# Optimizing self-exercise scheduling in motor stroke using Challenge Point Framework theory

*Abstract*— **An important challenge for technology-assisted self-led rehabilitation is how to automate appropriate schedules of exercise that are responsive to patients needs, and optimal for learning. While random scheduling has been found to be superior for long-term learning relative to fixed scheduling (Contextual Interference), this method is limited by not adequately accounting for task difficulty, or skill acquisition during training. One method that combines contextual interference with adaptation of the challenge to the skill-level of the player is Challenge Point Framework (CPF) theory. In this pilot study we test whether self-led motor training based upon CPF scheduling achieves faster learning than deterministic, fixed scheduling. Training was implemented in a mobile gaming device adapted for arm disability, allowing for grip and wrist exercises. We tested 11 healthy volunteers and 12 hemiplegic stroke patients in a single-blinded no crossover controlled randomized trial. Results suggest that patients training with CPF-based adaption performed better than those training with fixed conditions. This was not seen for healthy volunteers whose performance was close to ceiling. Further data collection is required to determine the significance of the results.**

## I. INTRODUCTION

Intensive and repetitive motor practice is crucial for recovery of upper extremity functions following a stroke [1]. Whilst the number of patients who need rehabilitation increases, availability of physical therapists and specialist gym facilities remains limited [2]. Many simple methods for unsupervised, self-led exercise programmes, e.g. paper-based instructions (such as GRASP [3]), achieve minimal participation due to a lack of patient motivation and engagement [4].

Serious games can provide an engaging and interactive platform to motivate patients to actively participate in self-driven therapy [5]. Studies such as [6] showed Wii-based movement therapy to be as effective as modified Constraint Induced Movement Therapy (CIMT) with high patient compliance. However, the vast majority of existing rehabilitation games, including bespoke rehabilitation hardware, rarely adapt to the patients condition resulting in diminished skill acquisition [7], [2].

Efforts to tailor serious games based on patients abilities have resulted in positive outcomes. The most developed paradigm is to assist a patient through active means [8]. Studies such as [9] and [7] have shown positive outcomes to assisting patients through physical active-robotic means. Though, such a strategy may encourage a patient to slack if the presence of assistance is detected and rely on complicated robotic devices [2]. Few studies have attempted to adapt only the virtual task dynamics. N. Hocine *et al*. showed increased movement amplitude over a graphics tablet work-space when dynamically adapting difficulty [10]. Though, their system required complex offline computation and allowed for unprescribed movements. Thus, limiting the ability to determine efficiency over current physical therapy practices.

Y Choi *et al*. [11] illustrated an implementation of the Challenge Point Framework (CPF) without changing real-world task dynamics. The adaptation employed elements of *flow* (first coined by Czikszentmihalyi [12]), Contextual Interference (CI), and Knowledge of Result (KR) to create an optimal learning experience [13]. The CPF conceptualizes CI and KR as practice conditions that are affected by the performer's skill level and the task difficulty [13]. CI is a learning phenomenon where interference during practice yields poor practice performance but results in a stronger long-term memory representation thereby yielding greater long-term performance [14]. KR describes the effect of providing feedback of performance to a learner to encourage a change in their action plan in a desirable way [13]. *Flow* is a psychology term used to conceptualize a learner's engrossment and effort within a task based upon their skill level and the level of challenge [12]. The CPF attempts to challenge performers at their optimal motor capacity, guiding them towards a state of *flow*, whilst randomizing a multi-task practice schedule which promotes long-term memory, at the expense of short-term performance. Y. Choi *et al*. proposed that randomizing practice order alone still contained a limiting factor of practice redundancy, whereby tasks that the performer finds most challenging will be favoured over easier tasks. However, their study only analyzed healthy volunteers and did not investigate their adaptive approach on a patient cohort.

N. Schweighofer *et al*. illustrated CI effects on long-term memory in chronic stroke patients when exposed to a pseudo-random schedule of training. The protocol consisted of patients performing 300 repetitions of three similar gripping tasks, over two days, using a grip-force device to track three identical trajectories that were merely phase-shifted to achieve differences in tasks. Long-term skill level was marginally higher following random training but not following fixed training. Given the similarity of tasks, adaptation was not necessarily influencing performance alone, due to skill transfer between tasks. In reality, patients will often train on vastly different motor skills [14].

The article [12] presents a theoretical approach to account for differences in skill level between two players competing in a game that involves a reaching-like movement. J. E. Duarte *et al*. discuss the intertwined relationship between player skill level, task difficulty, and motivation, by drawing upon concepts of both *flow* and the CPF. They hypothesize that dynamically adapting difficulty to regulate the level of success for each player will account for skill discrepancies whilst promoting both motivation and learning. Though, the experimental procedure allows for unprescribed movements, whereby CI levels are determined by player behaviour and game dynamics. Thus, no optimization of CI can occur.

Though it is recognized that difficulty adaption is required within serious games for stroke rehabilitation, research is still yet to uncover how best to optimize such adaption and structure training sessions. Many adaption techniques within literature employ ad-hoc solutions that rely on either specific robotic or game metrics, and lack generalization.

This paper describes a pilot study investigating the potential use of a theoretical CPF [13], following the implementation of Y. Choi *et al*. [11].

## II. METHODS AND MATERIALS

### A. GripAble System

Rehabilitation programmes take priority of lower-limb over Upper-Limb (UL) function despite the imperative requirement of UL function within Activities of Daily Living (ADLs) [15]. Thus, we used GripAble, depicted within Figure 1, to specifically target training of hand function within this study. The GripAble is a low-cost passive hand-grip promoting independent rehabilitation of grasp and upper limb function. The device is wireless and allows patients to engage in repetitive and meaningful training via software on an Android tablet at home or within clinic.

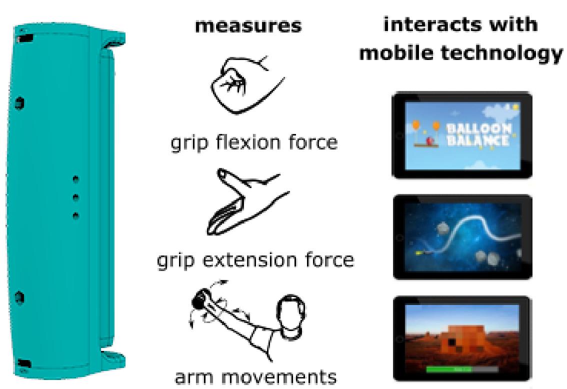


Fig. 1. GripAble hand-grip device and rehabilitation apps. The device is capable of measuring both finger flexion and extension force and wrist/arm motion depending on experimental protocol. Extension force is measured with the use of Velcro-straps that affix around the wrist and over the fingers.

The controller is ergonomic and compliant with a dynamic flexible moving shell allowing both isotonic and isometric muscle behaviours without compromising force sensitivity. Further detail of technical specifications and usability can be found within [16]. The GripAble software is able to capture and record grip-force, which is used within training games *e.g*. to track a trajectory by controlling a character.

### B. Patient Information

Stroke patients suffering from upper limb hemiparesis but cognitively able to understand and concentrate for the length of the study were recruited. Patients with significant co-morbidities *e.g*. visual neglect, severe cognitive impairment, and depression were excluded. All patients screened were admitted at Charing Cross Hospital at the Hyper-acute/Acute Stroke ward. Before patients were approached, permission to test each patient was approved by both the consultants and the research ethics committee (REC) at Imperial College London NHS Trust. Ethical approval was granted by the NRES Committee South East Coast-Kent Committee. Written informed consent was obtained from the participants after the nature of the study was explained.

Table I gives an overview of patients recruited for this study. 143 patients with arm-weakness were screened, of which 15 were recruited and 12 participated, aging from 43-96y ($66 \pm 17y$). The majority of patients excluded either suffered from severe wrist impairment, cognitive deficits that impaired their ability to follow instructions, or were due to be moved or discharged from the ward. Three patients failed to complete the study due to admission from the hospital, but their partial data sets have been included. Three patients withdrew consent. 12 healthy student volunteers were recruited aging 20-22y ($21 \pm 1y$). One volunteer was excluded from the study due to switching between dominant and non-dominant hands.

The Hospital Anxiety and Depression (HAD) scale and Edinburgh Handedness (EH) was administered prior to recruitment. Fugl-Meyer (FM) was administered following recruitment and once patients completed the study.

### C. Protocol

Candidates were comfortably seated, within a standard chair or sat up in bed, in front of a tablet (at a distance of 0.5m) with a GripAble placed in their non-dominant (healthy subjects) or hemiplegic hand (patients) and, if necessary, arm resting on a cushion with wrist in neutral position and elbow at 90.

Table II gives an overview of the protocol where BL is a baseline trial, TR are training trials (54 trials with duration fixed at 12 minutes for both groups and a flexible break after 6 minutes), PRE and POS are pre- and post- training assessments (9 trials) directly preceding or following a training session. A ten-minute rest interval following each training session was provided prior to a post assessment. Patients were asked to perform a visuomotor tracking exercise using wrist or finger movements. Nominal difficulty of tasks and regularity within trial space varied over the course of 5 training sessions (3 days) for the adaptive group, or remained constant for the fixed group, whilst ensuring intensity remained constant between both groups. Candidates were randomly assigned to either a Fixed (constant conditions) or Adaptive (varied conditions) group with no cross-over using the single-blind method.

TABLE I
PATIENT INFORMATION AND CLINICAL DATA (IS = ISCHEMIC, SC = HEMORRHAGIC, A = AMBIDEXTROUS)

| Patient ID | Age | Stroke type | Dominant side | Affected side | Post-stroke duration (days) | Gender | HAD | Sessions Completed | Group |
|---|---|---|---|---|---|---|---|---|---|
| pt001 | 73 | IS | R | L | 8 | M | 21 | 3 | 2 |
| pt002 | 68 | H | R | R | 12 | F | 7 | 5 | 1 |
| pt003 | 61 | IS | R | R | 4 | M | 10 | 5 | 2 |
| pt004 | 96 | IS | R | L | 15 | F | 23 | 5 | 1 |
| pt005 | 39 | IS | R | L | 7 | M | 21 | 5 | 1 |
| pt006 | 91 | IS | R | R | 11 | F | 6 | 5 | 2 |
| pt007 | 53 | IS | A | R | 11 | M | 0 | 5 | 2 |
| pt008 | 73 | IS | L | R | 9 | M | 13 | 4 | 1 |
| pt009 | 65 | IS | R | L | 5 | M | 1 | 5 | 2 |
| pt010 | 44 | IS | R | R | 6 | M | 20 | 5 | 2 |
| pt011 | 70 | IS | R | R | 2 | F | 4 | 5 | 1 |
| pt012 | 59 | IS | R | R | 6 | M | 21 | 2 | 1 |

TABLE II
PROTOCOL OVERVIEW

| Day: | 1 | 2 | 3 |
|---|---|---|---|
| Morning: | BL<br>TR 1<br>POS 1 | PRE 2<br>TR 3<br>POS 3 | PRE 4<br>TR 5<br>POS 5 |
| Afternoon: | PRE 1<br>TR 2<br>POS 2 | PRE 3<br>TR 4<br>POS 4 | PRE 5 |

Conditions within assessments (BL, PRE, and POS) were identical between both groups with a randomized order of tasks to allow performance to be an indicator of skill acquisition, as opposed to observing the effects of tracking error reduction. Training was split over the morning and afternoon periods to achieve high repetitions of tasks, which is necessary to promote learning, whilst preventing fatigue.

### D. The Challenge Point Framework

A new game, depicted within Figure 2, was developed for this study due to the specific protocol and data requirements between training sessions. Each trial began with a cue, to illustrate the GripAble movement that would control the character, followed by a count-down prior to starting the trial.

In [14], N. Schweighofer *et al*. represented three tasks using grip force and identical trajectories that were phase-shifted, which may have limited CI effects as both movement patterns and trajectories were similar resulting in less interference between tasks in randomized practice. We aim to increase task variability as this is more practical when applied to functional rehabilitation environments. Thus, we select wrist radial/ulnar deviation, supination/pronation, and finger flexion/extension to represent three individual tasks, each with corresponding trajectories to reinforce the required movement by association. These movements were selected as they vary in nominal difficulty and are each a different degree-of-freedom thereby requiring alternating neural patterns to produce the required motor behaviours.

Players were awarded points based on popping the bubbles by following the trajectory. Thus, Knowledge of Result (KR) is constantly provided throughout the study. Each trajectory variation contained varying amounts of bubbles based upon trajectory frequency and period.

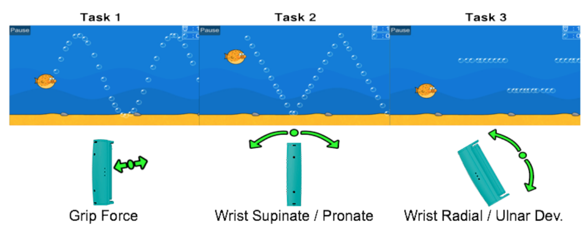


Fig. 2. Game and task design. Tasks 1, 2 and 3 are represented as unique trajectories and GripAble movement patterns. For each trial, the background scrolls from right to left with an animated fish character, giving the perception of player propagation through the trial. A cue of the GripAble movement pattern is then presented followed by a count down prior to propagating the trajectory. The time and score of the trial is always shown on the top right of the screen.

Two algorithms were used to adapt gameplay by varying both task regularity within trial space (prior to training), and the nominal difficulty of a task (within training). In [11] healthy volunteers performed best when exposed to both algorithms. Research has shown that randomizing tasks induces CI effects; though, Y Choi *et al*. expresses limitations due to practice redundancy of tasks that the learner can perform well. Thus, we not only randomize task order but also vary task regularity using Equations 1-4.

$$N_T(k) = N_{TT} \times \hat{\epsilon}(k) \tag{1}$$

$$\hat{\epsilon}(k) = \frac{\epsilon_s^{pre}(k) \times \epsilon_{s-1}^{pos}(k)}{\sum_i (\epsilon_s^{pre}(i) \times \epsilon_{s-1}^{pos}(k))} \tag{2}$$

$$\epsilon_s(k) = P(k) - P^{ref}(k) \tag{3}$$

$$P(k) = \frac{BubbleCount_k}{TotalBubbles_k} \tag{4}$$

where $N_T$ is the number of trials to be scheduled for a given task, $N_{TT}$ is the number of total trials, $k$ is a task, and $\hat{\epsilon}(k)$ is the normalized performance error for a given task. $\hat{\epsilon}(k)$ is calculated from $\epsilon_{s-1}^{pos}$ and $\epsilon_s^{pre}$, which are the post- and pre- assessment performance errors for the previous and current training sessions respectively. The denominator is a normalizing factor which ensures that $\sum_k(\hat{\epsilon}(k)) = 1$ [11]. Equation 3 illustrates how performance error is calculated for a given assessment session. The performance error $\epsilon_s(k)$ is calculated based upon the number of bubbles collected in each trajectory $P$ minus a $P^{ref}$ performance reference. We choose to calculate performance based on a finite score as the error is unbounded within the game context. We must normalize performance, as the bubble count is frequency dependent and may vary based on character speed. Pref was set at 80% of the total bubbles for each task, so as to be suitable for both controls and patients. The number of trials per task is limited to 8-32 trials to prevent one task from saturating a training block whilst still allowing the tasks that the performer finds most challenging to be practiced more often.

We vary nominal difficulty of tasks by changing the speed at which the character propagate through the level. Motor adaption of the background velocity, which affects both perceived character speed and trajectory frequency, was performed using Equation 5.

$$D_t(k) = D_{t-1}(k)\Big(1 + \alpha\big(P_t(k) - P^{ref}(k)\big)\Big) \tag{5}$$

where $t$ is a trial, $k$ is a task, $D$ is the difficulty for a given trial, $\alpha$ is a constant representing the learning rate, $P_t$ is the performance of the player for the current trial, and $P^{ref}$ is the performance reference. Trajectory repetitions (that are set to two) were truncated, so as to alter the challenge aspect without providing additional practice time.

### E. Analysis

We determine skill acquisition of candidates by calculating the average tracking error. We do not use performance error as this is a metric of success that may be affected by game dynamics (*e.g.* the diameter of the character). We first calculated error using the difference between trajectory and player path, shifting the trajectory to remove bubble propagation to the character at the start of the trial, and taking the Root-Mean-Squared Error (RMSE) for a given trial. The RMSE was calculated using a convolution with a window of 0.25 seconds taking the median of window samples to remove sporadic motion and grip artefacts. We then compute the median error across all trials of the same task, so as to not favour rare occurrences of good or bad performance, and use the mean of medians to compute the average performance across all tasks for a given assessment, so as to not disregard good or bad performance of an individual task. Initially we first check the data with a Shapiro-Wilk analysis, verifying whether the data has normal distribution. This test also identifies any outliers. A Levenes test was then used to highlight equal variances across the two study groups (fixed and adaptive), for both the control and patient cohorts. An unpaired two-sample T-Test was used to check for a statistically significant difference between any two groups. The significance level was $< 0.05$.

## III. RESULTS AND DISCUSSION

There was no significant difference between conditions in the baseline test of day 1 for controls, RMSE $\mu = 26.89 \pm 9.19$ and $\mu = 20.86 \pm 7.74$ for Fixed and Adaptive groups with t-test $p = 0.053$. This was also true for patients, $\mu = 26.21 \pm 9.53$ and $\mu = 28.11 \pm 10.88$ with $p = 0.58$.

In the delayed retention test on day 3 there was no significant difference for controls, where $\mu = 24.06 \pm 2.35$ and $\mu = 26.19 \pm 2.98$ with $p = 0.22$. This was also true for patients, $\mu = 25.12 \pm 10.75$ and $\mu = 19.59 \pm 3.67$ t-test with $p = 0.31$. Though results did not reach significance, we found that patients within the adaptive group performed better than those within fixed with a 22% relative average improvement in RMSE. This effect was not seen within controls. There were no significant differences when analyzing day 3 delayed retention test for each task, in the task order: finger flexion/extension, wrist supination/pronation, and wrist radial/ulnar deviation, where $F$ is Fixed and $A$ is Adaptive, for controls: $[F : \mu = 26.76 \pm 7.31, A : \mu = 31.87 \pm 2.15, p = 0.17], [F : \mu = 28.28 \pm 4.01, A : \mu = 28.85 \pm 8.25, p = 0.88], [F : \mu = 17.15 \pm 1.76, A : \mu = 17.85 \pm 2.09, p = 0.56]$ and for patients: $[F : \mu = 27.28 \pm 19.32, A : \mu = 23.42 \pm 5.31, p = 0.68], [F : \mu = 22.92 \pm 4.29, A : \mu = 17.81 \pm 4.49, p = 0.13], [F : \mu = 25.15 \pm 13.73, A : \mu = 17.55 \pm 2.75, p = 0.26]$.

Figure 3 shows trial errors over five training sessions for a patient in the adaptive group. Performance over day one varies considerably during training. Subsequent training sessions show improvement; though, error difference between trials still partially fluctuates. This is an expected hypothesis of CI, whereby short-term performance gains are compromised to promote use of the use of long-term memory. Error difference between post- and pre- assessments illustrate consistent performance.

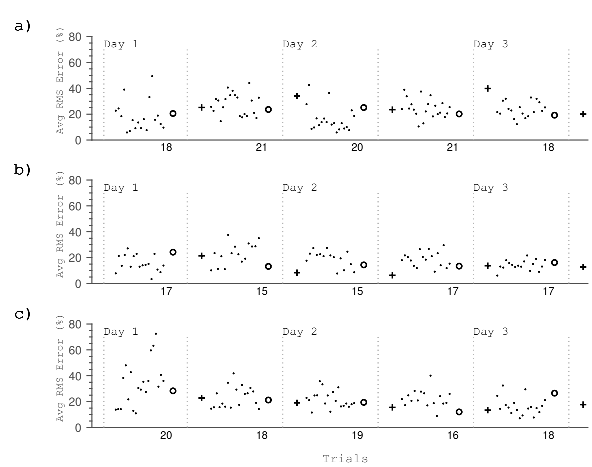


Fig. 3. Participant pt010 training trial errors over three days, where figures a-c) represent finger flexion/extension, wrist supination/pronation, and wrist radial/ulnar deviation. The dotted vertical lines represent morning or afternoon sessions. Each point on this graph is a trial, each circle and plus is the median error for post- and pre- tests. Task regularity has been shown along the x-axis.

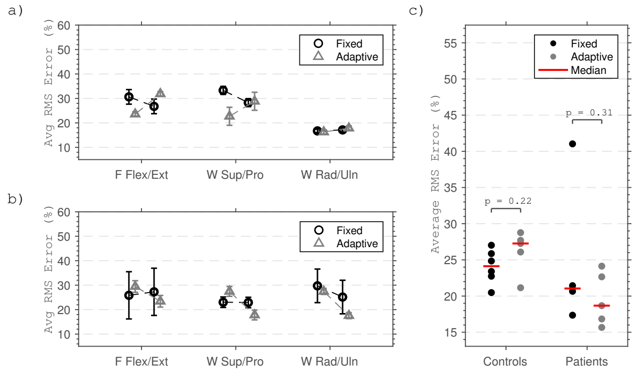


Fig. 4. a,b) Average RMSE and standard error for baseline and the delayed retention test on day 3 for each task and each condition, where a) is the control cohort and b) is the patient cohort. For each task shown, average baseline is the left point and performance on day 3 delayed retention test is the right point. Task labels are: F Flex/Ext for Finger Flexion/Extension, W Sup/Pro for Wrist Supination/Pronation, W Rad/Uln for Wrist Radial/Ulnar deviation. No significance for individual tasks on day 3 were found. c) Average performance of the three tasks on the delayed retention test on day 3 for fixed and adaptive conditions. The overall median has been shown to illustrate overall performance for each condition. T-Test p-values shown for comparison between conditions for each cohort.

Figure 4c depicts overall performance for all tasks for the delayed retention test on day 3 and illustrates that the adaptive algorithm caused controls to perform worse than those training with fixed conditions. Conversely, patients elicited signs of improvement when conditions of the task were adapted based on their performance throughout the study.

Figures 4 a) and b) show baselines (left points) and average performance of day 3 retention tests (right points) for each task. Performance was very variable in day 1 as participants were familiarizing themselves with the GripAble device.

Controls show no distinguishable affect for both wrist supination/pronation and radial/ulnar deviation by the end of day 3. Though, controls within the fixed group performed better than those within adaptive for finger flexion/extension, which may have solely contributed to a degraded overall performance when comparing across all tasks. Patients within the adaptive group showed a greater improvement across all tasks than those within fixed group. Though, this was most distinctive for both wrist radial/ulnar deviation and supination/pronation. Additionally, patients within the adaptive group elicited consistent performance, unlike those within the fixed group where standard error was generally greater for flexion/extension and radial/ulnar deviation.

Figure 5b depicts total repetitions for each task. Percentage difference between fixed and adaptive within each cohort have been shown for ease of comparison. Results show that the adaptive CI algorithm varied repetitions of tasks by approximately 3% overall for the control cohort and 17% for the patient cohort. Patients found wrist supination/pronation the least challenging in comparison to finger flexion/extension, with wrist radial/ulnar deviation being the most challenging. Considering the performance for patients on day 3 retention test (refer to 4b) showed an improvement of supination/pronation but it was practiced the least, infers that the adaptive difficulty may have contributed greatly to this performance gains.

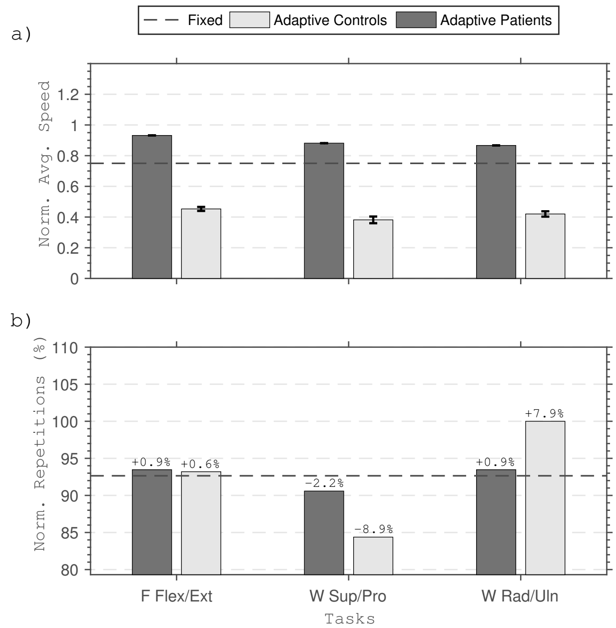


Fig. 5. a) Normalized average speed (difficulty) and standard error over all training sessions for each task and each condition. Normalizing scalar was the maximum difficulty. b) Normalized total repetitions over all training sessions for each task and each condition. Normalizing each task by total training sessions prior to scaling to a percentage. Relative increase/decrease of repetitions, from Fixed condition, has been shown as a percentage above each adaptive condition.

Figure 5a shows the average normalized difficulty across all training sessions for each task. Controls within the adaptive group were on average exposed to greater difficulty weighting than those within the fixed group. This, combined with the findings of Figure 5b, may support the notion of a ceiling effect, where tasks could be considered to be easy to perform for healthy volunteers. Conversely, patients within the fixed group experienced greater difficulty weighting. This, combined with the findings of Figure 4c, may infer that speed variation to modulate difficulty for motor tasks may cause patients to become spastic within the fixed group. Though, this theory lacks evidence as both groups were assessed using identical conditions following a rest interval post training.

Though, patients within the adaptive group elicited a relative improvement of 22% less RMSE than those within the fixed group, we did not find significance for conditions when analyzing over all tasks or individual tasks. A criticism that may limit the relative improvement of patients within the adaptive group is the presentation of KR. Though, we present KR throughout the study, patients may have not been aware of their performance on a trial-by-trial basis. This is due to the nature of presenting the score outside of the most focal area of the tablet screen, which is the character space. In addition, the score would reset for the next trial that shortly followed. Thus, there was little time to review and comprehend KR. Though, the protocol used differs from literature by allowing the task trajectories to be visually present at all times. This is a standard game dynamic implemented in a multitude of addictive mobile games. Though, presenting trajectories as such may have allowed patients to rely on motor planning as opposed to engaging long-term memory to increase their performance. Lastly, we did not consider modulating CI or KR based on the performers skill level. The CPF theorized that low levels of CI are preferable for beginning skill levels, whereas high levels of CI are preferable for more highly skilled individuals. In following Y. Choi *et al*. algorithms, we did not take into account that performers within the patient cohort may benefit from low levels of CI. A similar concept for KR also applies, where immediate or frequent feedback for tasks of high nominal difficulty may yield greater learning effect. Though, performance of tracking a trajectory is inherently distinguishable without the presence of KR.

Recruiting factors also limited our capacity to determine significance. Inclusion and exclusion criteria required at least some cognitive ability with voluntary motion of the wrist and fingers. Though, many patients failed to meet both requirements. In addition, trial repetitions were limited to 54 trials per training session. This was very low in comparison to Schweighofer *et al*. . whereby patients performed 150 repetitions within a single training session per day. Thus, total repetitions of training may have not been sufficient to affect long-term performance.

## IV. CONCLUSIONS

We argue that adaptive paradigms that not only can challenge patients at an optimal condition but also promote the use of long-term memory, aid in greater skill acquisition and long-term retention than simply adapting to motor conditions alone. The results that have been presented show that patients who train under adaptive conditions, whereby task practice order, regularity within trial space, and nominal difficulty were varied based on participants' performance, yielded greater long-term performance. In addition, patients training with adaptive conditions elicited consistent performance within the delayed retention test of day 3. This is important as patients are often unmotivated to rehabilitation programmes due to a slow progression and perception of inability to perform the tasks. Prior research within stroke rehabilitation has not explored the multitude of theories hypothesized within the CPF. To the authors knowledge, only one study (N. Schweighofer *et al*. ), explored CI effects within chronic stroke patients. Though, this is an individual component of the CPF. While this study does not offer a conclusive answer to the question of adapting task practice order and frequency to induce optimal levels of CI, and finding the optimal challenge point of task motor dynamics to inducing *flow*, it does aid identifying limiting factors of CI and optimal challenge adaption within stroke rehabilitation. It would be fruitful to pursue further research about the algorithms discussed within this paper using alternative game mechanisms that promote the use of long-term memory in task progression.

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