest that the system can compensate for the average error of output from both FSRs. The FSR is not able to provide precise force value but is capable of estimating the linear relation of the bar score and the force applied to the pressure films.

The objective of using 15 unitless scales is to measure the progress of the rehabilitation session for patients. Each patient's progress depends on the object shapes and grip position at the object (i.e., near the centre of mass, edge, etc.) and is not measured by the weight of the objects. Therefore, it is important to not use any scale comparison for the 15-unit scale introduced in the device.

Table 4, in the context of linear regression, suggests that the intercept value indicates that the projected value of the FSR's average analogue reading is 67 when the weight is zero. The estimated uncertainty or variability is shown by the 36.5 standard error. Put practically, this indicates that, with a 95% confidence level, the actual value of the average analogue reading may differ by around 36.5 units from the expected value.

Similarly, the intercept value of 0.5 suggests that when the weight is zero, the predicted value of the bar length score is 0.5. The standard error of 0.64 indicates the variability or uncertainty associated with this estimate. In this case, the actual value of the bar length score could deviate from the predicted value by around 0.64 units, with 95% confidence.

However, the adjusted R-square value indicates that the model may be too simple (underfitting) for the data, leading to poor performance. Still, a small standard error of slope indicates a more precise estimate and strengthens the evidence for a significant relationship between the bivariate. Therefore, opening the possibility for further study to develop a mathematical model for a more robust control algorithm.

Implementing a robust control algorithm based on a linear regression model may be one of the solutions to mitigate the variability and analogue data fluctuation from the sensor [13]. Nonetheless, the uncertainty of the system such as advanced mathematical modelling, external disturbances, dynamic changes, and human factors needs to be addressed properly.

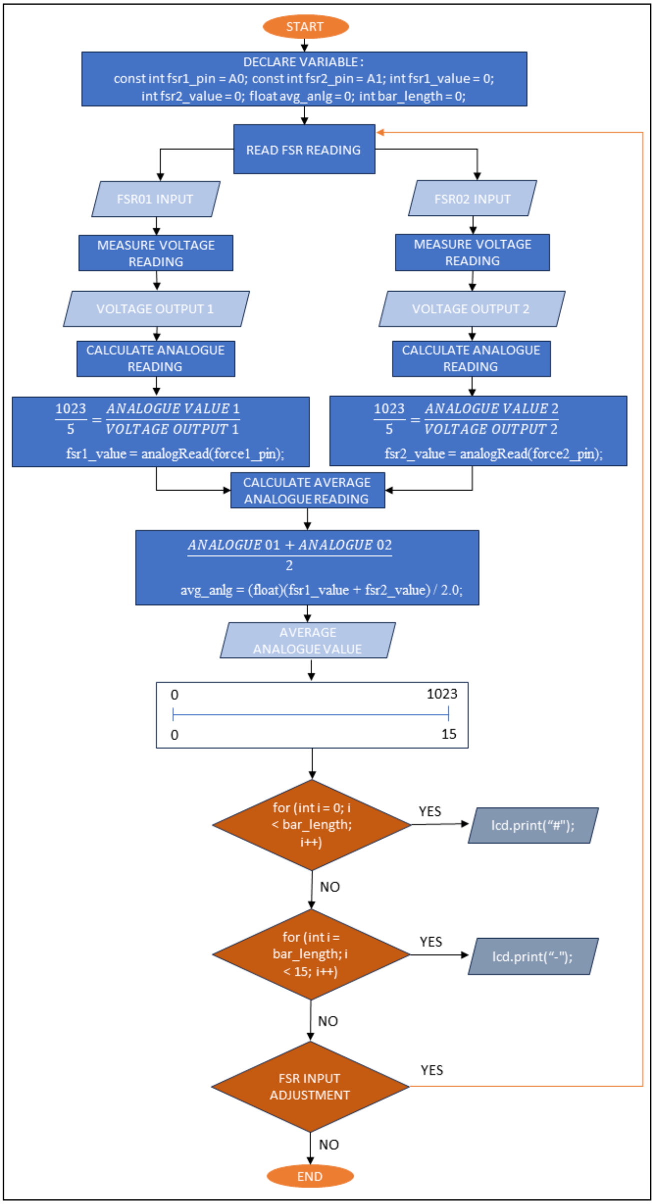

Figure 6: Coding flowchart for palm gripper device

Table 2: Data of average analogue reading of sensor and length of the graph with weight

Weight (g)	Bar length score	Analogue reading
10	1	140
20	3	240
30	6	430
40	7	498
50	7	560
60	9	634
70	10	690
80	11	720

Table 3: Statistical analysis of analogue reading and bar length score

	Average analogue reading	Bar length score
Number of points	9	9
Degrees of freedom	7	7
Residual sum of squares	258.00899	4.13298
Pearson's *r*	0.97651	0.98083

Table 4: Summary analysis of the relationship between analogue reading and bar length score

	Intercept		Slope		Statistics
	Value	Standard error	Value	Standard error	Adj. *R*-square
Average analogue reading	67.32221	36.54101	9.26055	0.77188	0
Bar length score	0.52059	0.64135	0.13785	0.01346	0

Different shapes evaluation

Weight and analogue readings are used for guidance in designing the bar graph to get a trendline in a laboratory scale calibration. However, the actual gripping or pinching process in rehabilitation sessions is not related to weight only. Other parameters involved during the process are gravity, friction force, centre of mass and surface area. All these parameters are important but not significant in measuring patients' rehabilitation progress.

Palm grips involve numerous forms of grabbing or holding techniques that are utilised in various activities or disciplines. For device experimentation, several objects were lifted without limiting to one gripping style for each object while trying to get as much surface area involved. The objects were divided into two categories big and small and tested with three healthy subjects with no medical issues in hand muscle or joint. The demographic of the subjects is shown in Table 5. The score of each subject represents the length of the 15-score bar graph.

Table 6 shows an example of a holding technique for big and small categories. A scatter plot matrix was utilised to depict bivariate connections between variable combinations of two object classifications and the score of each subject from Table 6. Each scatter plot in the matrix depicts the link between two variables, to investigate several associations in a single graphic [14]. There are many ways to express the degree of variability or error that may be anticipated in the results of the device used to evaluate palm grip for post-stroke rehabilitation. The Standard Error of Measuring (SEM) was used to validate the results. Any method is valid if it provides a rough estimate of the possible discrepancy between a person's observed score and true score because of factors including measurement uncertainty, performance variability, and additional sources of error [15].

Table 7 categorises the 10 specific objects into two main categories which are big and small objects. These classifications were made to observe the variations of bar length score between two different categories of objects in terms of size. The variations in the bar length were further observed by the inclusion of three subjects in the same age group. A set of matrix plots was established to understand the direction and strength of correlations between variables by visually examining the scatter plots derived from Table 7.

Table 5: Subject demographic information

Name	Gender	Age
Subject 1	Female	23
Subject 2	Male	23
Subject 3	Male	25

For each scatter plot matrix of the classified big and small object, the Adjusted R^2 was calculated and obtained using Origin 2023b. The adjusted R^2 determines the proportion of variance in the score of each subject. A model with a value of 1 completely predicts the score values of each subject. A number less than or equal to 0 indicates that the model has no predictive value. That said, all the calculated adjusted R^2 from Figures 7 and 8 suggest that the model can be predicted for different subject scores. Results for big objects show an Adjusted R^2 closer to 1 compared to small objects which shows a lower R^2 value which indicates that bigger objects for palm grip are more precise to draw a linear correlation for each subject. Furthermore, the scatter plot matrix patterns show a positive correlation for both categories. This signifies that as one variable rises, the other tends to rise as well [12], [14].

Table 6: Example of objects gripping position and sizes

Objects	Big	Small
Knife		
Book		
Mug		
Box		

On the other hand, Pearson’s *r* was also calculated for both categories. The correlation coefficient is a statistic that quantifies the degree and direction of a linear link between each subject and the gripping score. As the calculated R^2 and Adjusted R^2 suggest the positive linearity of the correlation, Pearson's r will consider the strength and direction of linear correlations. From the results, the highest value for adjusted R^2 is 0.7841 and the lowest value 0.63672 clearly shows minimal difference in subject score comparison. The difference in the *r*-value may occur because of gender differences between subjects. However, a positive value of *r* indicates that as one variable increases, the other variable tends to increase as well and is in line with the interpretation values of R^2 and Adjusted R^2 [12]. Pearson’s *r* for small objects shows a weaker positive linear relationship compared to big objects thus implying that smaller objects have less accuracy for the grip score of each subject[14], [16].

Based on the palm grip force comparison between small objects and big objects, it can clearly see a difference in *p*-values for every subject although the difference is small. The outcomes may differ depending on the heart rate, sleep, and other activities done by the subject prior to the data being assessed. Nonetheless, the methodologies used were accurate and reliable [15], [17]. However, the repeatability of the experiment can be achieved with a minor inaccuracy [6], [18].

Table 7: Table of subject score record (0 to 15 bar score)

No.	Object		Bar length score		
			Subject 1	Subject 2	Subject 3
1	Knife	Big	6	5	7
		Small	3	2	4
2	Book	Big	6	5	7
		Small	3	2	4
3	Mug	Big	6	5	7
		Small	3	2	4
4	Box	Big	6	5	7
		Small	3	2	4
5	Phone	Big	6	5	7
		Small	3	2	4
6	Saddle	Big	6	5	7
		Small	3	2	4
7	Screwdriver	Big	6	5	7
		Small	3	2	4
8	Tupperware	Big	6	5	7
		Small	3	2	4
9	Duster	Big	6	5	7
		Small	3	2	4
10	Bottle	Big	6	5	7
		Small	3	2	4

From the results obtained, good *p*-values suggest that the subjects have good muscle motor control skills [18]. This is because the FSR (RP-S40-ST) with a 10K Ω of resistance is very sensitive to the force applied on the surface of the FSR. The device can also be used with a higher resistance value to further increase the sensitivity of the FSRs. It is also true vice-versa as we decrease the resistance value, the FSRs will be less sensitive implying that a larger magnitude of force is required to achieve the same results as using a 10K Ω resistance [16], [19].

There was no obvious sign of hysteresis of the FSRs based on the evaluation. This indicates that the force applied to the FSRs was within the limits of the material wear and tear for the thin pressure-sensitive film of the FSRs [20], [21]. In the future, to improve the dependability of the FSRs, modelling the piezoelectric bender's hysteresis using the Bouc-Wen model is highly suggested. Nonetheless, major causes of hysteresis are often caused by instantaneous displacement rather than small voltage fluctuation[22]-[23].

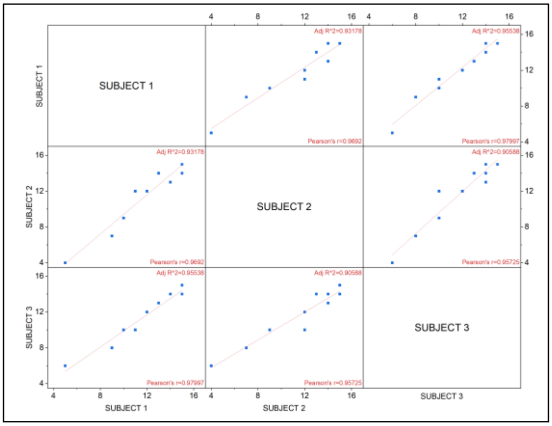

Figure 7: Scatter plot matrix of subject’s grip score comparison for big objects

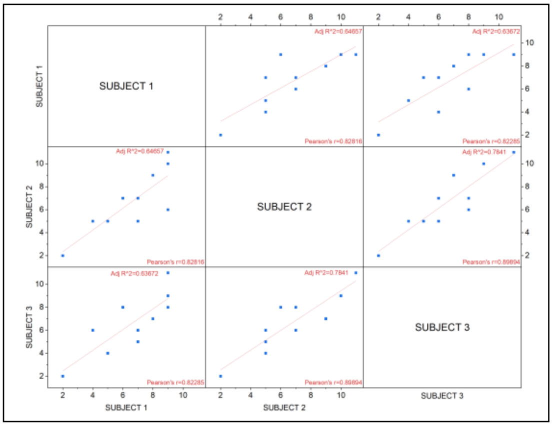

Figure 8: Scatter plot matrix of subject's grip score comparison for small objects

In conclusion, from the study, there is no solid guarantee that the selected sensors were dependable for an accurate measurement of a palm gripping force, but it is a great choice to measure a small magnitude of force per surface area within a controlled condition [16]. This is proven as the FSR calibration shows a precise reading although less accurate in comparison to the datasheet. All the tests show that sensors have similar readings when tested with 10K Ω resistance although the accuracy between the coding's theoretical value and actual output bar graph score value may vary due to the fluctuation of sensor reading and the deteriorating of the sensor itself over time [16], [24].

Conclusion and Recommendation

This study examines the systematic assessment to quantify palm gripping force in patients in terms of analogue reading of an FSR and representing it in 15 unitless bar scores for rehabilitation progress tracking. The assessment was a success by mapping the calibration to the bar graph of the LCD Screen. According to the study findings, the graphs demonstrated that both sensor measurements are acceptable for detecting and recording observed force. However, the measurements of the gripping force during rehabilitation are not limited to weight only. Other parameters such as the centre of mass, and friction of the objects are not taken into consideration when designing the 15 unitless bar score.

The device will provide biofeedback for patients undergoing hand rehabilitation which will improve patients' participation where the MRC scale is too complicated to support patients' motivation. The device will be the first portable sensory of its kind that can monitor dynamic hand movements and give biofeedback to patients.

Based on previous experiments, some recommendations are suggested based on efforts that have emerged throughout the conclusion of this project. This paper discussed the preliminary evaluation of the Palm Gripper Measurement Device on healthy subjects, hence a pre-clinical evaluation in controlled condition with hand grip and pinch weakness patients as identified by Rehabilitation Physician and Occupational Therapist need to be conducted for a more significant and relevant result. However, to prevent hysteresis errors, it is advisable for the device to incorporate a one-minute break between sessions. Longer break periods between sessions are advisable.

Contributions of Authors

The authors confirm the equal contribution in each part of this work. All authors reviewed and approved the final version of this work.

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Conflict of Interests

All authors declare that they have no conflicts of interest.

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