SUMMARY OF RESEARCH

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DEMOCRATIZING NEUROREHABILITATION

DEMOCRATIZING NEUROREHABILITATION:
How accessible are low-cost mobile-gaming technologies for self-rehabilitation of arm disability in stroke? - GripAble can enable more severely affected subjects to engage with self-training mobile software.

PLOS | ONE

RESEARCH ARTICLE

Democratizing Neurorehabilitation: How Accessible are Low-Cost Mobile-Gaming Technologies for Self-Rehabilitation of Arm Disability in Stroke?

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Abstract

Motor-training software on tablets or smartphones (Apps) offer a low-cost, widely-available solution to supplement arm physiotherapy after stroke. We assessed the proportions of hemiplegic stroke patients who, with their plegic hand, could meaningfully engage with mobile-gaming devices using a range of standard control-methods, as well as by using a novel wireless grip-controller, adapted for neurodisability. We screened all newly-diagnosed hemiplegic stroke patients presenting to a stroke centre over 6 months. Subjects were compared on their ability to control a tablet or smartphone cursor using: finger-swipe, tap, joystick, screen-tilt, and an adapted handgrip. Cursor control was graded as: no movement (0); less than full-range movement (1); full-range movement (2); directed movement (3). In total, we screened 345 patients, of which 87 satisfied recruitment criteria and completed testing. The commonest reason for exclusion was cognitive impairment. Using conventional controls, the proportion of patients able to direct cursor movement was 38–48%; and to move it full-range was 55–67% (controller comparison: p>0.1). By comparison, handgrip enabled directed control in 75%, and full-range movement in 93% (controller comparison: p<0.001). This difference between controllers was most apparent amongst severely-disabled subjects, with 0% achieving directed or full-range control with conventional controls, compared to 58% and 83% achieving these two levels of movement, respectively, with handgrip. In conclusion, hand, or arm, training Apps played on conventional mobile devices are likely to be accessible only to mildly-disabled stroke patients. Technological adaptations such as grip-control can enable more severely affected subjects to engage with self-training software.

Competing Interests: The handgrip technology reported is patented by authors PR, MM, EB, PB, with Imperial Innovations.

Introduction

The most important intervention shown to improve physical function after stroke is repetitive, task-directed exercises, supervised by a physiotherapist, with higher intensity leading to faster and greater recovery[1]. In practice, access to physiotherapy is significantly limited by resource availability[2]. For example, 55% of UK stroke in-patients receive less than half the recommended physiotherapy time of 45 minutes per day[3].

One solution to inadequate physiotherapy is robotic technology, that enables patients to self-practice, with mechanical assistance, via interaction with adapted computer games. While a range of rehabilitation robotics have been marketed over the last decade, and shown to be efficacious[4], they are not widely used due to factors such as high-cost (typically, $10,000–100,000), cumbersome size, and restriction to patients with high baseline performance, and who have access to specialist rehabilitation centres[5].

An alternative approach to self-rehabilitation, are medical applications (Apps), or gaming software, run on mobile media devices e.g. tablets or smartphones[6, 7]. Because such devices are low-cost ($200–500), and ubiquitous, they have the potential to democratize computerized-physiotherapy, especially in under-resourced settings, e.g. chronically-disabled in the community. Furthermore, their portability enables home use, while their employment of motivational gaming strategies can potentiate high-intensity motor practice. Accordingly, increasing numbers of motor-training Apps for mobile devices have been commercialised in recent years, and clinical trials are under way[8, 9]. However, since these devices are designed for able-person use, it is questionable as to how well disabled people can access them, and engage meaningfully and repeatedly with rehabilitation software.

This study assesses the degree of motor interaction that can be achieved by hemiplegic stroke patients using four types of conventional hand-control methods (finger swipe, tap, joystick and tilt) for mobile devices. An adapted controller of the same mobile devices[10], whose materials cost ~$100, was evaluated alongside. Since the latter interface exploits the fact that handgrip is relatively spared in stroke hemiplegia[11], and is sensitive to subtle forces, we expected that this would increase the range of arm-disability severities able to achieve meaningful computer-game control. In order to assess motor control, with minimal cognitive confounding (given that many softwares also have cognitive demands), we used a simple 1-dimensional motor assessment for all controller types.

Methods

Participants

Consecutive stroke patients with arm weakness were screened over 6-months at Imperial College NHS Healthcare Trust Hyper-Acute Stroke Unit, within 2-weeks of presentation. We excluded patients with cognitive impairment (Mini-Mental State Examination <27), given their therapeutic gains from physiotherapy are generally poorer than those of cognitively-healthy individuals, and for ethical reasons. Other exclusion criteria were: 1) premorbid arm disability, or dependency (modified Rankin Score >2), 2) comprehension difficulty, 3) sensorimotor neglect (clinically, or >25% errors with star-cancellation test), 4) arm pain, 5) significant co-morbidities, 6) subsequent MRI failed to confirm stroke.

Patients' arm disability was graded into one of three groups depending upon their score in the Upper Extremity section of the Short Fugl-Meyer Assessment (S-FM)[30]; FM): severe (0–4), moderate (5–8), and mild (9–12), where 12 is normal function. Arm power using MRC-grading, handgrip force using a manual dynamometer, handedness, mood and anxiety were also assessed. Recruited participants gave written and signed informed consent. Ethical approval was granted by the UK National Research Ethics Service, South East Coast Committee.

Subjects in the first three months were tested on their control of conventional game controllers; and in the second three months, on their control of the best-performing conventional game controller compared to a novel, adapted controller.

Conventional Game-Control Assessment

Subjects were asked to control a digital-screen cursor in the vertical plane using one of four hand-control methods employed by standard mobile or home-gaming devices: touch-screen swipe, tap, joystick and screen-tilt (Fig 1A). All subjects were tested on all four methods. For the first three methods, the cursor appeared on a 9.7-inch tablet; for tilt, a 3.5-inch smartphone. The joystick was integrated into a tablet-stand with which it interfaced (Atari Arcade Duo Powered). Devices were positioned to be most accessible and comfortable (e.g. in a stand or flat). Patients' elbows could be supported by pillows.

Software used was a basic maze game that had similar graphics and functionality between all four types of control method (swipe: "4Kids Maze", Gottaplay, 2014; tap, joystick: Maze-Craze, Atari, 2012; tilt: "Tilt Mazes Lite", Exact Magic Software, 2012). A maze was chosen in which one path ran approximately three-quarters the height of a landscape-orientated screen (10cm; or 7cm on a portrait-orientated smartphone). The cursor was positioned by the

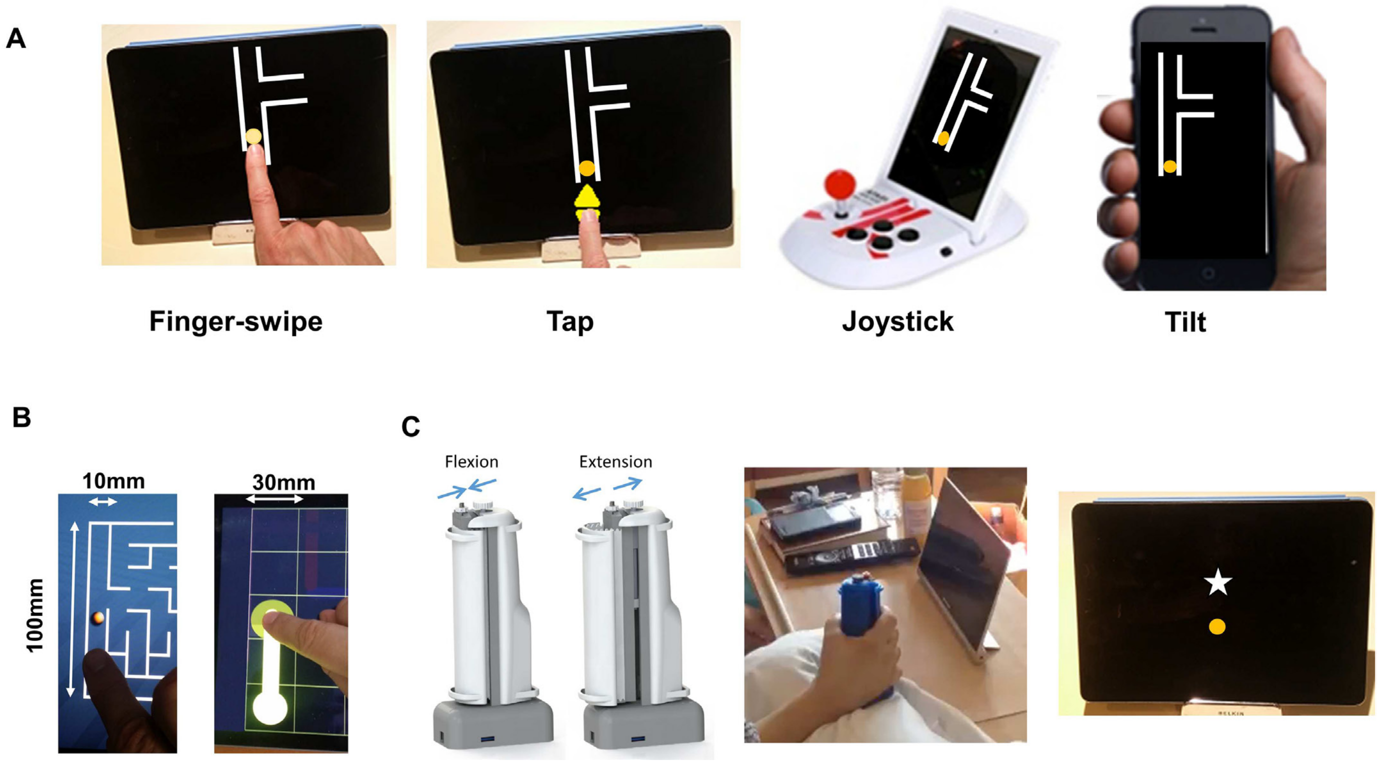

Fig 1. Control methods and devices trialled. Conventional control mechanisms were trialled using standard tablet and smartphone (**A, B**). Subjects were required only to move a cursor along a single vertical path, full-range, and then to an indicated vertical level (they were not tested on playing the underlying game). **B** shows software used for assessing swipe, with varying cursor size. There was no improvement in accessibility using a larger cursor. The novel control mechanism (**C**) is a wireless grip-force sensor that detects both finger-flexion and extension movements, the latter assisted by a fingerstrap holding the device within a partially-extended hand. Control software for **C** entailed moving a circle in a vertical plane towards a target star. Cursor and target stimuli dimensions and contrast are similar between all methods.

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examiner at the bottom of the path so that the only movement possible was up or down (Fig 1B). The remainder of the screen could be occluded. Cursor size was 1 cm diameter for swipe, and 0.8 cm for other methods. For tapping, the cursor was controlled by 2 x 1.5cm up/down arrows.

Subjects were asked to move the cursor across the range of the vertical path in both directions. They then had to move the cursor towards an indicated section, level with where a horizontal path connected (without needing to move it sideways). Subjects were scored according to their ability to control the cursor as follows: 0: no movement of cursor; 1: moves cursor but not consistently across entire vertical range; 2: moves cursor consistently across entire vertical range in both directions, but cannot direct it to highlighted section; 3: moves cursor consistently across entire vertical range, and directs it to highlighted section (Fig 2). Three raters were used during the study, who achieved >95% inter-rater consistency in scoring by this method.

Subjects were allowed up to a minute per trial. Each trial was conducted three times, and the median control score recorded. Subjects were tested with their hemiplegic, and separately unaffected, arms. Control-method order was counterbalanced between subjects.

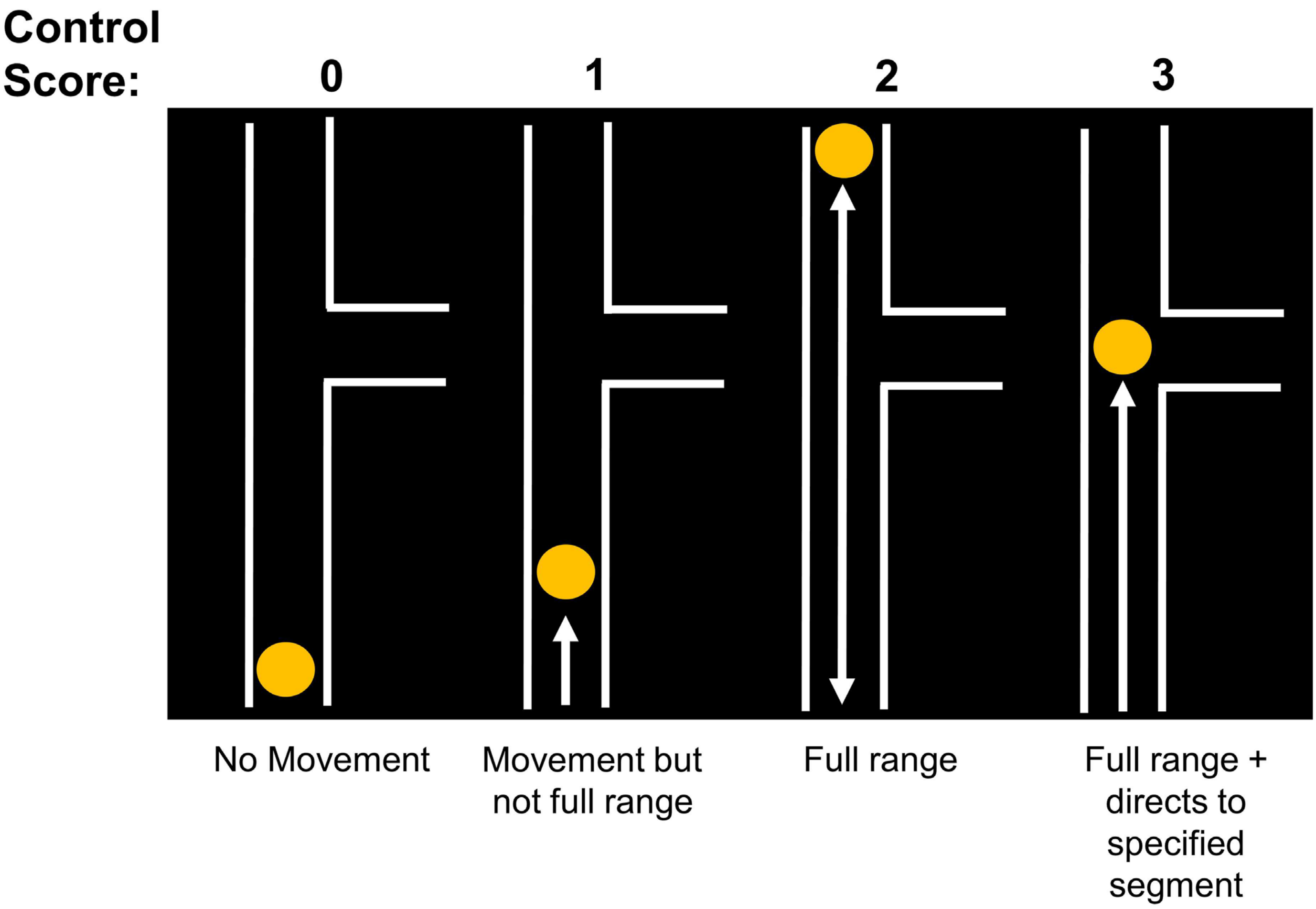

Fig 2. Cursor-control score. Subjects were asked to move the cursor three times up and down the longest vertical path, as well as to a position level with an indicated adjoining horizontal path.

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In order to assess the effect of cursor size and path direction, a substudy compared the swipe maze as described, with two alternative swipe software, that had larger cursors (2-3cm) and diagonal or horizontal path directions (Fig 1B; "FlowFree", Big Duck Games, 2013; Traffic Controller 2, MindMender, 2013). Instructions, as above, were applied to these software.

Adapted Handgrip Controller

Subjects were compared on their control of tablet swipe (as described above), versus an adapted, power-grip controller. This controller, designed for disability, utilises a patented force-sensing mechanism (flexible metal blade system) that allows functional, resistance-based training with high force sensitivity (0.1-50N) throughout the compliant range [10] (Fig 1C). The grip has adjustable compliance and girth, is portable and connects to a tablet wirelessly via Bluetooth. The handgrip also provides haptic (vibration) feedback, and senses inertial forces (accelerometer)–although these functions were not used in the current study.

Assessment of handgrip control used a software equivalent in cursor-movements and dimensions to that of the maze software. Handgrip force controlled a cursor that moved vertically; target positions were the upper and lower tablet-screen bounds, as well as a target star, the height of which was the same as the horizontal segment target in the conventional games. The star remained still or moved, the latter mode used for 2 –minute game play. Prior to assessment, the software is calibrated so that maximum cursor excursion is set to 70% of maximum voluntary contraction.

Statistical Analysis

A generalised linear ordinal logistic regression model (Generalised Estimating Equation, SPSS V.22) estimated how movement control (0,1,2,3) was influenced by factors: control method (swipe, tap, joystick, tilt, grip), and arm type (hemiplegic, unaffected), with covariate of arm disability (severe, moderate, mild). An independent correlation matrix structure was selected.

Handgrip-Control Sustained Performance

In a further cohort of 12 hemiplegic stroke patients, we assessed how performance accuracy using handgrip-control over 2 minutes of continuous game-play, related to arm disability. Accuracy was derived from root-mean square (RMS) distance-error between cursor and target (a moving star), calculated using a minimum moving error (MME) method, that reduces noise. At each time-point, RMS was calculated across a 15s window that it centred upon, and the lowest RMS error within this taken. The average across all such time-points was calculated, and regressed onto S-FM scores. These analyses were conducted in MATLAB (v2012).

Results

345 patients with arm-weakness were screened, of which 92 were recruited and 87 completed the protocols (Fig 3). The principle reason for exclusion (51%) was cognitive impairment or physical comorbidities significant enough to make it impractical and unethical to test patients. Tested patients had less severe neurological deficits than those excluded (NIHSS 5 vs 9; $p<0.05$. Table 1). Of those recruited, most patients had mild, rather than moderate or severe, arm disability (60% vs 20% vs 20%).

Conventional-Control Comparison

Control scores in the hemiplegic arm were strongly affected by arm disability level (Wald chi (1) = 44.5, $p<0.001$), with the proportion being able to use at least one conventional control to

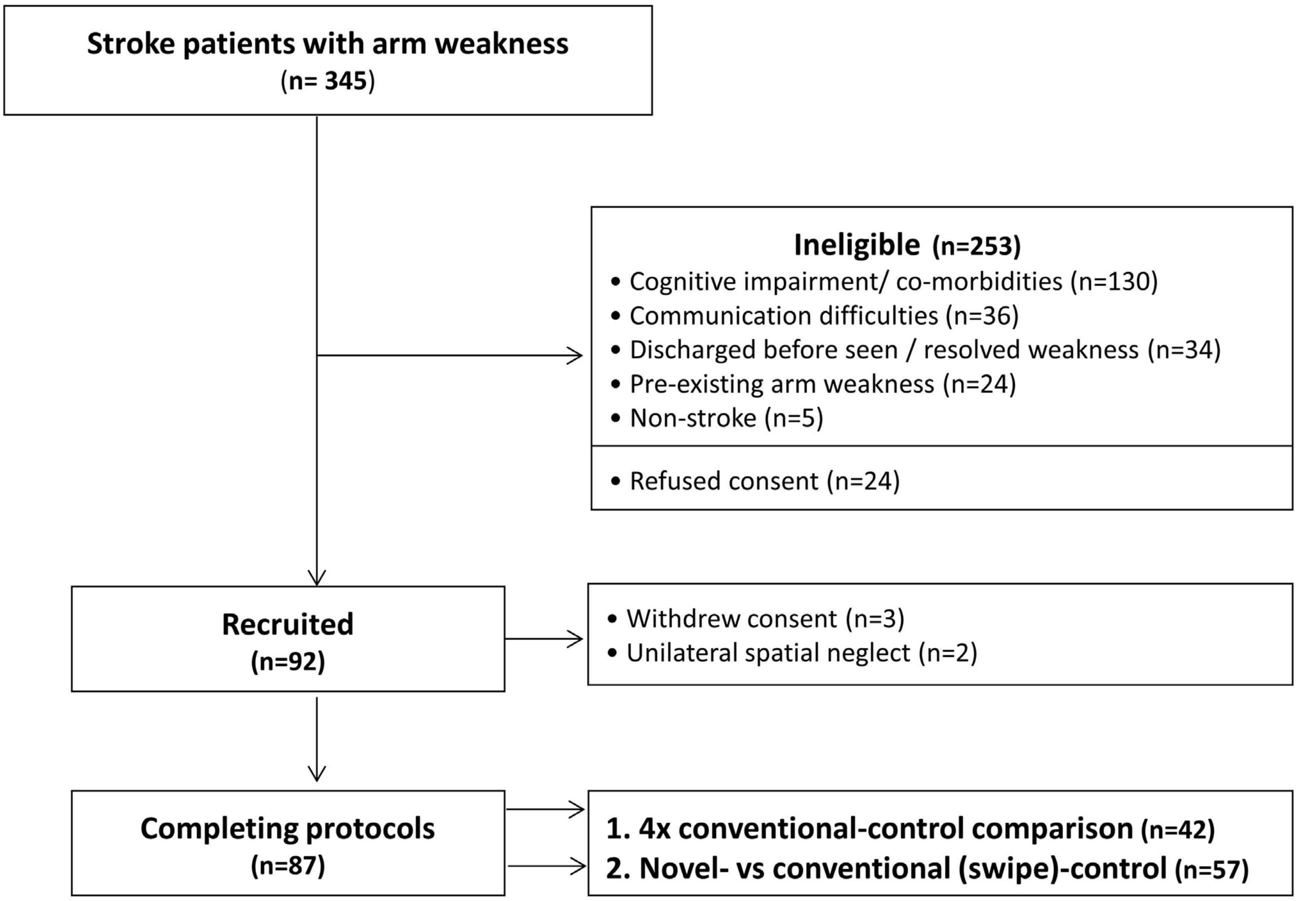

Fig 3. Recruitment flow diagram. This shows numbers of arm-paretic stroke patients screened, excluded and recruited, and reasons for exclusion.

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direct a cursor to target (score = 3) being 90% for mildly disabled, 36% for moderately disabled, and 0% for severely disabled (Fig 4A). However, control scores did not differ significantly between the four conventional control types (chi2(3) = 2.7; p>0.1), with the proportion of patients achieving a score of 3 being 48%, 45%, 38% and 38%, for swipe, joystick, tap and tilt,

Table 1. Patient demographics and baseline clinical characteristics.

	Tested	Not Tested
N	87	258
Age / yrs	65 (55–75)	72 (64–85)
Males / %	57	56
NIHSS–overall/42	5 (2–6)	9 (4–14)*
Hospital Anxiety and Depression Scale—/42	3 (1–3)	4 (1–10)
Edinburgh Handedness Inventory	100 (100–100)	-
Arm Specific Tests	**Weak Hand**	
Plegic hand-side	Right-hand: 42%	
Short Fugl Meyer arm function /12	8 (6–11)	
Hand Section Fugl Meyer /14	8 (2–13)	
Grip Force /Kg	13 (2–22)	

Median (interquartile range).
* p<0.05.

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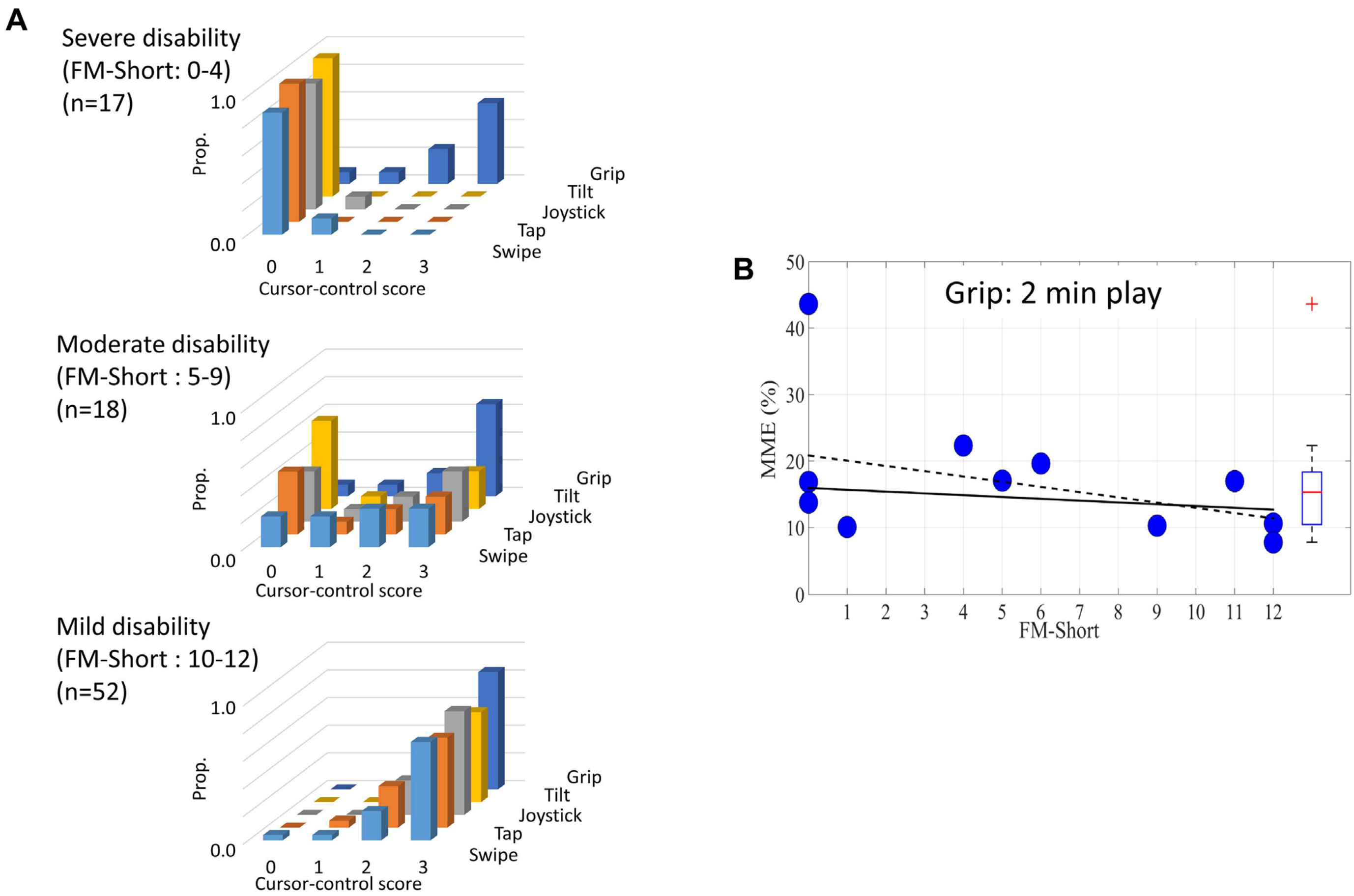

Fig 4. Control ability using conventional versus novel controllers. A: Proportions of patients achieving each level of cursor control (0–3) for each of the four conventional, and one novel (grip), control mechanism. Results are stratified according to severity of arm weakness (using Short-Fugl-Meyer score of the arm). **B**: Performance error on 2-minute tracking task controlled by grip-control, plotted against arm disability. A small trend towards less error with greater ability is non-significant whether or not the one outlier is included (dashed-line) or not (continuous-line) (p>0.1 for both)–indicating that tracking accuracy is largely independent of standard arm-function scores.

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respectively. There was no control type x disability interaction (chi2(3) = 1.5; p>0.1). There was also no difference in control scores comparing the three swipe software that varied in cursor-size (1–3 cm) and path-direction (n = 27; chi2(2) = 0.5; p>0.1).

Influence of arm (hemiplegic vs unaffected) on device control was seen as an interaction with disability (chi2(1) = 15.4; p<0.001), reflecting significantly poorer control using hemiplegic than unaffected arm in severely (p<0.001) and moderately disabled (p<0.05) subjects, but not mildly disabled. However, control was also poorer in the *unaffected* arm in severely disabled patients (score: 2.45), compared to unaffected arm of moderate and mild patients (score: 2.95–3; chi2(1) = 7.5; p<0.01).

Novel-Handgrip vs. Conventional-Control Comparison

Compared to finger-swipe–the best conventional control–the novel handgrip controller resulted in superior software control (chi2(1) = 20.2; p<0.001). The proportion achieving control-score of 3 was 48% for swipe vs 75% for grip; whilst the proportion achieving control-score of 2 or 3 was 67% for swipe and 93% for grip (all values quoted are using the hemiplegic arm). The superiority of grip over swipe was greater at higher levels of disability (device x disability interaction: chi2(1) = 10.2, $p<0.01$), e.g. in severely disabled subjects, control-score 3 was achieved in 58% with grip, versus 0% with swipe (Fig 4A).

Performance accuracy for 2-minute game play (measured as minimum moving error, MME) using grip control was minimally affected by disability severity (correlation with S-FM being non-significant: $r = -0.27$; $p = 0.21$). For example, performance in 3/5 patients with severe disability was within the range of mildly disabled patients (Fig 4B). An example of a patient, who scores 0 on tablet swipe, and then successfully controls a visuomotor tracking software with their severely disabled arm, using handgrip control, is shown in S1 Video.

Discussion

The first part of our study indicates that standard use of everyday mobile devices for arm physical therapy in stroke, is likely to be limited. Less than half of recruited subjects could direct a cursor using conventional tablet or smartphone mechanisms, with their paretic arm. Furthermore, patients in severe- or moderate-disability bands–for whom physiotherapy requirements and potential gains are higher—directed control in 0% or ~30%, respectively. Clinical trials looking at the potential benefits of tablet-based arm-training software, using standard controls [6, 9], will therefore be restricted to mildly-disabled patients.

The accessibility of mobile devices for arm training is likely to be even lower than that estimated here for several reasons. Firstly, we excluded 75% of hemiplegic patients, for reasons such as dementia, yet such subjects had higher disability than those tested. Given a steep fall-off in control as disability increased, and given this group's poorer cognition and co-morbidities, the excluded majority would probably be far less capable than we found. Furthermore, our motor test was limited to a single, one-dimensional movement, whereas training software typically entails practice for many minutes, more demanding tasks, in two dimensions etc.–all of which are likely to reduce successful performance.

It is likely that software factors, e.g. task simplicity, cursor size, in addition to interface mechanism, influence control[12]. However, we deliberately chose a task that had minimal cognitive demands, high-contrast graphics, and did not time-pressure patients. The fact that there were no performance differences between three types of swipe software (one of which is designed for arm rehabilitation, the other using a larger 3cm cursor) suggests that task-type or graphics are not major determinants for software inaccessibility. While even larger screen targets than those tested here[9], could enable more patients to engage, the range and utility of potential exercises is likely to decrease as the target size increases. Moreover, gross tapping is a relatively uncontrolled movement that could be achieved by truncal or flailing movements that are not the games' intended purpose.

The possibility that cognitive or visuoperceptual impairments, commonly found in stroke [13], may have reduced performance ability is discounted by the finding that patients achieved good control, with all methods, using their non-plegic hand. Whilst severely disabled patients did show mild impairment using their non-plegic hand, this is likely to reflect an ipsilesional motor deficit[14], rather than because of cognitive factors, given that cognitive impairment was an exclusion criterion.

In the only other study of its kind, 20 stroke patients were tested with a tablet using swipe and tap control[12]. Of these, 7/20 were able to swipe consistently, while 15/20 were able to complete a tapping game performed twice. While the latter figure suggests a greater potential for motor-training on tablets than found here, tapping accuracy in that study was only 50%. Furthermore, the test population was disproportionately mild, being a convenience sample, and excluded patients with severe hand weakness. Consequently, arm ability in that study relative to healthy controls was 92% (using the Fugl-Meyer scale), as opposed to 57% in our consecutively-sampled series, that is likely to be more representative.

In comparison to the best-performing conventional control method (i.e. swipe), we found that a simple, economical adaptation to mobile devices can significantly increase accessibility, particularly in more severely affected patients. A handgrip controller increased the proportion of *all* patients able to achieve cursor control by ~50% (relative to swipe); and enabled more than half of severely disabled patients to engage with tablet software, as compared to 0% using any other method.

The reason why handgrip enables superior control compared to other methods most likely arises from the differential pattern of arm weakness found after stroke. Hence gross-grasp is one of the least affected movements, whereas individuated finger movements, wrist extension and supination–required for swipe, joystick or tilt—are more impaired[11]. Furthermore, the fact that the majority of severely hemiplegic patients were not just able to move the cursor across the entire range, but were able to *direct* cursor control, underlies a previous finding, that fine-grip control may be independent of grip strength[15]. This is also apparent during the demanding 2-minute tracking task, in which handgrip accuracy of severe hemiplegics was similar to that of more able patients. The grip controller enables this fine control by calibrating software to patients' maximum strength, and sensing forces across a wide range.

While we have shown that grip-control, relative to other control methods, increases the proportion of patients able to engage with rehabilitation software, our study does not address the question of whether such repetitive practice would lead to functional benefits. Although power-grip is one of the least affected arm functions following stroke [11], there are multiple aspects of grip control that are deranged after stroke, e.g. smoothness, force distribution and grip-release[15–18], even when other aspects e.g. tracking accuracy, are performed well. Software could therefore be designed to train these more affected aspects of grip control, as well as to encourage finger-extension over flexion. For example software can be calibrated so that a patient's grip-neutral position is matched to a cursor location at screen bottom, and the only hand movements able to move the cursor upwards are finger extension (assisted by a strap holding the controller in the hand). A related question is whether repetitive exercise of a single action e.g. graduated grip flexion-extension, could confer functional benefits beyond those of the action practiced. At least five trials of robotic hand-trainers in stroke have shown that frequent hand-training e.g. grasping or finger exercises, result in functional gains not only in the hand, but also in more proximal arm movements[19–22], that may reflect automatic upper-arm posturing during distal actions such as gripping, and generalisation of motor learning[23]. Whether this result could be repeated on a larger scale, in patients' homes, using portable electronic aids such as that tested here, are relevant future research directions.

The hand-grip interface described here is one example of several portable arm-rehabilitation innovations developed in recent years, commercially available at relatively low-cost ($500–3000). The MusicGlove® for instance is a wearable sensor that interfaces with PC-based software, designed for home-training of grip and individuated finger movements[24]. The Tyromotion Pablo® is an isometric powergrip sensor that interfaces via a wire with desktop-PC software. Other devices that interact with computer software are designed for wrist or upper-arm training, e.g. the Kinestica Bimeo®, as well as the digital handgrip tested in the current study, that has a separate accelerometer capability (not assessed here). Future studies will be required to determine the range of patient abilities for whom each device may be a useful training aid. We would hypothesise from the profile of arm disability after stroke[11], that the power-grip tested here will be more suited to patients with severe disability, whereas aids training individual finger movements, or anti-gravity proximal arm movements, would be more relevant to patients with milder disability.

In summary, our study highlights a major limitation of everyday mobile technologies for arm training after stroke, and suggests one low-cost method by which restricted interaction can be overcome. Whether or not improving access to physiotherapy-based computer games translates into increased self-training by patients, and ultimately functional benefits, are questions for future research.

Supporting Information

S1 File. Raw-data of conventional versus novel control experiment (relates to Fig 4).
(XLSX)

S1 Video. Demonstration of a severely hemiplegic patient attempting tablet control using swipe, and novel hand-grip controller. The patient's only recorded arm movements are flickers of finger flexors (FM-S 1/12). The patient was able to successfully engage with a visuo–motor tracking software using the grip controller tested in this study.
(MP4)

Author Contributions

Conceptualization: PR MM EB PB.

Data curation: PR MM.

Formal analysis: PR MM JLL EB PB.

Funding acquisition: EB PB.

Investigation: PR MM TN KZ SF.

Methodology: MM JLL EB PB.

Project administration: PB.

Resources: MM JLL EB.

Software: MM JLL EB.

Supervision: PS EB PB.

Validation: PR MM TN KZ SF EB PB.

Visualization: PR MM PB.

Writing – original draft: PR MM PB.

Writing – review & editing: PS EB.

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BALANCING THE PLAYING FIELD

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RESEARCH **Open Access**

Balancing the playing field: collaborative gaming for physical training

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Abstract

Background: Multiplayer video games promoting exercise-based rehabilitation may facilitate motor learning, by increasing motivation through social interaction. However, a major design challenge is to enable meaningful inter-subject interaction, whilst allowing for significant skill differences between players. We present a novel motor-training paradigm that allows real-time collaboration and performance enhancement, across a wide range of inter-subject skill mismatches, including disabled vs. able-bodied partnerships.

Methods: A virtual task consisting of a dynamic ball on a beam, is controlled at each end using independent digital force-sensing handgrips. Interaction is mediated through simulated physical coupling and locally-redundant control. Game performance was measured in 16 healthy-healthy and 16 patient-expert dyads, where patients were hemiparetic stroke survivors using their impaired arm. Dual-player was compared to single-player performance, in terms of score, target tracking, stability, effort and smoothness; and questionnaires probing user-experience and engagement.

Results: Performance of less-able subjects (as ranked from single-player ability) was enhanced by dual-player mode, by an amount proportionate to the partnership's mismatch. The more abled partners' performances decreased by a similar amount. Such zero-sum interactions were observed for both healthy-healthy and patient-expert interactions. Dual-player was preferred by the majority of players independent of baseline ability and subject group; healthy subjects also felt more challenged, and patients more skilled.

Conclusion: This is the first demonstration of implicit skill balancing in a truly collaborative virtual training task leading to heightened engagement, across both healthy subjects and stroke patients.

Keywords: Social interaction, Collaboration, Rehabilitation, Stroke, Physical exercise, Patient engagement, Exergames, Robotics

Background

Physiotherapy intensity is a well-recognised determinant of stroke recovery, although questions of method, timing, scheduling, etc., are still debated [1]. Video games have been highlighted as a means to increase therapy intensity, by enabling round-the-clock access to exercises, independent of professional supervision, while incentivizing through stimulating feedback. Exercise games ('exergames') can replicate aspects of conventional physiotherapy such as repetitive joint stretches, functional manipulation, difficulty adaptation, while manipulating motivational and cognitive variables [2–4]. Incorporation of these factors can increase therapy efficiency, and facilitate skill transfer to real world function [5].

Recently, virtual therapy involving two or more players has been proposed as a means of further increasing intrinsic motivation, engagement and social inclusion [6–12]. By promoting social interaction alongside entertainment, the appeal of gamification can be extended to a broader audience who may otherwise be disinterested due to age, impairment, cognitive or experiential issues. Furthermore, playing with another patient, a carer, or a relative at the hospital or at home can prevent patient isolation.

Compared to single-player training games, multiplayer games are more engaging, with the level of impact

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depending partly upon participant personality traits [6, 12]. To date, the majority of multiplayer rehabilitation exergames do not elicit true motor interactions, in the sense of each individual's performance being directly influenced by the other. For example, it is common for multiplayer games (e.g. [6, 13]) to divide goals into subtasks that can be completed independently by the players (whether or not simultaneously), without the performance of one player being influenced by the other(s) [14, 15]. By contrast, visuomotor learning paradigms that physically connect two subjects, can enforce inter-subject interactions, evident as a performance benefit not only for the weaker, but also the stronger partner (as shown in healthy populations) [16]. This occurs through models of motor planning based upon a connected partner's intentions, communicated both visually and haptically [17]. However, to provide physical-coupling between two subjects requires the integration of a complicated robotic system which is not broadly applicable during home-based rehabilitation, an area where technology and gamification can make a significant difference. Therefore, this study aims to virtualise many of the latent aspects of a physical connection, using visual-coupling and task design alone, to enable more accessible and cost-effective sensor-based systems (e.g. MusicGlove [18]) and ultimately for these systems to benefit from such strategies. Despite removing the ability to physically assist patients, by defining a new paradigm in virtual human-human interaction, we aim to promote better (force) control and player engagement, regardless of any underlying skill mismatch between the participants. This should also prevent natural motor 'slacking' a common issue when using active assist devices. By utilising sensor-based technology which are both sensitive and work on functional movements (e.g. contributing to activities of daily living), more efficient rehabilitation can be achieved, as active participation from the impaired limb is required if a patient is to ultimately recover volitional and functional movement.

A significant issue in the design of multiplayer games, particularly amongst disabled users, is how to permit differences in skill-levels between players, and allow for effective gameplay, participation and enjoyment by all players [3, 19, 20]. If player abilities are not correctly balanced, the challenge will be too high and quickly lead to frustration for the less skilled player; while the more skilled player will not be challenged and is likely to become bored. A related concern is how to design a multiplayer game that inhibits natural slacking behaviour, in which one player (usually the less-skilled one) becomes disengaged, even though the overall game performance is maintained [21, 22]. For example, in the cooperative-mode of the classic pong game [11, 13], interaction between the partners is not required as the game can be completed with only one player active (e.g. the skilled player can score points even if the less skilled player misses). Although multiplayer functionality can promote exergame engagement, it is unclear which type results in the most effective interaction, especially for less-able subjects who are in danger of 'falling behind'.

Inter-player relationships broadly fall into one of four types of human-human interaction [14, 15].

Co-activity characterised by a divisible task that either player can complete independently.

Competition each player interacts with the partner to fulfil their own goal and ultimately prevent the other player fulfilling their aim.

Cooperation the players work together to complete the task but have different roles (such as assistance i.e. master-slave, or educator-student).

Collaboration the interacting players are assigned the same role and need to work together to complete the task.

Previous rehabilitation games involving multiple players have focused on either co-active or competitive ([6, 11, 13]) types of interaction[1]. However, collaborative and cooperative interactions have several beneficial properties which can further promote motivation [10, 23]. These include: i) players needing to work together to achieve a common goal, thus promoting positive teamwork; ii) neither player is able to slack as the task is not divisible; iii) communication between players can help complete the task and promotes increased social inclusion. Additionally, in the case of collaboration, iv) having similar roles and task-goals enables consensual interaction, potentially empowering the patient by not a priori assigning them the role of the 'learner', and ultimately reducing the need for explicit instructions (with the latter requiring linguistic and cognitive aptitude). Given the theoretical advantages of collaboration, relative to other forms of inter-player interactions, we describe here a novel physical-training, social-gaming software, that embodies true collaboration. The aim of this proof-of-concept study is to elucidate on the effects of dual-player collaboration on human-human performance based on individual sensorimotor control whilst interacting in a visually-coupled task (i.e. there is no haptic or physical coupling between the dyads). This is compared with an equivalent single-player version, alongside user-experience, in both able and disabled subjects[2].

Methods

Balancing act: multiplayer collaborative gaming

A motor-training paradigm was designed such that two subjects could train concurrently, while interacting and skill-sharing, regardless of baseline differences in subject ability. The two players may be, for example, a therapist and a disabled patient, two patients with differing disabilities, or even a sports-person and their coach.

The following characteristics were considered to be advantageous for an efficient training game:

Simple A simplified game, both in terms of strategy and graphics (e.g. 2D), allows individuals to focus on gameplay and sensorimotor control, while reducing distraction.

Dynamic A continuously changing task places higher demands on motor control, and encourages visuomotor coordination, sustained attention, and player engagement.

Multifaceted metrics Performance feedback to subjects in an immediate and readily-comprehensible fashion (e.g. points collected), can motivate them to achieve task goals and maintain practice [24]. Concurrent information can be extracted to quantify how subjects interact, and examine the (social) strategies deployed.

Secondly, we considered these characteristics to be necessary to foster true social interaction:

Interactive The partners are virtually connected (visually and/or haptically), with their actions influencing each other's behaviour. This promotes social interaction and may motivate training.

Collaborative The two players contribute equally to achieving the task goals, thus enhancing positive social interaction.

Locally redundant Redundant control refers to the ability of one partner helping the other achieve a common goal (e.g. a therapist supporting a cup being lifted by a patient). However, to avoid slacking or complacency, which prevents learning, redundancy should be local, meaning the task cannot be achieved by only one of the participants alone.

It was hypothesised that these features should, i) make the task achievable by impaired individuals who could not succeed alone, and ii) increase the difficulty for the better performer by having to compensate for the worse performer. Furthermore, we expect engagement to increase through inter-subject interaction [4], because of greater task assistance and achievement (for the inferior partner), and being challenged and/or requiring altruistic behaviour (from the superior partner).

Example embodiment: Balloon Buddies™

Game description

Based on the above properties, a **two-player game** whose features could facilitate and motivate physical training was created. Figure 1 shows an overview of the game, which comprises a dynamic balance, represented by a ball on a horizontal beam, developed within a 2D physics simulation engine. The ball is represented by a circular sprite (the 'buddy'), which is subject to physical forces, and is free to roll across the top of a rigid beam or roll off the beam subject to gravity and frictional forces. The beam is lifted at each of its ends by balloons controlled by each player, with the 2D kinematics of the beam described by

$$\begin{bmatrix} h \\ \theta \end{bmatrix} = \begin{bmatrix} \frac{y_1+y_2}{2} \\ \arcsin\left(\frac{y_2-y_1}{L_{\text{beam}}}\right) \end{bmatrix}$$

where y_1 and y_2 are the height of each end of the beam respectively, L_{beam} is the length of the beam, h is the height of the beam centre and θ is the angular position of the beam. Upward movement of each balloon is controlled by a player varying their power-grip force, applied via a digital force transducer. The more grip force applied, the higher the balloon rises. Downward movement occurs passively by relaxing the grip, in conjunction with gravity. The grip transducer used here is compliant, highly sensitive, and interacts wirelessly with a standard Android tablet [25–27]. Prior to gameplay, the software is calibrated based on the maximum power-grip ability of the user.

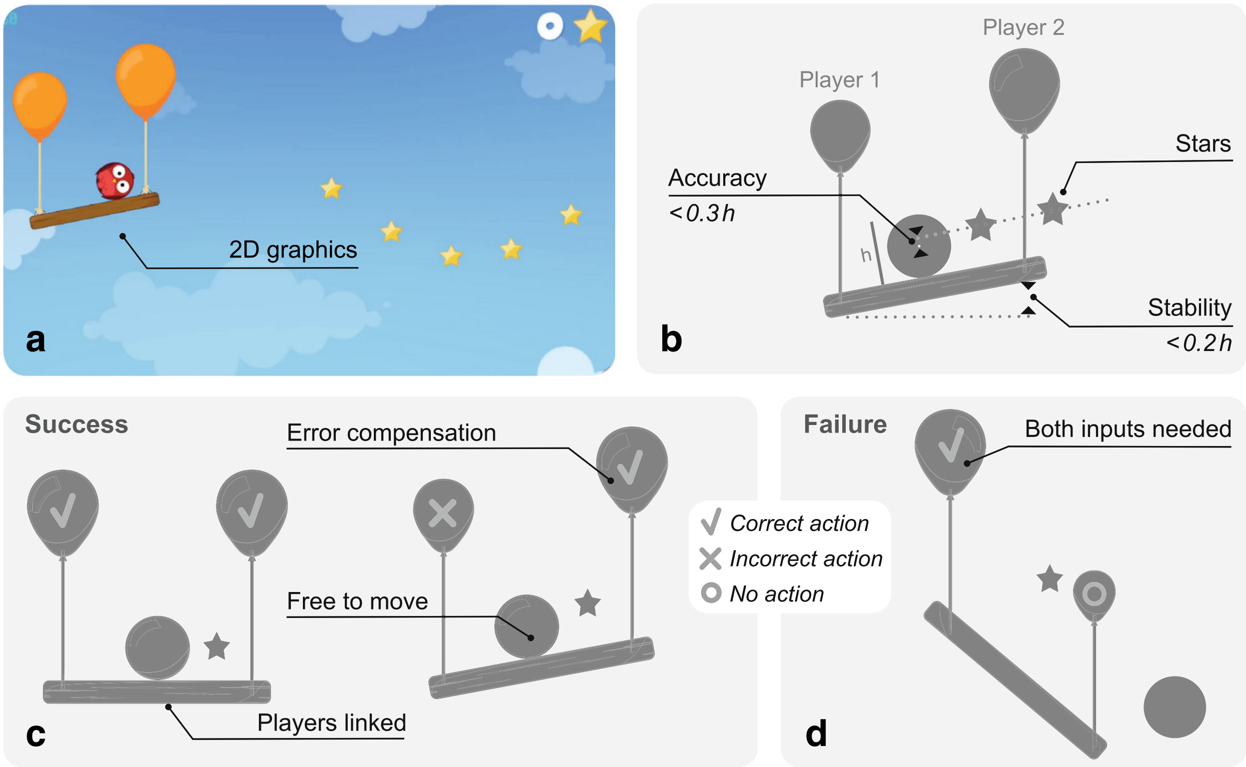
The vertical translation y_i applied to a specific balloon is driven by the calibrated force $\hat{F}_i$ from player $i \in \{1, 2\}$, according to

$$c\dot{y}_i + y_i = k\hat{F}_i, \quad i \in \{1, 2\}$$

with force visualised through the balloon's inflation (Fig. 1). Smooth game dynamics is ensured by stiffness (k) and damping (c) terms, controlling sensitivity of the position to force and smoothness of the control, respectively. For healthy subjects $k = 1$, while for patients $k = 1.8$. For both groups, c is not defined a priori, and is instead tuned by the software to ensure that the dynamics are critically damped and have a fixed settling time ($t_s = 0.09$ s for healthy and $t_s = 0.25$ s for patients)[3]. The game and associated graphical elements are presented in Fig. 1a. During gameplay, the whole platform scrolls at a constant speed ($v \approx 22$ mm/s) horizontally. All parameters (k, t_s, v) were chosen through initial testing, using independent groups of healthy and patient subjects, based on a subjective trial-and-error procedure.

The primary aim of the game is to vary the height of the beam so that the buddy matches a moving target height. A secondary aim is to keep the buddy from rolling off the beam, requiring players to keep the beam horizontal. Players need to simultaneously control the height and inclination of the beam using their combined inputs. The target height is represented by a specified trajectory, shown as stars, which are 'collected' by colliding them with the buddy. Star collection results in the visually-presented game score incrementing and is accompanied by positive auditory feedback. If the buddy

Simple • Dynamic • Multifaceted metrics



Interactive • Locally redundant • Collaborative

Fig. 1 Overview of the Balloon Buddies™ game. **a** A screenshot from the game, **b** the three performance metrics defined within the game: number of collected stars, accuracy (based on the distance between the buddy centre and the ideal trajectory), which should be > 30% of the buddy's diameter *h* and stability (based on the distance between the two ends of the beam), which should be > 20% of the buddy's diameter *h*. **c**, **d** Different scenarios are shown highlighting the local redundancy of the game, i.e. errors can be accommodated (**c**), but neither player can slack as both inputs are required (**d**)

falls from the beam, it is inactivated for three seconds, before reappearing and dropping onto the beam. During this period, it is not possible to catch stars, thus resulting in a lower final score. For healthy subjects, the target trajectory was described by a pseudo-random function, $y = \sin(0.15x) + \sin(x) + 0.5\sin(0.6x)$, where x is the horizontal translation, with similar functions selected in previous motor learning studies to ensure random but smooth trajectories [28]. To make it easier for patients, a predictable sinusoidal target trajectory, $y = 1.5\sin(0.5x)$, was employed[4].

Independently of us, Vanacken et al. have previously introduced a similar ball-balancing task ('Balance pump') as a mini-game within their virtual rehabilitation solution targeting multiple sclerosis [23]. The main differences are, (a) their study did not define or explore the implicit skill balancing nature of the elicited interaction, (b) they utilised arbitrarily placed static targets, with no time constraints, and (c) we define a multidimensional scoring system including both performance and motor control measures. We believe (b) is more likely to lead to sequential interaction rather than continuous balanced collaboration as elicited by the smooth continuous trajectory of moving targets which is used in our study. Moreover, by defining additional measures (c), such as stability, it allows patients to achieve targets regardless of their ability to just hit stars.

In order to determine the effectiveness of dual-player functionality, a **single-player mode** of Balloon Buddies™ was created. This differs from the above in that the only input is player-mediated grip-control to the left balloon. The right balloon automatically follows the ideal trajectory, independently of the player's actions.

Game properties

The game described satisfies the desired properties for a physical-training game, outlined in the previous section. It has **simple rules**, and uses uncomplicated, intuitive 2D graphics, with minimal distractions. Visual cues and feedback are overlaid onto the buddy system so as to avoid saccades. For example, the buddy's eyes close (to indicate 'sleeping'), when the beam is horizontal and buddy is stable. The grip-force applied by each subject is depicted in realtime, by the size of each balloon. The task is **dynamic**, in that the buddy is free to move continuously (vertically or rolling horizontally) subject to 'physical' forces (e.g. gravity, drag, friction). Several **metrics** have been defined, including number of stars collected, accuracy of trajectory pursuit, and stability of the beam (Fig. 1b).

Of particular relevance here are the game's social-interaction features. Thus, the paradigm is **interactive**, with players connected by the beam such that their collective actions have consequences on both the buddy and one another. For example, Fig. 1c and d highlights that if either one of the players perform poorly (by either under- or overshooting), for a continuous period, this will lead to the buddy rolling off the beam, unless the other player takes corrective actions e.g. by matching their grip-force. Additionally, the task is **collaborative** as the players must work together to collect stars. Each player is assigned the same role, i.e. controlling the height of the beam, without a defined leader. Finally, as Fig. 1c highlights, the task is **locally redundant** in that the buddy and beam system can tolerate intermittent mistakes whilst maintaining performance. For instance, even if one player falls behind in their trajectory pursuit, the other player can perform a compensatory manoeuver enabling star capture, before returning the balloon to stabilise the beam (Fig. 1c). However, such compensation is achievable only within a small range of poor performances, hence inhibiting slacking behaviour. This local redundancy enables intrinsic skill balancing within the game without requiring an additional individual skill matching procedure. However, the global difficulty level, affecting both partners, can be adjusted, for instance between healthy-healthy and patient-expert dyads, by specifying different trajectories and/or system parameters.

Game validation

In order to assess the versatility of the software, and to see if impairment affects collaborative behaviour: i) pairs of healthy subjects, and ii) hemiparetic stroke survivors interacting with a single healthy expert subject, were tested. Figure 2 gives a general overview of the healthy-healthy and patient-expert experiments performed.

Study 1: healthy-healthy experiment

Participants: Healthy, right-handed subjects without arm disability or cognitive impairment, were recruited and consented. Handedness was assessed by the Edinburgh Handedness Inventory (EHI). Subjects were paired randomly into dyads for dual-player game participation.

Protocol (Fig. 2c): Initially, the two participants played the single-player mode (A) on separate tablet-PC screens, (30 stars, 1 min). They then played the dual-player game (B) on a common tablet using constant game parameters. This play order was repeated thrice (i.e. ABABAB). Following this, they played an additional dual-player game where the control of the left player was perturbed (i.e. an increase in their sensitivity). The aim of this was to explore the effects on collaboration, when increasing the difficulty for one of the partners. Subjects were not told about this change and used their right hand for each trial. Participants were requested to refrain from talking or gesturing to each other during gameplay, so as to reduce the possibility that interactions occurred because of factors unrelated to gameplay. At the end of the experiment, participants were provided with questionnaires probing engagement and user experience (Appendix A).

Study 2: patient-expert experiment

Participants: Consecutive stroke patients with arm weakness were screened over 3 months at Imperial College NHS Healthcare, within 2-weeks of presentation. Exclusion criteria were: 1) cognitive impairment (Mini-Mental State Examination < 27), 2) premorbid arm disability, or dependency (modified Rankin Score > 2), 3) comprehension difficulty, 4) visual impairments, 5) arm pain, 6) significant co-morbidities, 7) subsequent MRI failed to confirm stroke. No distinction was made between haemorrhagic or ischaemic stroke. Patients were assessed using the Fugl-Meyer Upper Extremity (FMUE: 0-66 scale), and short form of the Fugl-Meyer (S-FM: 0-12 scale), Edinburgh Handedness Inventory (EHI), and Hospital Anxiety and Depression Scale (HADS). Approval for the study was given by the South East Coast Research Ethics Committee and all participants signed an informed consent form prior to any study-related procedure. Each patient was paired with the same healthy expert subject (right-handed male, 25 years old). This healthy subject spent two hours playing the single-player game prior to the study, which was long enough to have a stable performance over the patient-expert trials and is highlighted by their average single-player score. In this paper we denote this trained, healthy individual as 'expert', and use this label to differentiate this healthy subject from the novice healthy subjects which participated in Study 1.

Protocol (Fig. 2d): Patients first played in single-player mode (A), followed by dual-player mode (B) alongside the healthy expert. This order was repeated twice (i.e. ABAB design). Fewer repetitions occurred in this protocol than the healthy-healthy protocol in order to limit patient fatigue. During dual-player games, verbal communication was permitted between patients and expert. All trials were played with the impaired hand by patients, and right-hand by the expert. Calibration of the handgrip-control function relative to the patient's maximum grip-force was conducted prior to each game. To reduce the level of challenge for the patient-expert dyads, game dynamics were

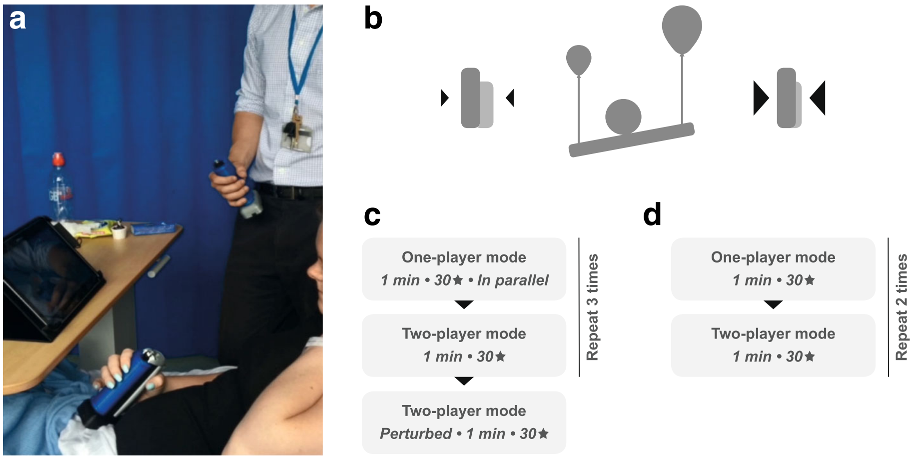


Fig. 2 Experimental Description. **a** Hemiparetic patient and healthy expert playing the game on a tablet by controlling a grip transducer; **b** grip force controls balloon size and height; **c** healthy-healthy experimental protocol; **d** patient-expert experimental protocol

also simplified, by adjusting friction, angular drag of the buddy, control sensitivity (k) and using a simple sine-wave trajectory (see "Game description" section for details).

Data analysis

Performance metrics

The following game-specific performance measures (see Fig. 1b) were defined. All metrics were used to compare subjects performance between task conditions (i.e. single-versus-dual player modes).

1. **Nr. of stars collected:** A star is 'collected' when any part of the buddy diameter contacts any part of a passing star. This is a gross indicator of players' ability to track the target trajectory, and is presented to subjects in real-time, as a cumulative score in the top right corner of the screen.
2. **Accuracy:** Computed as the percentage of time-frames in which the centre of the buddy lies within a narrow vertical margin ($<30\%$ of the buddy's diameter) of the reference trajectory (line connecting midpoints of stars). Whilst correlated with the 'nr. of stars collected', 'accuracy' represents finer control, and is a more challenging metric to achieve a high score on, as subjects can collect stars without being very accurate. Accuracy was displayed to participants at the end of the trial.
3. **Stability:** Reflects the degree with which the beam is held horizontally, and is computed as the percentage of frames where the vertical difference between the two ends of the beam is less than a certain threshold ($<20\%$ of buddy's diameter). Compared to other metrics, it is a better indicator of partner cooperation since it requires partner matching, rather than trajectory tracking. It is also a measure of control smoothness since the trajectory can be tracked accurately even though the beam moves chaotically in a seesaw manner (i.e. low stability). Stability feedback is provided during gameplay by the buddy closing its eyes when the stability condition is met. In order to encourage collaborative behaviour, bonuses appear when the plank is stable for a certain time (i.e. four seconds), in the form of stars worth three points instead of one point.

Motor control measures

The following game-independent motor control measures were computed directly from the grip-force signals. To remove noise and spurious artifacts, force data was forward-backward filtered using a 10th order low-pass Butterworth filter with a 5Hz cut-off. All measures were used to compare intra-subject motor control across task conditions (i.e. single-versus-dual player modes).

1. **Effort:** Estimated as the root-mean-square of filtered force, which takes into account both expected force bias and variation.
2. **Smoothness:** Computed as the spectral arc length (SPARC) of the first derivative of the filtered force data [29], which is a sensitive and robust measure of smoothness, e.g. for evaluating intra-subject task-differences during motor control experiments.

Questionnaires

Following completion of all games, subjects were provided with questionnaires that assessed their engagement and preference of single-versus-dual player modes (Appendix A). The engagement questionnaire, based on the Intrinsic Motivation Inventory (IMI) consisted of questions divided into three subscales: enjoyment and interest, perceived competence, effort and importance [30, 31]. Subjects graded their opinion, referring to either single- or dual-player modes, on statements (e.g. 'I tried very hard on this game') using a scale from 1 to 7 (1 = 'completely untrue', 4 = 'neutral' and 7 = 'very true'). Healthy subjects were provided with five statements per subscale (15 statements in total); for patients this was reduced to two statements per subscale (6 statements in total). The second part of the questionnaire evaluated user preferences of each player mode, as well as being questioned on which player mode subjects felt they 'put most effort in', 'were the most skilled' and 'were the most pressured'. A box for free text comments was also provided. Patients were also asked if they wanted to continue playing and for those answering 'no', were asked for their reason.

Statistical analysis

Non-parametric, paired statistical tests were used throughout e.g. Mann-Whitney U (MWU) for testing performance differences between single and multiplayer scores, because of relatively small sample sizes, non-Gaussian distributions of the variables of interest, and an intra-subject design. For comparison of questionnaire results between player modes, a two-way Friedman test for the IMI questionnaire (>1 question per category) and MWU for the user-experience questionnaire (1 question per category), were used. Correction for multiple comparisons was made using the Bonferroni method. Spearman correlation coefficients (ρ) were computed to measure associations between variables (e.g. IMI subscales, scores, etc.). Standard errors were calculated on the correlational values using a bootstrapping method on the data (e.g. age vs. scores) and 10,000 random resamples [32]. This allowed p-values to be estimated (e.g. between game-modes) to elucidate on significant differences across correlations by taking the difference between the variables of interest and counting the number of samples above or below zero (multiplied by two for a two-tailed test). To highlight relationships (e.g. between single-player and multiplayer scores), best fit lines were computed using ordinary least squares.

Table 1 Demographics and information for the healthy and patient experimental groups

	Healthy	Stroke survivors
Group size [nr. of subjects]	32	16
Age [years]	26.3 ±4.5	70.3 ±19.7
Gender [M/F]	23/9	10/6
Dominant hand [R/L]	32/0	15/1
Affected side [R/L]	n/a	7/9
FMUE [/66]	n/a	51.3 ± 13.6
S-FM [/12]	n/a	9.3 ± 2.7

Results

Participants

Table 1 gives an overview of the numbers and characteristics of participants involved in both the studies.

Healthy-healthy experiment

Performance analysis

A learning effect over three trials was seen in both single- and dual-player modes, across all three performance measures except during dual-player stability (Fig. 3; corrected for multiple comparisons). This learning effect occurred predominantly between trials T1 and T2 (or T3), whereas significant differences between T2 and T3 performance were never present. Therefore, the first trial was considered training, and trials T2 and T3 were pooled for further analysis.

There was no significant difference between single versus dual-player modes with regards to the number of stars collected ($p = 0.34$) or stability ($p = 0.25$). However, on average, accuracy decreased during the dual-player condition (15.1 ± 7.9% vs. 13.0 ± 5.3%; mean ± std; $p < 0.05$). For each trial, the maximum number of stars that could be collected was 40 (including bonuses).

To test whether there was a differential effect of game-mode across dyadic members, in terms of their individual skill levels, the relative effect of dual-player versus single-player mode for each member was compared with the difference in performance of the two partners during single-player mode. Figure 4a highlights correlations between relative single-player skill and relative dual-player improvement across all three performance metrics ($p < 0.001$; in all cases), such that the better a subject's (single-player) performance, relative to their partner, the greater the drop in performance when jointly playing with them. Conversely, the worse a subject's (single-player) performance, relative to their partner, the greater the improvement seen during dual-player gameplay.

Regardless of the mode of interaction, meaningful engagement in many inter-personal activities e.g. tennis, chess, depends upon ability matching. Therefore, performance as a function of partner disparity (in terms of their individual performances) was analysed. Figure 4a highlights that there is no tailing off in the (linear) relationship between partner disparity and dual-player benefit at higher disparities (e.g. that would otherwise be seen as a sigmoid or other non-linear shape). This suggests that our paradigm offers the greatest gains for the poorest performers (when playing with the most skillful players). Figure 4b reinforces this result by showing that there is no association between absolute dual-player performances and partner-mismatch (the latter measured as lower worse-to-better partner score ratios; stars: $p = 0.58$; accuracy: $p = 0.68$; stability: $p = 0.97$). This suggests

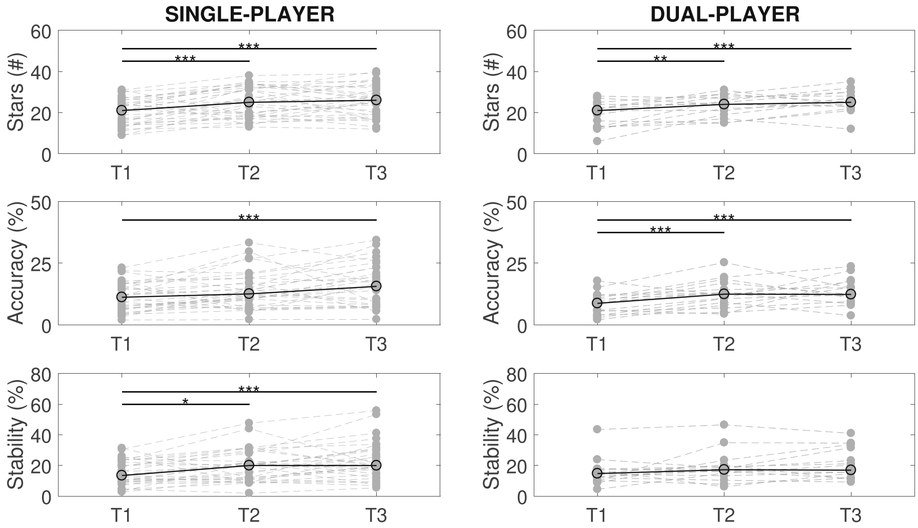


Fig. 3 Healthy-Healthy Learning Effects. Scores during both single and dual-player modes over the three turns (T1, T2, T3) plotted for the three performance metrics: stars, accuracy and stability (*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$)

that the collaborative task is robust across a wide range of partner mismatches. Similarly the control of one player was perturbed in the dual-player game (trial T4), thereby increasing difficulty asymmetrically within a partnership. This was found to significantly deteriorate performance in terms of stability only, but not star collection or accuracy (Appendix B).

Effort and control smoothness were compared across game modes as a function of partner disparity (Fig. 5; stability only). The results highlight that playing with a better partner significantly reduces the effort for the worse performing partners and vice versa for the better partner ($\rho = -0.27, p < 0.05$). Conversely, smoothness generally improves in the more inferior partners, but worsens

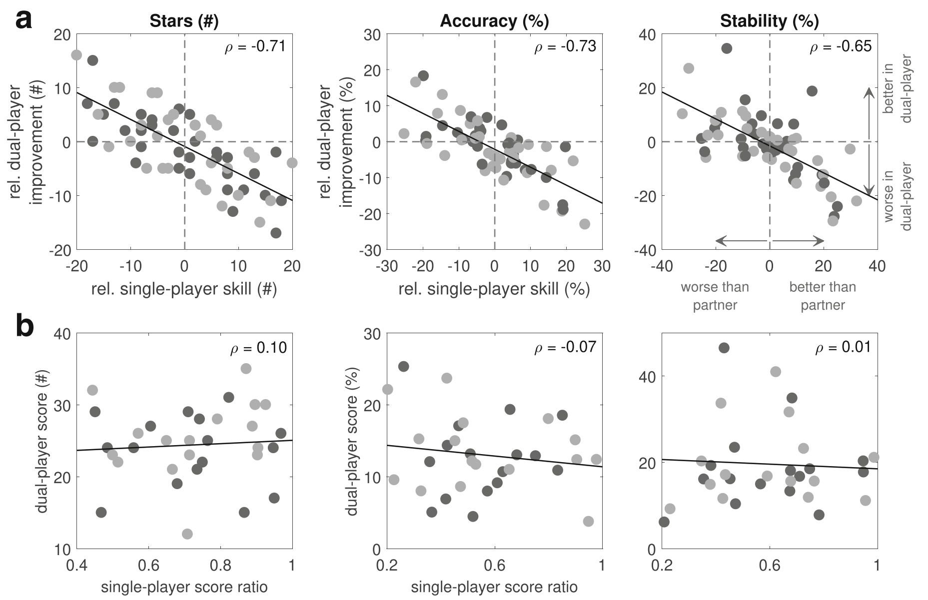


Fig. 4 Healthy-Healthy Performance Measures Analysis. Comparison of single- and dual-player performances as a function of individual relative ability: **a** The relative improvement during multiplayer is positively correlated to the relative skill (i.e. difference in performances) of the other partner during their single-player turns. **b** The dual-player score does not depend on the individual performance ratios (worst divided by best player). The different circle colours highlight the different turns (T2 - light gray and T3 - dark gray)

in the relatively superior players ($\rho = -0.23, p = 0.069$), although the latter is an insignificant result. Nevertheless, this suggests that the compensation provided by the better partner allows poorer players to reduce their effort and focus a little more on their control.

Qualitative game assessment

Subjects expressed a preference for dual-player mode (Fig. 6a), with 22/32 participants (69%) favouring this condition, as opposed to only three participants (9%) preferring the single-player mode ($p < 0.01$), with the remaining subjects indifferent. The main reason given for favouring dual-player mode was that this made the game 'more fun and unpredictable'. At the same time, dual-player mode was perceived to increase pressure ($p < 0.01$) and effort ($p < 0.05$). There was no significant preference for either mode in terms of self-reported skill ($p = 1.0$). Comments about the game were enthusiastic, e.g. the design was 'original and fun', 'an interesting and motivating scenario', and 'I liked the visuals'. There were no significant differences in self-reported difficulty comparing single vs. dual-player modes ($p = 0.16$; single-player: 7 ± 1; dual-player: 8 ± 2.5; out of 10; median ± interquartile range). A positive correlation was present between the perceived player competence and actual single-player scores (stars: $\rho = 0.49, p < 0.01$; accuracy: $\rho = 0.56, p < 0.001$; stability $\rho = 0.51, p < 0.01$), but not between the perceived player competence and dual-player scores (stars: $\rho = -0.07, p = 0.71$; accuracy: $\rho = -0.04, p = 0.82$; stability: $\rho = -0.04, p = 0.82$). No significant correlations were found between perceived effort or pressure, and the (single or dual-player) scores.

The IMI was answered more positively, in terms of Enjoyment & Interest, during dual-player mode ($p < 0.001$; Fig. 6b). However, there was no significant difference between game modes for Perceived Competence ($p = 0.60$) or Effort & Importance ($p = 0.17$). Correlations were also compared for the three IMI categories across the two gameplay modes. The only significant differences in correlation was found between Enjoyment & Interest and Perceived Competence (single-player: $\rho = 0.38, p < 0.05$; dual-player: $\rho = 0.007, p = 0.97$). Significant correlations were found between Enjoyment & Interest and Effort & Importance for both game modes (single-player: $\rho = 0.39, p < 0.05$; dual-player: $\rho = 0.51, p < 0.01$). No significant correlations were found between Perceived Competence and Effort & Importance in either game mode (single-player: $\rho = 0.27, p = 0.13$; dual-player: $\rho = 0.23, p = 0.21$).

Patient-expert experiment

Participants

One hundred consecutive stroke patients presenting with arm paresis secondary to acute stroke were screened. Figure 7 highlights the reason for patient exclusion leading to 16 subjects participating in the study. Table 1 provides characteristics of the recruited patients.

Performance analysis

Table 2 shows the average values (mean ± std) for the five metrics (stars, accuracy, stability, effort, smoothness) within the different game modes (single or dual) and trials, for both the healthy expert and patient players. No differences were found across the two trials (T1, T2), so the data was pooled across trials for subsequent analyses. As expected, all patients (using their paretic hand) performed worse than the healthy expert during single-player mode, with single-player scores (mean±std) for patients (stars: 15.3 ± 8.3, accuracy: $8.1 \pm 6.9\%$, stability: $8.1 \pm 8.3\%$) and expert scores across ten trials (stars: 44 ± 0, accuracy: $87.6 \pm 10.6\%$, stability: $94.7 \pm 1.4\%$) significantly different ($p < 0.001$ for all). The expert's single-player score highlights that they were playing at a high and consistent level, especially the achievement in terms of the highest number of stars possible across all ten trials.

Given that all patients were worse than the expert during single-player mode, and that dual-player mode benefited the inferior partner of healthy-healthy pairs, dual-player (patient-expert) mode was analysed in terms of patient performance relative to their single-player score. Figure 8 shows plots of dual-player improvement

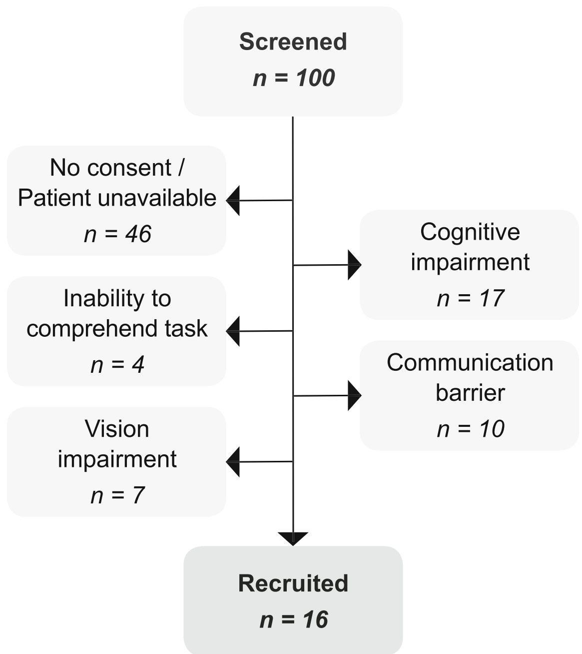


Fig. 7 Patient Protocol. Reasons for exclusion in the cohort of stroke patients with arm weakness

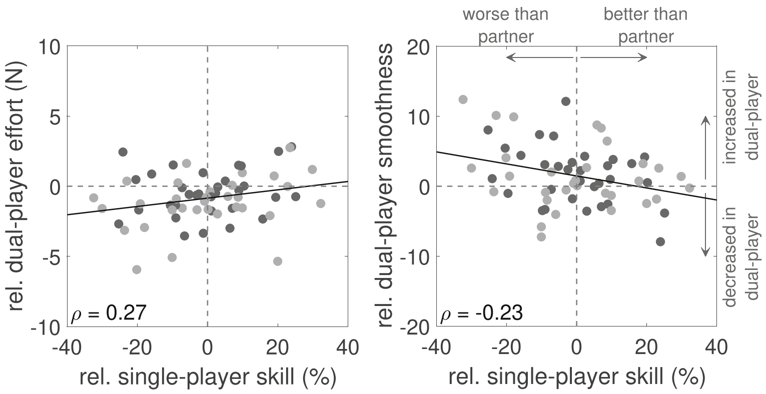


Fig. 5 Healthy-Healthy Motor Control Analysis. Comparison of single- and dual-player effort and control smoothness as a function of relative individual ability: **a** Relative improvement of effort during dual-player is positively correlated to the relative skill (i.e. difference in stability performances) of the individual during the single-play mode ($p < 0.05$). **b** Conversely, the relative improvement of control smoothness in dual-play is negatively correlated to the relative skill between the partners ($p = 0.069$) although insignificant

against (single-player) patient ability highlighting that not only did the majority of patients benefit from the dual-player mode (i.e. number and size of positive y data-points; stars: $p < 0.05$; accuracy: $p = 0.07$; stability: $p < 0.001$; MWU test comparing game modes), but similarly to the healthy-healthy study, the extent of this improvement correlated with the extent of patient ability (Fig. 8; stars: $\rho = -0.51, p < 0.01$; accuracy: $\rho = -0.45, p < 0.05$; stability: $\rho = -0.43, p < 0.05$). The performance measure in which the largest number of patients benefited from dual-player mode was stability. In some cases, stability rose from < 3% during single-player mode to nearly 40% during dual-player collaboration.

The effect of the game-mode on patient effort and control smoothness was examined. Figure 9 highlights the effect of relative ability compared to the expert's performance on effort and smoothness (shown for stability only, as per analysis in healthy-healthy experiment). During single-player, patient effort was not significantly

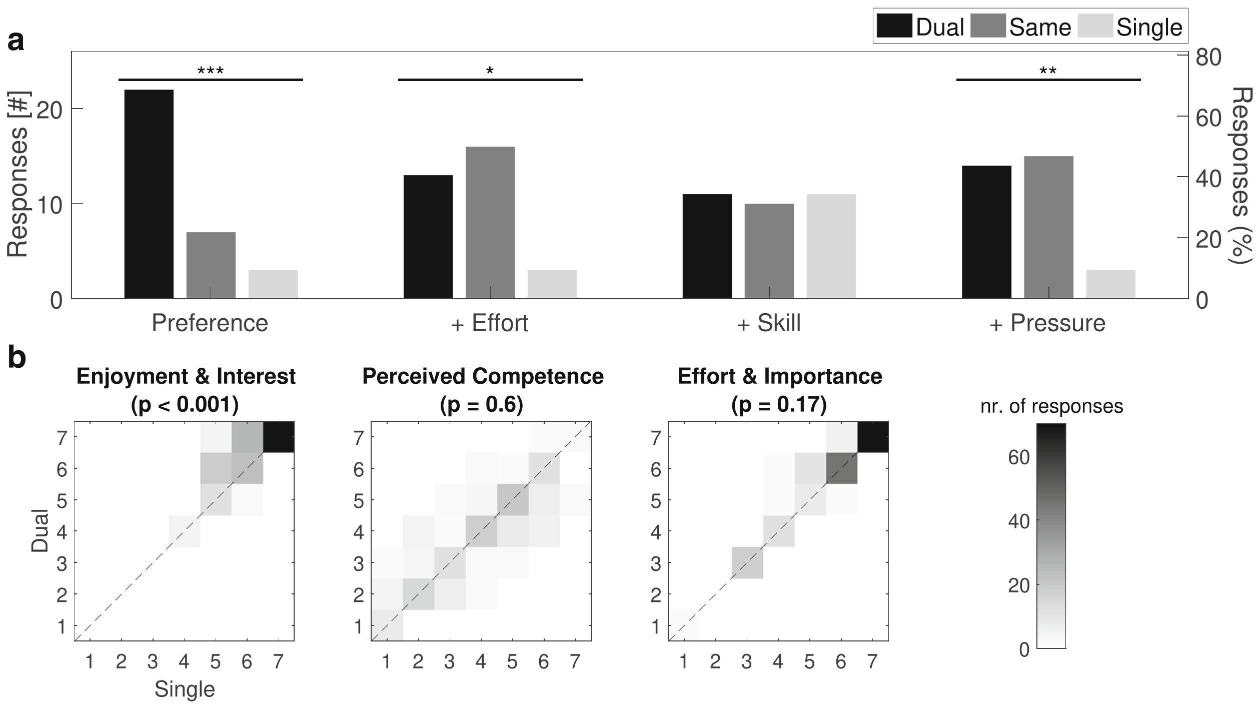


Fig. 6 Healthy-Healthy Questionnaire Responses. **a** Histograms of user experience responses. **b** Joint distributions for single and dual-player responses to Intrinsic Motivation Inventory statement categories (*$p < 0.05$,** $p < 0.01$,*** $p < 0.001$)

Table 2 Average values (mean ± std) for the five metrics (stars, accuracy, stability, effort, smoothness) within the different game modes (single or dual) and trials, during the patient-expert study (key: P - patient, E - expert)

	Expert single-player	Patients single-player		Patient-Expert dual-player	
	(10 reps)	T1	T2	T1	T2
Stars(#)	44 ± 0	14.9 ± 7.4	15.7 ± 9.4	17.3 ± 7.2	19.7 ± 8.1
Accuracy (%)	87.6 ± 10.6	7.7 ± 6.1	8.4 ± 7.9	9.6 ± 5.8	11.2 ± 8.5
Stability (%)	94.7 ± 1.4	7.3 ± 7.1	8.9 ± 9.5	24.8 ± 10.2	23.1 ± 11.5
Effort (N)	10.8 ± 0.9	10.2 ± 4.4	8.4 ± 4.1	P: 8.4 ± 4.1	P: 8.2 ± 3.6
				E: 13.1 ± 1.6	E: 13.4 ± 1.6
Smoothness	21.9 ± 4.6	18.1 ± 7.2	16.4 ± 4.3	P: 15.4 ± 3.4	P: 17.4 ± 3.9
				E: 18.1 ± 3.7	E: 19.0 ± 4.5

different to that of the healthy expert (9.3 ± 4.3N vs. 10.8 ± 0.9N, respectively; $p = 0.08$; unpaired MWU test); whereas patients were inferior to the expert in terms of smoothness (17.2 ± 5.9 vs. 21.9 ± 4.6; $p < 0.01$). Figure 9 shows that there is little association between patient performance and the effect of dual-player mode on effort or smoothness.

Relationship between impairment, age and performance

The effect of dual-player mode on patients, in terms of arm disability (rather than game performance) and age, was explored. Figure 10 shows that single-player performance across patients was, as expected, positively correlated with arm ability (Short-Fugl-Meyer; S-FM score), and negatively correlated with age, for all three performance measures. The effect of dual-player mode (i.e. interacting with an expert partner) was to slightly increase the magnitude of correlation for stars and accuracy, while decreasing it for the stability score. In the case of arm ability, the effect of dual-player mode was to significantly switch the correlation from positive-to-negative, suggesting that the expert provided proportionately greater (stability) compensation for patients with greater impairment (stars: $p = 0.71$; accuracy: $p = 0.98$; stability: $p < 0.05$; tested using a nonparametric bootstrap method). For age vs. scores, there were no significant differences between single and dual -player modes across all the metrics (stars: $p = 0.34$; accuracy: $p = 0.10$; stability: $p = 0.36$).

A related question is whether the relative benefits of dual-player mode amongst patients depended upon general arm ability and age. Figure 11 shows that dual-player improvement was found to correlate negatively with general arm ability, but only for stability ($\rho = -0.41$; $p < 0.05$) and not for stars ($\rho = 0.01$; $p = 0.94$) or accuracy ($\rho = 0.07$; $p = 0.69$). For correlations of dual-player improvement with age, there were no significant correlations with dual-player improvement. However, a small negative trend (i.e. slightly greater improvement for younger patients) exists for accuracy ($\rho = -0.29$; $p = 0.11$), while a possible positive trend for stability ($\rho = 0.096$; $p = 0.64$) appears to be weakened by subjects > 90 years old who benefit less from dual-player interaction. Dual-player improvement in the number of stars collected was independent of age ($\rho = -0.08$; $p = 0.65$).

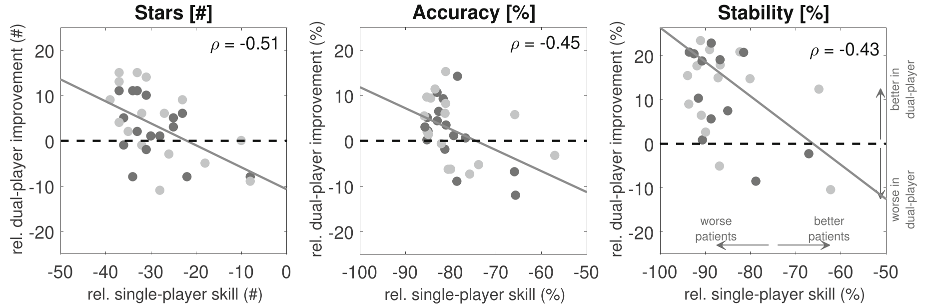


Fig. 8 Patient-Expert Performance Measures Analysis. Effect of dual-player mode in patient-expert experiment for star-collection, accuracy and stability performance metrics. Relative improvement during dual-player interaction is seen for the majority of patients (especially in terms of stability). Furthermore, the greater the skill difference between patient and healthy expert, the greater the improvement afforded by the dual-player mode (stars: $p < 0.01$; accuracy: $p < 0.05$; stability: $p < 0.05$)

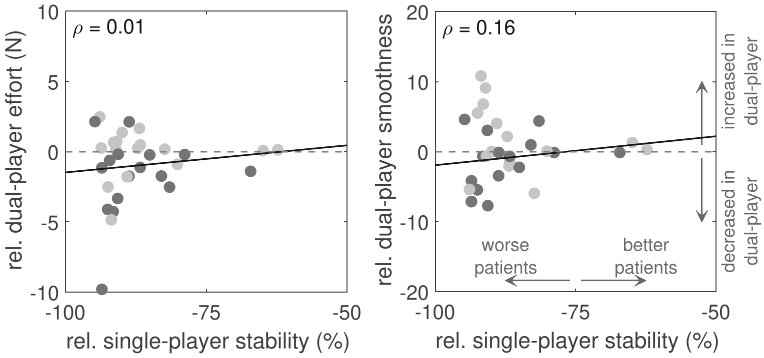


Fig. 9 Patient-Expert Motor Control Analysis. Comparison of single- and dual-player effort and smoothness during patient-expert experiments: **a** Patient effort during dual-player, relative to single-player, mode is independent of patient stability during single-play ($p = 0.94$). **b** Control smoothness during dual-player, relative to single-player, mode is independent of patient stability during single-play ($p = 0.37$)

Qualitative game assessment

Figure 12a shows that similarly to the healthy subjects study, patients significantly preferred dual-player to single-player mode (88% vs. 6%; $p < 0.001$) and felt that the dual-player mode allowed them to put more effort in (63% vs. 13%; $p < 0.05$). Contrary to the healthy subjects, patients felt that dual-player interaction made them more skilled (63% vs. 13%; $p < 0.05$), but not feel more pressured (25% vs. 31%; $p = 0.65$). Typical participant comments included that dual-player mode was 'more fun', 'motivating', 'easier with the guidance of an expert player'; 'enjoyable, motivating and innovative'; and 'the visuals were impressive'. Nine of the 16 (56%) participants wanted to continue playing that same day; while out of the remaining seven patients, a further five (31% of total patients) wished to play again on another day. Participants found the dual-player game significantly less difficult (4.5 ± 3; median ± IQR; out-of-10) than the single-player mode (7 ± 2.5; $p < 0.01$). Figure 12b also highlights that patients expressed significant preferences for dual-player mode in terms of all three categories (Enjoyment & Interest: $p < 0.01$; Perceived Competence: $p < 0.01$; Effort & Importance: $p < 0.001$) of the IMI tested.

Discussion

Visual-coupling alone achieves an engaging zero-sum game

Results from the healthy-healthy study showed how collaboration influences the joint performance, by improving the score of the worse player while increasing the challenge for the better partner. Importantly, the difference in individual skill levels of the two players did not influence the performance, while interaction with a more skilled partner did not require more effort during dual-player interaction. The patient-expert study demonstrated that all patients were able to successfully play both the single and dual-player game modes regardless

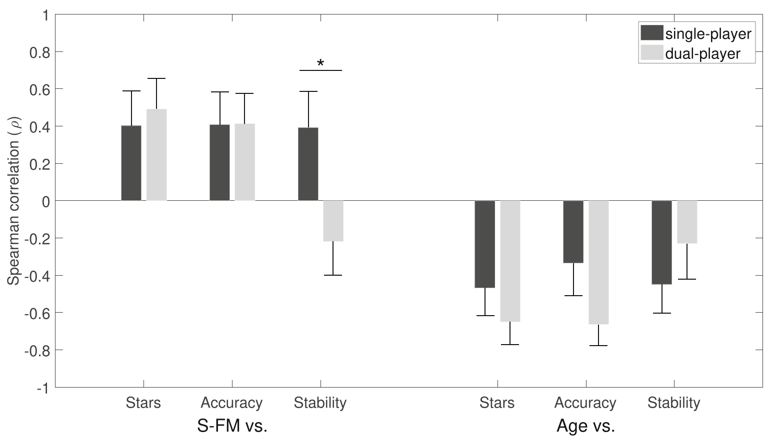


Fig. 10 Patient-Expert Performance-Impairment Correlations. Comparison of single and dual -player game modes on Spearman correlations (ρ) between performance and general arm ability (Short-Fugl Meyer; S-FM), or performance and age, for each of three main performance metrics. Correlations are shown as mean and standard error calculated from 10,000 bootstrap samples. Based on these bootstrap distributions, differences between single and dual-player game modes in terms of correlation are also shown (*$p < 0.05$ for S-FM vs. Stability only)

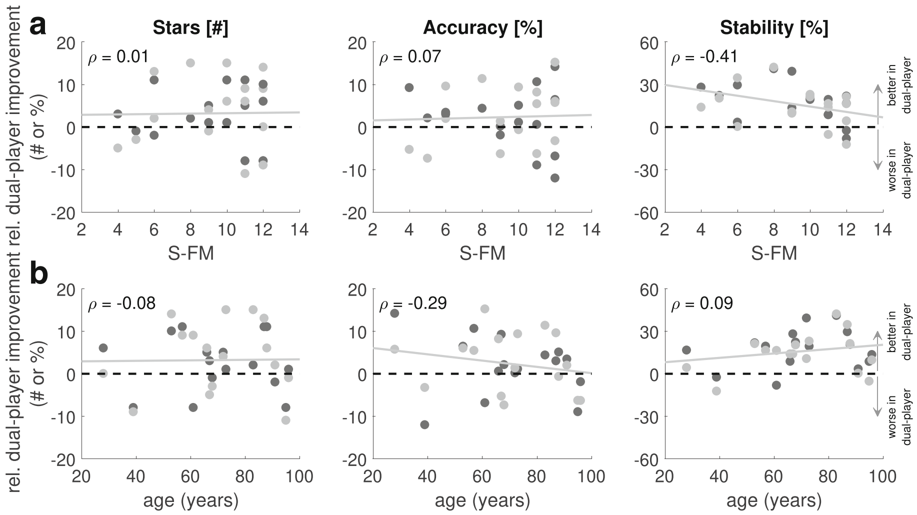


Fig. 11 Patient-Expert Relative Performance. Relative dual-player improvement as a function of (**a**) general arm ability (S-FM) and (**b**) age, in patients, measured across the three scores

of impairment and age. Game performance was shown to dramatically improve during the dual-player mode, especially for the less skilled patients, with the expert partner providing support and compensation to keep the beam horizontal. Ultimately, this enabled the patients to collect more stars and be more accurate, while having a similar level of effort and smoothness. As expected, scores (i.e. stars and accuracy) generally got worse with impairment and age. However, the relative improvement (in terms of stars collected) during dual-player interaction showed no correlation with either impairment or age.

The results suggest that the joint performances are driven by an averaging process or zero-sum game based

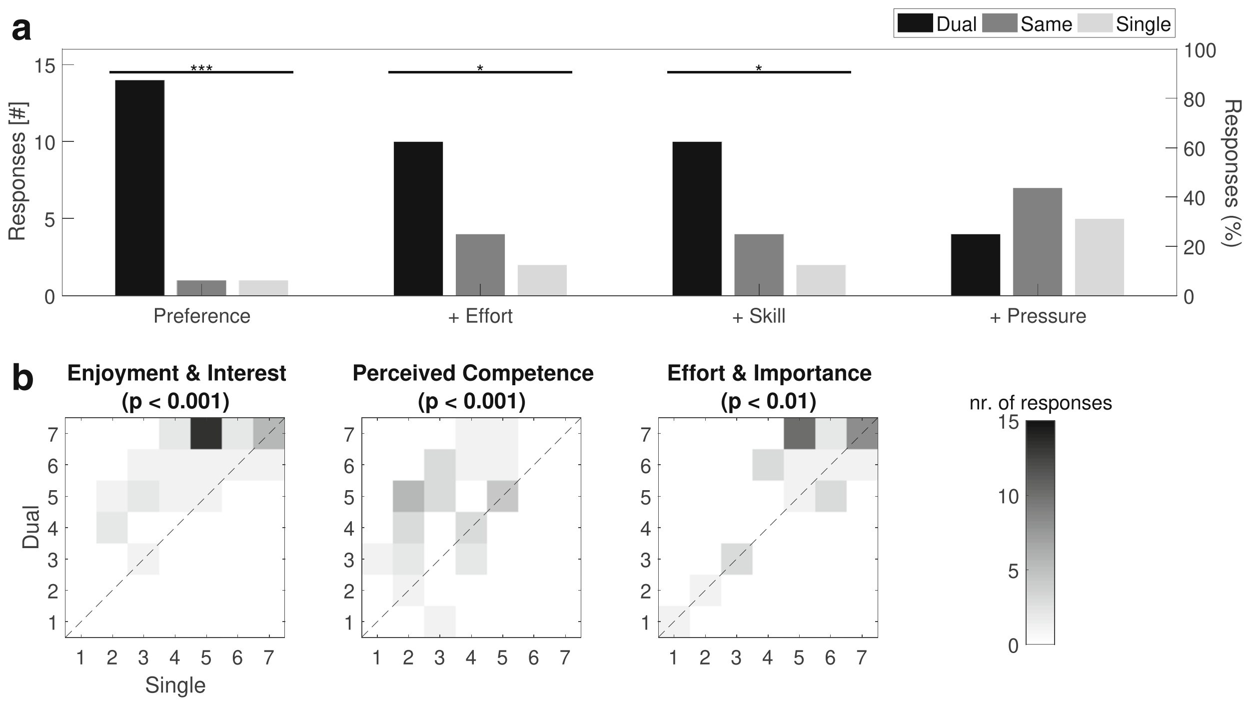


Fig. 12 Patient-Expert Questionnaire Responses. **a** Histograms of user experience responses. **b** Joint distributions for single and dual-player responses to Intrinsic Motivation Inventory statement categories (*$p < 0.05$,** $p < 0.01$,*** $p < 0.001$)

on the individual skill levels of the partners. By modifying the level of challenge experienced by each partner, they are more likely to achieve an appropriate 'challenge point', whereby the joint challenge and skill level are balanced (regardless of their individual skill levels) [33]. An appropriate challenge point is defined as the perception of engaging in challenges at a level appropriate to one's capacity, and results in an intense focused concentration in the moment and a perceived sense of control over one's actions [3, 4]. Moreover, the intrinsic skill balancing is not simply an averaging of the skill levels. Regardless of the ability of an individual, they would not succeed if playing with, for example, a (virtual) partner who was either completely constant or very noisy (i.e. very unskilled). This suggests that there is an operating band associated with the relative skill levels which permits a range of different skill levels to successfully play together while preventing either partner from completing the task alone.

Both healthy-healthy and patient-expert participants indicated a strong preference for the dual-player game over the single-player version. The dual-player mode increased enjoyment, perception of competence and self-reported effort amongst the patients, while giving them the sense of increased competence without increasing the pressure they felt. Therefore, individuals with and without sensorimotor limitations, found the collaborative game significantly more engaging than the single-player equivalent, and can be attributed to the skill balancing and social aspects that the multiplayer game affords.

Collaborative gaming for physical training

The simplicity of the task implies that patients can also use the game to train with a variety of movements (e.g. grip, elbow flexion-extension, ankle plantar flexion-extension) and different rehabilitation devices. By increasing their engagement compared to playing alone, patients are more likely to increase the number of repetitions they perform and the effort they put into the training, which could ultimately lead to greater gains in performance [34, 35]. This game can be used in different rehabilitation scenarios involving, but not limited to, i) patients training with a therapist or relative, for instance a grandmother playing at home with her grandchild; or ii) patient-patient training e.g. whilst still at the hospital bedside or within community centers. Due to the low skill level of both partners in scenario (ii), the game parameters would (in some cases) need to be further adapted. In fact, by modifying different game parameters such as trajectory, background, speed, bonuses, obstacles etc., the game can be designed to incrementally increase the global challenge level for the dyad as their combined skill level increases with practise. For example, more difficult levels can be unlocked as the game progresses.

Local redundancy balances the playing field and prevents slacking

The main focus of this multiplayer gaming concept is collaboration, promoting positive teamwork and social rehabilitation. Competitive games have been previously introduced [11, 13], where competition seemed to motivate some patients, but also discourage a significant proportion of them. However, the pong game used in these studies does not involve continuous interaction, in contrast to our game, and thus the results cannot be directly compared. Andrade et al. have previously developed a multiplayer rehabilitation game involving true interaction and collaboration [10]. The players receive haptic feedback providing additional information of the interaction, but have independent (orthogonal) control inputs so that an individual cannot help a patient to succeed in the task. This means that the game is not redundant, as one player's action cannot compensate for a mistake from the other. In fact, it is the locally redundant nature of our interactive task that produces a challenging, but accessible exergame, for both partners independent of their relative skills, without requiring an additional skill-rating or skill-balancing algorithm (e.g. [36]). Previously, Vanacken et al. have introduced a ball-balancing concept utilising arbitrarily placed static targets, in contrast to a smooth continuous trajectory which is used in this study [23]. Our analysis has shown that, beyond just collaborative interaction, individuals of different skill levels can play together continuously (and without slacking), ultimately enjoying it more than single-player mode and suggesting that participants are more likely to exercise longer during dynamic multiplayer collaboration.

Local redundancy is achieved by ensuring that the players' control inputs are non-orthogonal so that the actions of one player can compensate for the incorrect actions of another player, i.e. the control inputs are redundant. However, fully redundant inputs can easily lead to slacking behaviour, as either of the inputs can perform the actions for the other player and human motor control naturally minimises effort [22]. Therefore, the two inputs are 'physically' coupled (in the virtual world) so that only through active control from both inputs can it ensure that the end-effector (e.g. the buddy) can be moved correctly (without allowing the buddy to fall). Furthermore, defining the interaction in this manner allows the dyad to employ different strategies to complete the task. For example, during patient-expert collaboration, the expert seems to concentrate on minimising the buddy falling by increasing stability (i.e. by following the movements of the patient).

Relation to actual physically-coupled paradigms

The collaborative rehabilitation games outlined in this paper are related to recent work investigating sensorimotor interaction in humans [16, 17, 37–39]. In [16, 17], pairs of subjects were connected by a virtual, but physically rendered, elastic band providing additional haptic information to the partners. The elasticity of the connection, meant that the partners could not rely on each other in order to succeed, implying neither could slack, a similar property elicited by this game. In contrast to our task, the partners could also work independently, which would not be adequate for neurorehabilitation where the patient requires assistance to move or control their limb. Both worse and better partners improved performance in [16], which is likely due to the additional haptic communication [17]. It would be interesting to study whether haptic feedback in combination with local redundancy could enhance the social rehabilitation experience further. However, using sensor-based technology (without active haptic feedback) provides decentralised therapy tools that are affordable and can be used both in-hospital and at-home. By combining these tools, such as the grip-force sensor used in this study, with socially engaging gaming concepts, patient engagement can be increased, ultimately leading to better patient compliance during rehabilitation.

Limitations of the current study

The lack of a reactive single-player mode, e.g. based on an intelligent agent, could also be a factor as to why subjects had reduced performance and preference during the single-player version. A reactive agent, that could perform compensatory behaviour similar to the expert partner, could potentially increase the joint performance and also adapt to the partner as their ability progressed [16, 17]. Whether a patient would prefer playing with a human partner or computer agent would need to be further explored alongside any performance gains, which was beyond the scope of this study. Another limitation of the current study, necessary due to practical considerations, is the limited number of trials performed. This meant that patient motivation over longer training times could not be explored. Therefore, the next steps would be to explore the effect of our collaborative task during a longer motor learning paradigm involving healthy subjects and patients to see if (a) more efficient learning occurs and, (b) to examine if patients are more motivated to train for longer periods. We will also explore in more detail social aspects of interaction (e.g. conversation, playing with a relative vs. stranger, etc.) which are important to both performance and motivation [13, 40]. For instance, we will explore conditions where the dyads are either permitted or prevented to communicate during interaction and analyse the effect on their performance and qualitative evaluation. Beyond conversation, complete blinding of the participants to the gender, age, and demographic of their partner would also be an interesting avenue to explore.

Conclusion

We have presented a framework to develop truly collaborative multiplayer gaming enabling two players to train together. The framework allows for the development of games that are simple, dynamic and interactive. A central property of the concept is its local redundancy, enabling players to help each other to succeed at the task, without replacing each other's action entirely. This forces them to actively participate concurrently. Results from our healthy-healthy and patient-expert experiments highlight that: i) due to local redundancy, the game and scores can be modulated by the more skilled partner, although only within the bounds that the impairment or skill of the weaker partner allows, and ii) neither partner is able to 'slack' regardless of impairment, age and differences in relative skill levels. In the future, we expect new 'collaborative gaming for physical training' concepts to be developed, based on this simple framework, with the aim of increasing motor learning efficiency and patient engagement during virtual therapy tasks. The exploration of human-like agents during human-computer interaction scenarios alongside increased training times and the influence of social aspects, and their effect on performance, long term motivation and motor transfer, should also be studied.

Endnotes

[1] Note that the interactions in many previous studies are denoted as collaborative or cooperative. However the tasks specified in these studies do not require an exchange of information between the partners, e.g. in the Pong game, only an individual working alone is required to return the puck at any point in time [6, 11, 13]. Relative to Jarrassé et al.'s comprehensive taxonomy of interactive behaviours [14] these definitions have been used inconsistently and should actually be classified as co-active interaction.

[2] Despite the many social implications of such a collaborative virtual task, examining social elements such as the effect of verbal communication was not considered during this study.

[3] This force-to-height mapping is implemented using the Unity© 'SmoothDamp' function.

[4] A short video showing the game being played by a patient and therapist is provided as Additional file 1.

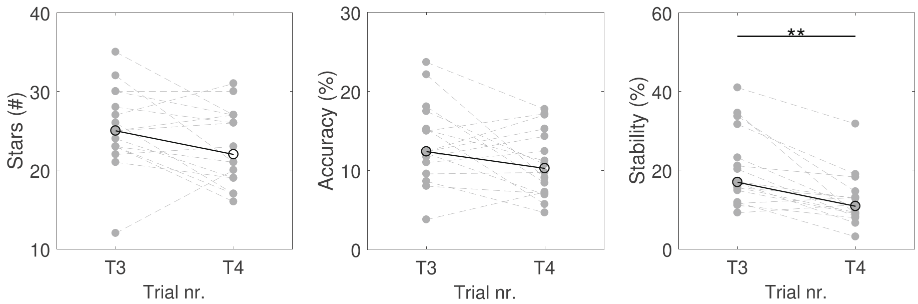


Fig. 13 Healthy-Healthy Perturbation Results. Highlighting the difference in performance between turns T3 and T4 due to the perturbation introduced to the control of one of the partners prior to T4 during the healthy-healthy experiment. Only the stability metric shows a significant decrease (**$p < 0.01$)

Appendix

(A) Questionnaires

Game experience

The following questions were asked to assess the experience of the players during the game and compare the single and multiplayer modes:

QD Rate the difficulty of the 2 game conditions, from 0 to 10.
QP Which game condition did you like the most? [Single, Same or Multi], Why?
QE Which game condition did you put the most effort into? [Single, Same or Multi]
QS During which game condition did you feel the most skilled? [Single, Same or Multi]
QP During which game condition did you feel the most pressured? [Single, Same or Multi]
QC Any comments (e.g. gameplay, feedback, visuals)?

Intrinsic motivation inventory

The following questions were asked to assess the intrinsic motivation during both game conditions (single and multiplayer):

1. I tried very hard on this game [P]
2. I think I am pretty good at this game [P]
3. This game was fun to play [P]
4. I did not put much energy into this
5. This game did not hold my attention at all
6. I was pretty skilled at this game
7. I thought this was a boring game [P]
8. I am satisfied with my performance at this game
9. I put a lot of effort into this
10. I enjoyed playing this game very much
11. I did not try very hard to do well at this game
12. This was a game that I could not play very well [P]
13. I thought this game was quite enjoyable
14. It was important to me to do well at this game [P]
15. I think I did pretty well at this game, compared with the others

Note: [P] indicates the questions selected in the patient version. This questionnaire uses a Likert scale from 1 to 7 (1 = not at all true, 4 = somewhat true and 7 = very true)

(B) Healthy-healthy perturbation results

Figure 13 highlights the change in multiplayer scores between turn T3 (normal control) and T4 (perturbed control). Using a MWU test, it can be seen that only the stability metric decreases significantly. For the perturbed controller, a small increase of force now results in a larger change in the balloon's height implying that balancing the beam is indeed harder to achieve. Moreover, the players were surprised by the sudden sensitivity and needed some time to adapt to this new control. Besides this effect on the stability, the performances were overall conserved, indicating that although the stars and accuracy scores decrease, the players still manage to collaborate efficiently. This strengthens the hypothesis that partners with different abilities are able to play together. For instance, a patient who experiences difficulties producing smooth movements (e.g. due to spasticity) may be helped by a healthy partner who can compensate for this.

Additional file

Additional file 1: Video showing the Balloon Buddies™ game being played by a patient and therapist. (MOV 73318 kb)

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Availability of data and materials
Please contact author for data requests.

Authors' contributions
MM, NK, PR, PB, EB devised and developed the Balloon Buddies^{TM} concept, and wrote the manuscript. NK wrote the code, designed the graphics and

implemented the game into Unity©. NK supervised and collected the healthy-healthy study data. AR supervised and collected the patient-expert study data. MM and NK performed the data and statistical analysis in Matlab©. All authors read and approved the final manuscript.

Ethics approval and consent to participate
Approval for the study was given by the South East Coast Research Ethics Committee and all participants signed an informed consent form prior to any study-related procedure.

Consent for publication
All authors have approved the manuscript for publication.

Competing interests
The grip-force sensor technology reported is patented by authors MM, PR, PB, EB, through Imperial Innovations. A company has been incorporated with the intention of commercialising both the handgrip and software.

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POSTER 1

POSTER 1: Feasibility trial of a low-cost, self-administered gaming system for upper limb exercise in stroke.

Self-administered gaming exercises (GripAble) for stroke arm disability increase exercise duration more than two-fold, and repetitions more than ten-fold compared to standard care.

SELF-ADMINISTERED GAMING EXERCISES FOR STROKE ARM DISABILITY INCREASE EXERCISE DURATION BY MORE THAN TWO-FOLD AND REPETITIONS MORE THAN TEN-FOLD COMPARED TO STANDARD CARE

Imperial College London

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Background & Aims

Benefits of upper limb(UL) rehabilitation after stroke are strongly dose-dependent [2]. The current daily duration of supervised, active UL exercise in standard stroke-inpatient settings is ~20 minutes; while number of exercise repetitions is ~30 [1]. Increasing the amount of UL exercise by increasing therapist time is generally too costly for state-funded healthcare. We conducted a feasibility trial of a low-cost (<$1000) self-administered gaming system for UL exercise in a cohort of stroke inpatients, measuring the dose and intensity of UL exercises completed relative to standard care.

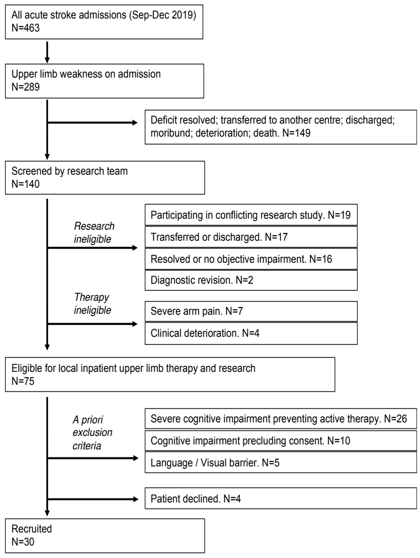
Aims

The study had three main objectives; to test the fidelity, feasibility and acceptability of the intervention and research design.

A secondary aim was to estimate the amount of supplementary, self-directed UL exercise achieved by participants.

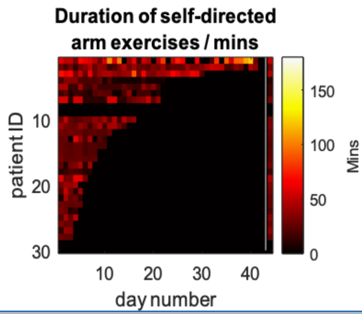
Methods

All stroke survivors (≤1month post stroke) with new UL weakness (of any severity) were screened over 3months (September-December 2019) at a central London stroke centre (See Figure 1.). Participants were taught in a single session to use the self-administered gaming system (GripAble) (See Figure 4.), which was then provided to them for the remainder of their inpatient admission. Baseline participant data was collected to demonstrate the sample characteristics (See Figure 2.). Participants continued their conventional rehabilitation, as guided by their treating clinical team. Records of participant adherence with the intervention (duration of exercise and number of exercise repetitions) were automatically logged via an inbuilt electronic data capture system and corroborated by participant self-report. At study end point, a technology acceptance survey [3] and research feedback form were administered. In order to support a robust feasibility evaluation, detailed study records including recruitment and retention data, adverse events logs and study support notes were maintained throughout the study period and retrospectively reviewed.



Baseline characteristics	Min.	Mean	Max.
Age	42	70.3	89
Male sex	0	0.53	1
Premorbid mRS	0	0.83	1
NIHSS	3	8	3
Haemorrhagic subtype	0	0.27	21
Time since stroke	2	11.13	28
Baseline MOCA score	8	19.57	28
Barthel Index score	15	46.17	95
Baseline Fugl Meyer score	9	33.27	58
Baseline fatigue score	2.3	5.057	7.3
Baseline pain score	0	1.47	8
Depression score (HADS)	1	5.47	14
Anxiety score (HADS)	1	5.5	14

Figures 1-4 *(Above & clockwise)*: **1.** *Recruitment flow diagram* **2.** Table of p*articipant characteristics* **3.** *Self-exercise duration: Heat map* **4.** *Adapted UL exergaming device(GripAble) in use with a research participant*



Results

30 participants were recruited (See Figure 1.). Mean enrolment duration was 14days. 26/30 participants were able to use the system; 11 requiring some support by any abled person (e.g. relative). All participants (including those unable to use the device) indicated a high overall technology acceptance rating (78%), with 73% reporting that they would have liked to continue using the device. 56% found the device easy to use and understand. 64% felt that the device promoted arm recovery. Mean daily time engaged in self-administered exercises was 24.8 mins (SD: 32)(See Figure 3.). Mean daily number of exercise repetitions was 373 (SD: 492). There were no adverse events recorded. All participants rated the research protocol including the information provided, the process of consenting, the assessments completed, and the researcher visits as "Satisfactory". 82% of participants cited willingness to be randomised.

Conclusions

Overall, the research protocol and intervention were found to be safe, feasible and acceptable within this heterogenous group of stroke survivors. Self-directed gaming exercises for UL disability increased exercise time by more than two-fold, and UL repetitions more than 10-fold, compared to standard care, including in patients with moderate-severe disability and cognitive impairment. Further work is needed to determine clinical efficacy outcomes and cost effectiveness. Protocol details for pilot work are available via ClinicalTrials.gov.uk: NCT04475692.

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POSTER 2

POSTER 2: An exploration of associations between technology acceptance and individual characteristics of stroke survivors.

The accessibility and acceptance of technology varied between participants. Technology-based intervention (GripAble) was accessible to 86% of the participants and acceptable to 78%".

Imperial College London

AN EXPLORATION OF ASSOCIATIONS BETWEEN TECHNOLOGY ACCEPTANCE AND INDIVIDUAL CHARACTERISTICS OF STROKE SURVIVORS

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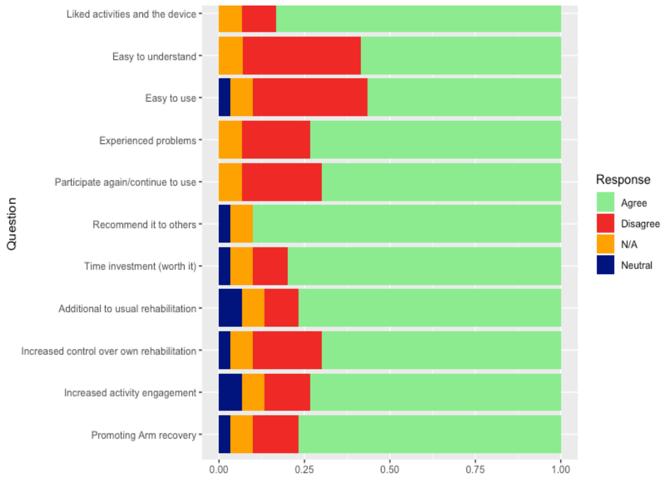
Background & Aims

Digital technology healthcare platforms are changing the way we deliver and access health services. We depend now more than ever before on effective remote healthcare delivery models. In stroke care, technology has long been acknowledged as a mechanism to extend stroke rehabilitation beyond the threshold of conventional care resources. However, as yet, technology adaptation within the stroke population remains low. There is an urgent need to ameliorate this. Little is known about factors influencing technology acceptance amongst this specific patient cohort. We investigate the complex interactions between patient characteristics, technology accessibility, technology acceptance and technology adaptation.

Methods

We conducted a feasibility study [1] of a technology-based upper limb intervention for stroke survivors. A heterogeneous group of stroke inpatients (n=30) implemented a self-directed upper limb intervention over a mean enrolment time of 14days. Participant demographic and clinical characteristics were collected on enrolment. Technology accessibility was based on participants' competence in using the system; assessed on enrolment and graded by a research therapist using a 4-point scale (*Unable to use*, *Supervision/support required*, *Support for set up only*, *Independent with all aspects of use*). Adherence with the system was recorded via an automatic data capture system for the duration of the observational period. We used the technology acceptance model (TAM) (Davis, 1989) to design a survey examining the acceptability of the system amongst stroke survivors. The TAM is comprised of two primary domains relating to the participant's intent to use the technology: (i) *perceived usefulness*, (ii) *perceived ease of use*. Sub-questions were ranked on a three-point Likert scale. Statistical interactions were examined between participant characteristics (including mood, cognition, functional status and motor impairment severity), user competence rating, end-point technology acceptance variables and individual records of intervention adherence. A network interaction model was inferred using the de-sparsified graphical lasso algorithm.

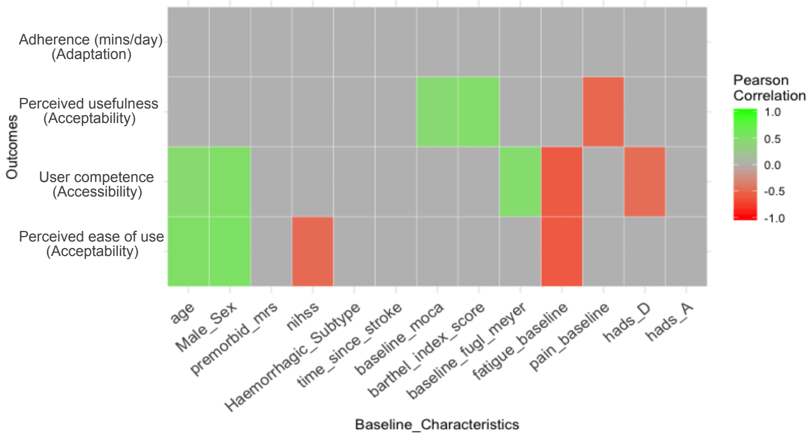


P14: "It inspired me to do something. Some (activities) harder than others- I found ones that worked for me"

P7: " found it very useful, I would say it definitely helped with boredom. (Additional to rehabilitation) everything I do is so that it will help me improve and regain my confidence"

P20: "I find it a very nice game, good and very interesting. Sometimes I go to touch it and it doesn't work, sometimes I want to play but it doesn't work."

Figure 1. *(Above) TAM survey results graph* **Figure 2.** *(Below) Interactions between variables*



Results

This technology-based intervention was accessible to 86% of participants and acceptable to 78% (See Figure 1.). 40 significant interactions were observed between 23 examined variables (See Figure 2.). A positive partial correlation was observed between male sex and both perceived ease of use (partial corr.=0.35, *P*=.028) and perceived usefulness (justification of time investment (partial corr.=0.31, *P*=.047) and consideration of technology as additional rehabilitation (partial corr.=0.34 , *P*=.032). An inverse partial correlation was observed between stroke severity (NIHSS) and perceived ease of use (ability to understand the technology components (partial corr.=-0.34, *P*=.034)).

Conclusions

The accessibility and acceptance of technology varied between participants in this heterogeneous group. Technology, like all interventions, should be tailored to the individual, we provide a model of interactions to support the implementation of digital healthcare platforms within diverse and multimorbid patient groups. These insights may be leveraged to meet unprecedent service demands in the wake of the current global health pandemic as we move to embrace novel models of healthcare delivery.

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OPTIMIZING SELF-EXERCISE SCHEDULING

Optimizing self-exercise scheduling: Patients training with GripAble and a 'Challenge Point Framework' adaptation performed better than those training with fixed conditions.

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Elasticity improves handgrip performance and user experience during visuomotor control

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Passive rehabilitation devices, providing motivation and feedback, potentially offer an automated and low-cost therapy method, and can be used as simple human–machine interfaces. Here, we ask whether there is any advantage for a hand-training device to be elastic, as opposed to rigid, in terms of performance and preference. To address this question, we have developed a highly sensitive and portable digital handgrip, promoting independent and repetitive rehabilitation of grasp function based around a novel elastic force and position sensing structure. A usability study was performed on 66 healthy subjects to assess the effect of elastic versus rigid handgrip control during various visuomotor tracking tasks. The results indicate that, for tasks relying either on feedforward or on feedback control, novice users perform significantly better with the elastic handgrip, compared with the rigid equivalent (11% relative improvement, 9–14% mean range; $p < 0.01$). Furthermore, there was a threefold increase in the number of subjects who preferred elastic compared with rigid handgrip interaction. Our results suggest that device compliance is an important design consideration for grip training devices.

1. Introduction

Interaction with the environment involves the exchange of forces while manipulation requires skillful force control and is a sensitive measure of motor condition [1,2]. For hand and finger training, this motivates *isometric training* based on force control without the need to support overt movements, for example using a force-sensing handle such as Tyromotion's Pablo device (www.tyromotion.com). Grip force control can also be used for human–machine interfaces and teleoperation applications, e.g. control of surgical robotics [3], and as a tool to study ergonomics and handgrip design [4]. Furthermore, grip strength is a pervasive clinical outcome supported by dynamometry-based isometric measurements (using the Jamar handgrip) [5,6]. Isometric training has been shown to enable the learning of force fields applied on virtual movements associated with the exerted isometric force and that this learning transferred to real (isotonic) movements [7,8]. However, such systems for isometric control or strength do not support the kinematic aspect of training which is an intrinsic part of manipulation and activities of daily living (ADLs) [9].

Grasping of objects involves grip aperture modulation and shaping of the hand, and often involves interaction with soft objects or manipulation [10]. This suggests that grip training should involve learning to shape one's hand across a range of joint angles similar to natural grasping tasks. Moreover, allowing the stretching of muscles can reduce collagen build-up in the joints and prevent further biomechanical issues such as contractures [11]. The MusicGlove system promotes finger individuation through finger tapping [12], while Neofect's Smartglove can measure overt movements of the digits using bend sensors [13], with both interfacing to virtual environments for training. A recent study in 12 chronic stroke patients with moderate hemiparesis comparing two weeks of movement-based training using the MusicGlove system to both isometric grip training and conventional therapy showed superior functional outcomes [12].

While skilful force control is critical to efficient manipulation, it may be helped by using additional joint position sensing. Indeed, proprioception can be divided into both static and dynamic components, and relies on various types of mechanoreceptors and skin afferents, including muscle spindles, Golgi tendon organs and skin stretch senses [14]. The different afferents respond in a variety of ways to different stimuli, for example muscle spindle receptors signal both the length and rate of change of muscles hence contributing to both the static and dynamic components [15]. The static component senses the stationary limb while the dynamic component involves the estimation of limb position and velocity during either volitionally generated active movements or passively induced motions. In fact, active movement itself as opposed to endpoint postures is thought to provide the greatest acuity for localization [16]. Therefore, elastic as opposed to isometric interaction will provide additional coordinated kinaesthetic information facilitating control and learning by playing a vital role during the planning and execution of voluntary movements [17,18]. A recent study comparing virtual learning based on isometric force information demonstrated the beneficial effect of additional elastic deformation on control and learning [19]. Damage to the neural circuits mediating proprioceptive function, e.g. due to an infarction in thalamic or parietal brain areas, can impair a patient's ability during goal-directed movement, prehension, accurate aiming, reaching and tracking movements [20,21]. This can occur in up to half of stroke patients and therefore technology that can stimulate proprioceptive feedback during active training are essential.

The vast majority of ADLs require a functioning hand. This explains why individuals with complete loss of movement capabilities select recovering arm and hand function as their number one priority for improving their quality of life [22]. Unfortunately, 77% of stroke survivors are affected by arm–hand weakness and poor control [23], while impaired hand function is also common in other neurological diseases such as cerebral palsy and multiple sclerosis. Hand function is also commonly impaired as a consequence of rheumatological and orthopaedic conditions such as symptomatic hand arthritis which is estimated to affect over 300 million worldwide [24]. The only intervention shown to improve arm function is repetitive, task-specific exercise, but this is limited by the cost and availability of physiotherapists [25,26]. To address this issue, we are developing affordable devices to promote independent training of hand function from the ward to the home. These simple devices provide accessible functional rehabilitation by working on improving hand function through the use of engaging virtual therapy games controlled via sensors. With such devices, it is possible to train hand functions through individuated finger movements or whole hand grip force control [27].

So how can one train using both force control and hand kinaesthesia with a passive device using no actuators? To manipulate objects such as a soft ball, one has to control the force which is coupled to motion through the object's elasticity. Similarly, we have created an elastic handle with a spring mechanism in series with a force transducer yielding force-sensing coupled with movement deformation. In a recent study, we showed that this sensitive mechanism enables even severely impaired patients to interact with a mobile tablet PC who would otherwise be unable to use such technology by conventional means, i.e. swiping, tapping and tilting [28].

This device has enabled us to study the effect of elasticity and resulting proprioceptive information on grip control. We have carried out a usability study with 66 healthy individuals, contrasting the elastic

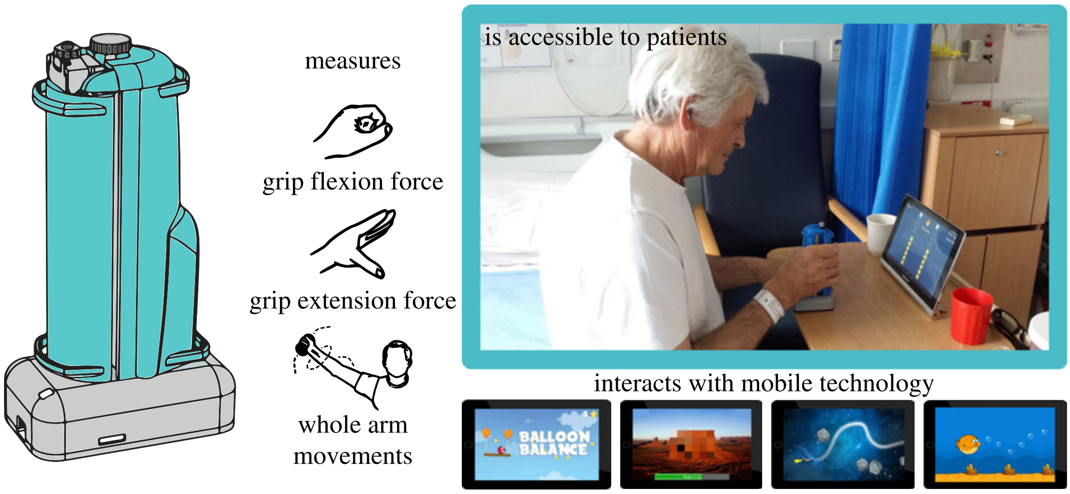

Figure 1. Overview of the interactive handgrip and mobile virtual training package including the motor behaviours the handgrip affords, alongside a photo of a patient using the digital handgrip and screenshots of some of the training games that have been developed.

behaviour that this handgrip affords to isometric-equivalent interaction during visuomotor tracking tasks. We used two types of tasks, namely, one relying predominantly on feedforward information while the other relies on continuous sensory feedback. The digital handgrip and mobile-based virtual therapy platform used for this experiment are described in the next section, followed by the description of the visuomotor tasks and experimental protocols. The results presented in the following section reveal advantages of the elastic interaction over pure isometric information for grip control, alongside the influence of different factors on performance and preferences during the different interaction modalities.

2. Material and methods

2.1. Digital handgrip

We have developed an innovative digital handgrip that allows patient-led therapy and objective assessment of the upper limb. It comprises a force-sensing mechanism which enables the handgrip to deform elastically when squeezed [29]. Additional motion tracking sensors allow the simultaneous training and assessment of a variety of hand and upper-arm movements such as grasping and lifting an object. The handgrip interacts with specially designed app-based therapy games. These virtual therapy games are designed to be highly motivating, accessible to all ages and levels of cognitive function, and to automatically adapt to the ability of the individual. Figure 1 shows an overview of the handgrip concept including mobile-based virtual gaming therapy.

In this study, the internal structure of the handgrip consists of either the elastic force-sensing mechanism [30] or a completely stiff structure (isometric version) connected to a bidirectional ± 5 kg 1 degree-of-freedom (d.f.) load cell (Phidgets 3133_0 micro load cell CZL635). Two external shells are mounted to one side of the load cell and the opposite side of the internal structure, respectively. These shells have been ergonomically designed to fit comfortably within the power grasp of a human hand with the rear shell located against the thenar eminence and the front shell in contact with the phalanges. Externally, there is no difference between the elastic and rigid handgrips. Grip extension can be facilitated with the use of straps (not shown).

The force-sensing mechanism uses a novel variable stiffness mechanical structure, coupling force and movement [30]. This mechanism is free from friction and backlash while supporting a range of bidirectional spring-like movements in grip flexion and extension. The device is highly sensitive and able to capture barely visible 'flicker' movements, which are often exhibited by individuals in the acute phase following physical impairment. It is worth noting that once completely compressed, the elastic handgrip will measure any additional grip force in an isometric manner up to the maximum force of the load cell (i.e. 50 N). The rigid version of the handgrip transmits the force exerted between the phalanges and thenar eminence entirely isometrically with no movement of the two shells occurring.

The handgrip sensitivity is only limited by the resolution of the 10-bit analogue-to-digital convertor (ADC) onboard the microcontroller unit (MCU), and noise introduced by the electronic circuitry. To further elevate the ADC resolution, an oversampling strategy has been implemented increasing the force

Table 1. System characteristics and salient values associated with both elastic and rigid handgrip devices.

system characteristic	possible values	values used
range	$\pm$50 N	0–20 N
resolution	0.0288 N bit^{-1}	0.0288 N bit^{-1}
sensitivity	<1.5 N	<1.5 N
ROM[a]	$\pm$10 mm	0–10 mm (flexion)
grip aperture (unloaded)	55–75 mm	65 mm
compliance[a]	0.06–0.5 mm N^{-1}	0.2 mm N^{-1}

[a] Applicable to the elastic handgrip only.

resolution to 0.0288N/bit. The peak-to-peak noise of the load cell, pre-amplifier and MCU was measured as less than 50-bits post-oversampling which implies a sensitivity of less than 1.5 N. The sensitivity is further increased by digitally filtering the noise (pre-downsampling) using a fourth-order Butterworth filter with a cut-off frequency of 100 Hz. An inertial measurement unit (IMU, Bosch BNO055) is used to track the motion of the handgrip while a 10 mm coin vibration motor (Precision Microdrives 310-103), which is located under the rear shell, enables vibro-tactile stimulation during handgrip interaction (although both these functions are not used in this study). The electronics (MCU, pre-amplifier, IMU, vibrator drive circuits, bluetooth transmitter and battery) are housed in the base of the handgrip, which enables capture and wireless transmission of the force and motion data to a tablet PC at a sampling rate of 50 Hz. In this study, only the force data are analysed. Table 1 summarizes the system characteristics associated with the handgrip devices and the values chosen for this study. For the remainder of this paper, we refer to *soft* interaction as that provided by the novel elastic force-sensing mechanism which flexes when squeezed (i.e. measures force alongside movement) and *rigid* interaction as that provided by the stiff structure which does not flex when squeezed (i.e. only measuring the isometric force).

2.2. Visuomotor control tasks

Two different tasks, corresponding to two tracking conditions, are used to test feedforward and feedback control, respectively. In both tasks, the subject controls the vertical position of an on-screen cursor proportionally to their grip force to track a continuous reference trajectory. In the *feedforward condition*, motion planning is promoted by scrolling the background horizontally at a constant speed relative to the cursor. At any point in time, this enables the subject to see the reference trajectory up to 5 s before they have to react to it and thus they have time to plan the necessary grip force action (i.e. squeeze or relax) in advance of the action being required. In the *feedback condition*, the subject has to follow the cursor but has no visible reference trajectory. This is achieved by moving a reference target centrally in the vertical plane based on an unknown but continuous reference path. The subject is tracking this path by trying to align the cursor with the target at all times. As the subject is unable to plan the required action, they will rely on the instantaneous visual information alongside knowledge of their current grip force state, perhaps relying more on fast kinaesthetic sensing rather than on slower visual feedback [31,32]. Figure 2 shows the visual information presented during each of the tasks. Both tasks have been gamified, with the feedforward task defined through a 'SpaceWay' game whereby the cursor is a spaceship and the reference trajectory is shown as a path of space dust to follow. The feedback task is defined through a 'StarShooter' game whereby the cursor is a crosshairs and the target is a moving purple star.

Three reference trajectories have been used to test the tracking abilities across subjects and devices (elastic or rigid version). The trajectories tested are a sin-to-chirp (S2C) function, a pseudo random binary sequence (PRBS) and a harmonic series (HS). Figure 3 shows the target trajectories alongside example data from a subject using either the elastic or rigid handgrip. The S2C trajectory was tested on both the feedforward (FF) and feedback (FB) tasks, while the PRBS trajectory was tested on the FF task only and the HS trajectory was tested on the FB task only. Table 2 summarizes which subject groups (T1 or T2) were tested with which task condition (feedforward or feedback).

For each subject group and device tested, the reference signals were kept fixed and lasted for approximately 2 min. To follow the reference trajectory, the subject was required to increase their grip flexion force which proportionally increases the vertical cursor height on the screen. Releasing their grip force (grasp relaxation) will allow the cursor to return back towards the bottom of the screen.

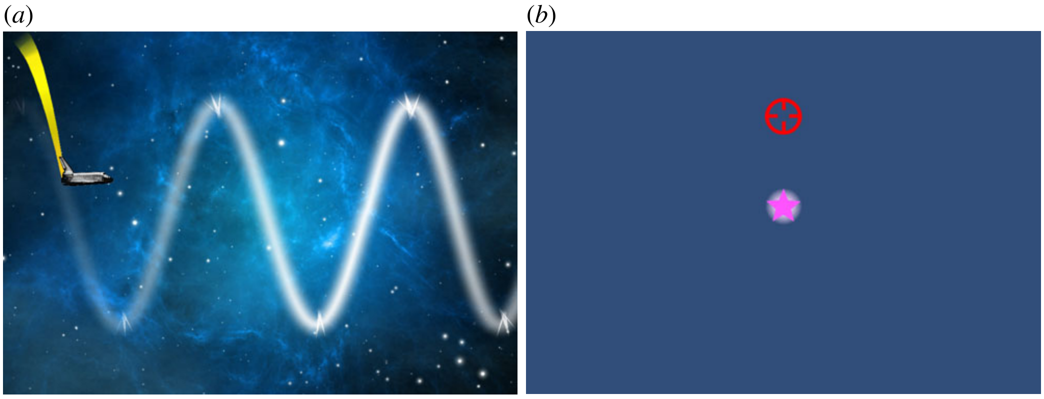

Figure 2. Screenshots showing the feedforward task ('SpaceWay' game; (*a*)) and feedback task ('StarShooter' game; (*b*)).

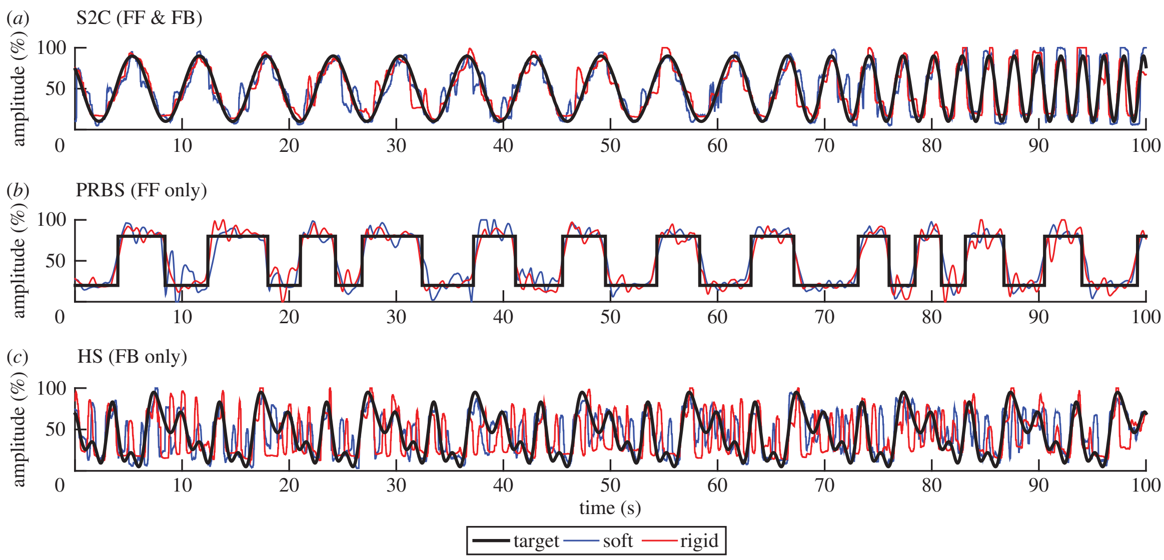

Figure 3. Sample trajectories from one representative subject tested during the visuomotor control tasks alongside example data from both soft (blue) and rigid (red) interactions. (*a*) Sin-to-chirp (S2C) waveform tested under both feedforward and feedback conditions, (*b*) PRBS waveform tested under the feedforward condition only and (*c*) HS waveform tested under the feedback condition only.

Table 2. Overview of the trajectories performed by the two different subject groups (T1 = 34 subjects and T2 = 32 subjects).

order tested	group T1 (feedforward)	group T2 (feedback)
first	S2C	S2C
second	PRBS	HS

2.3. Participants

Thirty-four healthy adults ranging from 20 to 77 years in age (mean ± 1 s.d.: 43.0 ± 17.7 years, gender: 15F/19M) were recruited for the feedforward condition, 32 healthy adults ranging from 17–67 years in age (37.8 ± 15.0 years, gender: 18F/14M) for the feedback condition. Participants had no known impairment, and were all right-handed with an average handedness score of 79.2 ± 38.2 based on the Edinburgh Handedness Inventory. There were no significant differences in the ages, gender or handedness of the two healthy subject groups (age: $p = 0.21$, gender: $p = 0.33$, handedness: $p = 0.51$). The two groups represent a diverse cross-section of society with a uniform gender distribution and ages spanning six decades. Half the subjects had an age of 40 years or older thus age-matching to many neuromotor impairments such as stroke. Table 3 summarizes this information in more detail.

2.4. Experimental protocol

None of the subjects had previous experience of the device or tracking task. To remove any learning bias, an SR/RS block protocol was employed whereby half of the subjects started with the soft (S) or rigid (R)

Table 3. Average characteristics describing the two different subject groups (used during the feedforward and feedback tasks) and combined together.

	group T1 (FF)	group T2 (FB)	combined (FF and FB)
No. subjects	34	32	66
age (years)	43.0 ± 17.7	37.8 ± 15.0	40.4 ± 16.6
gender	15F/19M	18F/14M	33F/33M
handedness	85.5 ± 20.9	67.9 ± 56.6	79.2 ± 38.2

device. The subjects were seated comfortably at a table with a 10-inch tablet PC situated approximately 30 cm in front of them. The device was connected wirelessly to the tablet PC. The subjects were initially instructed to hold their first assigned device in their right hand in a comfortable and consistent position, and to use this same position across all trials. They then performed 2 min of the S2C tracking task, followed by a 1 min rest and then 2 min of the PRBS (FF group) or HS (FB group) tracking task. They were asked to answer six questions on a questionnaire pertaining specifically to that device after completing both trajectories. The same steps were then repeated for the alternative handgrip device. Finally, two additional questions were answered on the questionnaire.

2.5. Questionnaire

The following six questions were answered by each participant, once for each device, directly following a device trial block (S or R). Each question was rated on a discrete five-point Likert scale.

— Q1: How well do you think you *performed*?
— Q2: Did you *enjoy* using the device?
— Q3: Did you experience any *discomfort* while using the device?
— Q4: Do you think you *improved* whilst using the device?
— Q5: Did your hand feel *fatigued* after using the device?
— Q6: Did you feel in *control* when using the device?

Two additional questions were asked at the end of the session which were also rated on five-point Likert scales.

— QG: How often do you play computer, tablet or smartphone *games*?
— QP: Which device did you *prefer* to use?

2.6. Data analysis

The ability for an individual to track a target trajectory (y) was measured using the root mean squared (RMS) error. Initially, the subject's response ($\hat{y}$) during a trial is aligned to y using the position of maximum cross-correlation. This removes any systematic error due to the cursor not being displayed as a single-point onscreen. For each trial, the error is calculated in a moving window, enabling the minimum error across windows to be extracted. Consequently, this metric describes the best error achieved for a given period of tracking and mitigates any short-term or sporadic artefacts e.g. due to accidental movements, lapses in subject concentration, or fatigue. The RMS error (E) is computed at each time step using

$$E_n = \sqrt{\frac{1}{W} \sum_{k=n-W/2+1}^{n+W/2} (\hat{y}_k - y_k)^2}, \tag{2.1}$$

where N is the total number of samples in the trial, W is the length of the window and E_n is calculated in the range $[W/2+1, W/2+2, \ldots, N-W/2]$ to prevent boundary effects. The final performance metric (for a given trial and window length), defined as the minimum moving error (MME), is given by

$$\mathrm{MME} = \min_n(E_n). \tag{2.2}$$

2.7. Statistical tests

To test significant differences, non-parametric Mann–Whitney U (MWU) tests were chosen due to the relatively small sample sizes ($N = 32/34$) and underlying distributions associated with the variables of interest. In the case of the performance data (i.e. MME), the distribution is skewed and has a fixed [0,100%] range. The questionnaire data are discrete, but ordinal, and therefore can be analysed using the same assumptions. For these tests, a χ^2-test was not appropriate due to the expected small frequencies of some of the entries. Paired tests were used to compare soft and rigid interactions, while an equivalent unpaired MWU test was employed while testing across different populations (i.e. feedforward versus feedback task conditions). Only individual pairwise comparisons (i.e. no multiple comparisons) were required.

Interactions between performance differences, preference and device testing order were analysed using Fisher exact (FE) testing under the null hypothesis of pairwise independence. Differences in performance between the two handgrip types was computed as a binary variable indicating whether the MME was better for soft or rigid device interaction. Preference was extracted from the questionnaire data as a binary variable indicating whether a particular subject preferred the rigid or soft device (with neutral data points ignored). The device testing order is already a binary variable indicating which device was tested first. Thus, all three variables can be treated as binary and therefore categorical data.

Linear regression was used to analyse relationships between age and performance for each device, task and trajectory. Both ordinary least squares (OLS) and robust least squares (RLS) were used. RLS uses an iterative reweighted least-squares method based on a bisquare function allowing outliers to be either ignored or proportionally weighted when computing best-fit lines.

To test the effects of gaming experience on performance, a non-parametric Kruskal–Wallis (KW) test was performed. It is worth noting that this test makes the assumption that the gaming experience data are categorical rather than ordinal. The effect of age and gaming experience on preference was analysed using FE tests. A binary age variable indicating whether a subject was young (less than or equal to 40 years) or old (greater than 40 years), a binary gaming experience indicating whether a subject was experienced (plays games weekly or more) or inexperienced (plays games monthly or less), and a binary preference variable (calculated as before) were used in this analysis. As these tests proved insignificance (see Results section), no further (post-hoc) significance testing was required.

3. Results

3.1. Performance

Figure 4 shows comparative box plots of the MME for the two devices tested (soft or rigid) across the four task types (FF_{S2C}, FF_{PRBS}, FB_{S2C} and FB_{HS}). For each task, a paired MWU test was used to infer whether the median difference in performance was significant and is shown for each of the four tasks. The best error was calculated in a 30 s analysis window (i.e. $W = 30$), which was felt to be an adequate compromise between length and rejection of spurious events. Appendix A describes in more detail reasons behind this choice of W alongside sensitivity analysis highlighting that the performance differences between the devices is not strongly affected by the choice of W.

The relative pairwise difference between the MME across the two devices are $FF_{S2C} = 10.3 \pm 27.1\%$, $FF_{PRBS} = 8.8 \pm 17.9\%$, $FB_{S2C} = 14.4 \pm 26.4\%$ and $FB_{HS} = 11.4 \pm 17.7\%$ (mean ± s.d.), indicating that the soft handgrip enabled better performance than the rigid equivalent. This relative MME difference is normalized by the MME of the rigid device to highlight the relative improvement for the soft interaction compared to the more conventional rigid handgrip interaction. This difference is consistent across all conditions ($p < 0.05$) with the feedback condition showing high significance ($p < 0.01$) when tested using a paired MWU test. Across all tasks, the relative MME difference is $11.2 \pm 22.6\%$ in favour of soft interaction.

3.2. Questionnaire

Figure 5 shows the collated results for the eight questions across both tasks, corresponding to 66 subjects. Results of the device preference (QP panel) and gaming experience (QG panel) questions are displayed as individual five-point histograms and highlight the distribution across the answers given. The six questions (panels Q1 ... Q6) show joint frequency distributions between the paired answers associated with both the soft and rigid handgrips. The axes of Q3 and Q5 have been inverted so that for all six

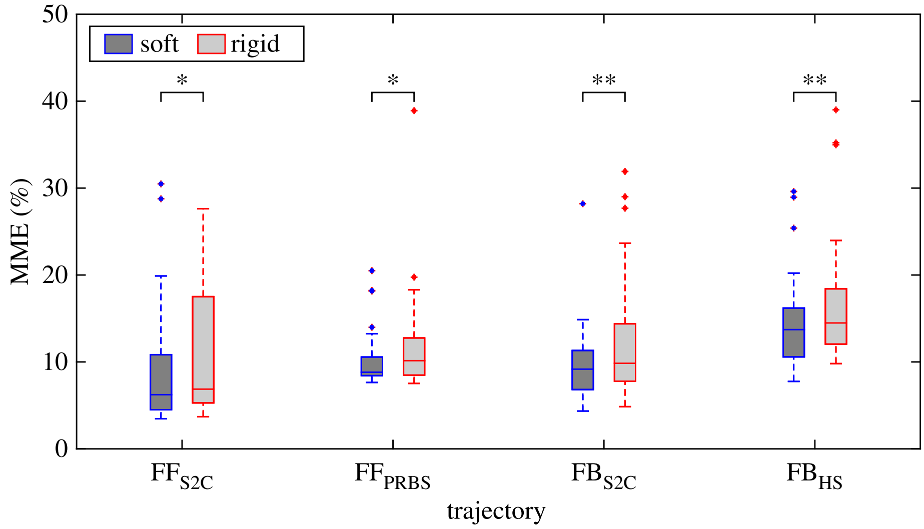

Figure 4. Comparison of minimum moving error between soft and rigid interaction for the four tasks. FF indicates feedforward and FB indicates feedback conditions. S2C is the sin-to-chirp, PRBS is the pseudo random binary sequence and HS is the harmonic series trajectories. Asterisk indicates a significant difference of $^*p < 0.05$, $^{**}p < 0.01$.

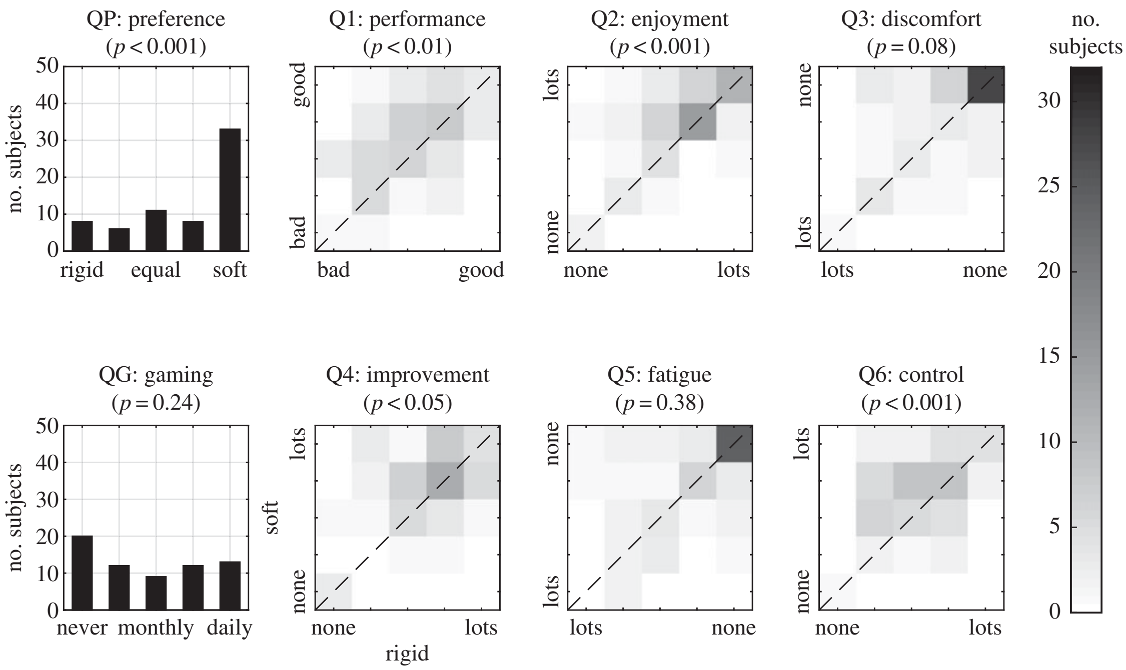

Figure 5. Results from the questionnaire shown as univariate five-point histograms (QP, QG; left column) or five-point joint frequency distributions (Q1 . . . Q6).

questions, negatively perceived answers are presented towards the bottom-left while positive answers are towards the top-right. For each question, a paired MWU test was performed to highlight if the median of the difference between soft and rigid answers (Q1 . . . Q6) or the distribution itself (QG, QP) is significantly different from zero, with the results shown above each plot.

Subjects found the soft force measuring handgrip advantageous to the rigid one due to several factors. Over 62.1% of subjects preferred the soft handgrip, 21.2% preferred the rigid device and approximately 16.7% showed no preference (QP, $p < 0.001$). Subjects thought they performed better (Q1, $p < 0.01$), enjoyed interacting more (Q2, $p < 0.01$), improved more (Q4, $p < 0.05$) and had better control (Q6, $p < 0.01$), when using the elastic handgrip. Subjects felt they had the same level of discomfort and fatigue for both device modalities, with over 28/66 subjects experiencing no fatigue or discomfort at all.

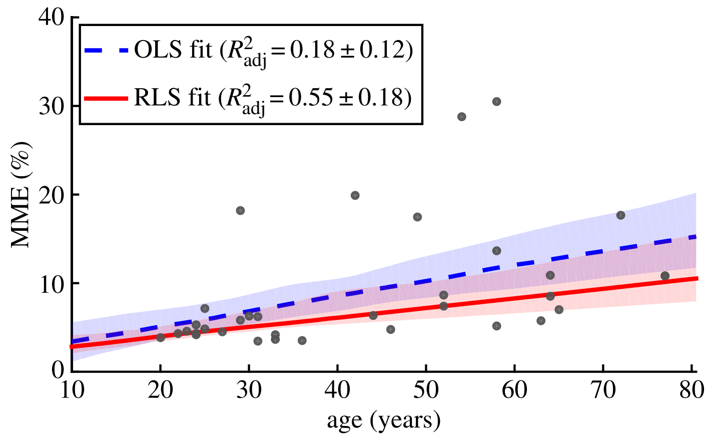

Figure 6. Scatterplot of performance (MME) versus age during the FF_{S2C} task using soft interaction. Also shown are both OLS and RLS fits and associated R^2_{adj} values.

3.3. Interactions

An analysis was performed to investigate the interplay between performance, preference and other experimental variables such as device testing order, age and questionnaire responses, yielding the following results.

3.3.1. Gaming experience has no effect on performance or device preference

KW tests revealed that, for both rigid and soft handgrip interaction, there were no significant differences in performance corresponding to the level of gaming experience ($p > 0.05$ across all tasks and interaction modalities). FE tests also showed that, for both feedforward and feedback conditions, gaming experience did not have an effect on device preference (FF: $p = 0.67$ and FB: $p = 1.0$).

3.3.2. Age affects performance but not differences in interaction modalities or device preference

FE tests revealed that, for both feedforward and feedback conditions, age does not have an effect on device preference (FF: $p = 1.0$ and FB: $p = 0.61$). Unpaired MWU revealed that performance differences between soft and rigid interaction for younger (less than 40 years) and older (greater than or equal to 40 years) subjects were insignificant across all tasks (FF_{S2C}: $p = 0.76$, FF_{PRBS}: $p = 0.19$, FB_{S2C}: $p = 0.31$ and FB_{HS}: $p = 0.83$).

To understand the effect that age has on performance, linear models were computed between the age of the subjects (continuous-independent variable) and the MME during each task (continuous-dependent variable). To mitigate the effects of outliers, RLS alongside OLS was used. Figure 6 shows example (OLS and RLS) linear fits alongside the $R^2{}_{adj}$ goodness-of-fit values during the FF_{PRBS} task; 95% confidence intervals are shown computed through bootstrapping (using 1000 resamples). Across all eight conditions (four tasks and both interaction modalities), the average $R^2{}_{adj}$ value was higher for the RLS method (OLS: $R^2{}_{adj} = 0.22 \pm 0.17$ and RLS: $R^2{}_{adj} = 0.31 \pm 0.11$) highlighting that the presence of outliers was likely in the datasets. Therefore, further analysis was only performed using the RLS method.

The average slope of the RLS linear model was positive (RLS: $slope = 0.12 \pm 0.05\%/\text{year}$), highlighting that regardless of the interaction mode or task, MME does increase with age. Figure 7 shows the median and interquartile range (IQR) of each slope, computed using the bootstrapped data, contrasting rigid and soft device interaction across all tasks. These results suggest that soft interaction may give less age-related performance deficits for certain types of task (i.e. FF_{S2C}, FF_{PRBS} and FB_{S2C}). However, these differences were found to be insignificant (FF_{S2C}: $p = 0.50$, FF_{PRBS}: $p = 0.10$, FB_{S2C}: $p = 0.36$ and FB_{HS}: $p = 0.98$).

3.3.3. Do performance differences between the rigid and soft handgrips have an effect on device preference?

FE tests revealed that for three of the four trajectories, device preference was not associated with differences in performance (FF_{S2C}: $p = 0.20$, FF_{PRBS}: $p = 0.39$, FB_{S2C}: $p = 0.07$ and FB_{HS}: $p < 0.05$). Specifics of this association in the FB_{HS} task highlighted that the majority of subjects who performed better with a particular device preferred that device (soft: 16/20, rigid: 4/5).

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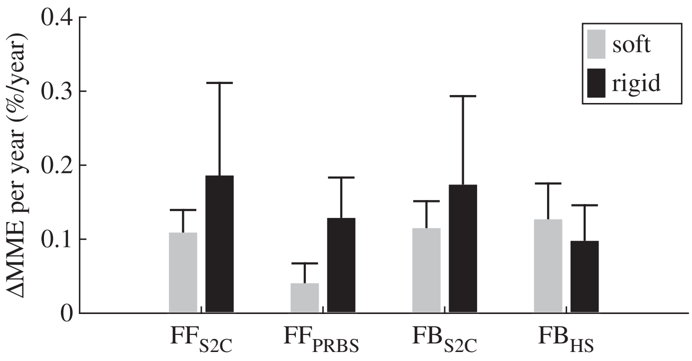

Figure 7. Comparative bar graphs highlighting the distribution of the slopes for age versus performance (median ± IQR) comparing soft and rigid interaction. Slopes were computed using RLS linear fits.

3.3.4. Subjective sense of performance, enjoyment and control influences the preference for soft handgrip interaction

FE tests revealed that, across both task types (FF and FB), device preference was dependent upon differences in responses for three of the six questions. Specifically, preference was influenced by a different perception of performance (question Q1: $p < 0.001$), enjoyment (Q2: $p < 0.05$) and control (Q6: $p < 0.01$). It was not influenced by the other questions regarding discomfort (Q3: $p = 1.0$), improvement (Q4: $p = 0.12$) and fatigue (Q5: $p = 0.63$) for which both soft and rigid handgrip devices were found to provide similar advantages (figure 5). Further analysis of the specifics of this interaction highlighted that these associations were because subjects who felt they performed better with a device (soft: 28/28, rigid: 6/8), enjoyed using that device more (soft: 18/21, rigid: 3/4) and felt they controlled the device better (soft: 27/30, rigid: 5/7) usually preferred that device. Similar analysis of interactions between actual performance differences and questionnaire responses found no significant associations.

3.3.5. The order in which the devices are tested affects the preference of and performance with the soft device

FE tests revealed that for two of the tasks, the device testing order (i.e. soft followed by rigid or vice versa) did have an effect on performance (FF_{S2C}: $p = 0.16$, FF_{PRBS}: $p < 0.05$, FB_{S2C}: $p < 0.01$ and FB_{HS}: $p = 0.44$). Further analysis of the specifics of these associations highlighted that they were due to subjects who started with the soft device performing similarly (FF_{PRBS}: 7/17, FB_{S2C}: 8/17) while for subjects who started with the rigid device, the majority of subjects performed better with the soft device (FF_{PRBS}: 15/17, FB_{S2C}: 15/15) during these two tasks. This indicates that practising with the soft device helped using the rigid one, but not the converse.

FE tests revealed that device preference was also dependent on the order that the devices were tested, showing significance for both tasks (FF and FB: $p < 0.05$). Further analysis of the specifics of this association highlighted that it was due to subjects who used the soft device first being (13/25) undecided in their preference, while subjects who used the rigid device first were (28/30) in favour of the flexible device.

4. Discussion

During all the visuomotor tracking tasks, subjects showed an 11% relative improvement in performance when using the soft compared with the rigid handgrip. Moreover, there was a threefold greater preference for the soft interaction with subjects feeling they could perform better, enjoyed it more and had increased control with it. Our results support neurophysiological and behavioural studies suggesting that kinaesthesia enhances motor control [17,18,33–35], and shows for the first time that functional grip trainers can facilitate performance and subjective experience by being elastic rather than rigid.

In our experiments, overall performance in the feedback task was reduced relative to the feedforward task (figure 4), indicating that generally subjects found this type of task more challenging. Larger errors for the FB_{HS} task can potentially be attributed to the lack of movement planning afforded by the feedback condition which makes (pseudo) random trajectories especially challenging [36]. Differences between the interaction modes in terms of relative MME error were also more pronounced for the feedback condition, while only the FB_{HS} task exhibited associations between performance and preference.

Differences in the availability of somatosensory feedback is the major difference between the soft and rigid controllers. Specifically, isometric control lacks significant contributions from proprioception due to the lack of movement. Zhai *et al.* [33,34] hypothesized that it was this additional sensory information that enabled novice users to have superior performance when comparing 6 d.f. control using an elastic or rigid upper limb interface. In comparison to our study, this work involved only proximal arm control (i.e. not functional grip force control), used fewer and only young subjects and incorporated only a single feedback-type condition. Their subjective evaluations also highlighted that isometric control was both more difficult and fatiguing during continuous tracking tasks. With more training (greater than 20 min), the performance of the two input devices converged to a similar level with the authors suggesting that the manipulation shifted from closed-loop to a more open-loop behaviour. In the feedback condition, we hypothesize that the additional kinaesthetic feedback provided by the soft handgrip would be especially useful, which may explain the difficulty in dealing with the feedback task observed in the isometric condition. A similar positive effect of the addition of elasticity was observed in a recent study in which virtual learning based on isometric force information and an inverse dynamic model of the arm during constrained movements was improved by physical compliance and led to better learning [19].

The handgrip testing order was found to influence the performance and preference between the two devices. The number of (soft followed by rigid handgrip) and (rigid followed by soft handgrip) test blocks were randomly assigned and of equal number, ensuring that overall effects were still valid. Interestingly, subjects who started with the rigid handgrip were significantly superior with and unanimously preferred the soft device. *A priori*, this effect might be interpreted as an effect of more training before using the second, soft device, and also by the fact that the subjects had just used this device allowing them to clearly focus on its qualities. However, this hypothesis is contradicted by the distinctly different results obtained for the subjects who ended with the rigid device but did not necessarily prefer it. This dissymmetry of appreciation of the two devices depending on the order they had been practised with suggests a clear preference and performance improvement with the soft handgrip.

The influence of age on performance highlighted an age-related reduction in grip control capabilities for both feedforward and feedback-type visuomotor tasks. Similar correlations between age and decline in (isometric) grip force control have been found in previous studies (e.g. [37–39]). Older subjects generally had a smaller error when using the soft device, suggestive that the additional kinaesthetic information it provides may be useful for older subjects during grip control of visual tracking tasks. Despite this, experience was found to have no relation to performance indicating that the handgrip and tasks defined in this study can be used by anyone regardless of previous exposure to games and associated skill levels involved. Future studies will investigate a similar question regarding elastic versus rigid handgrip interaction in patients affected by arm–hand weakness and poor control, e.g. due to stroke.

In conclusion, our results demonstrate that, regardless of age and experience, coupling force and position through an elastic structure has positive effects in terms of performance and subjective experience during grip force control. We hypothesize that this advantage is due to the coupled movement, providing additional sensory information including (dynamic) proprioceptive and cutaneous feedback. Therefore, device elasticity is an important consideration when designing new grip measurement devices and further enables the training of hand dexterity and strength alongside functional movements. This should be considered when designing a handgrip for training and rehabilitation, or more generally as a human–machine interface.

Ethics. The study was approved by the Imperial College Research Ethics Committee with all participants giving written and signed informed consent prior to participation.

Data accessibility. Our data are deposited at the Dryad Digital Repository: http://dx.doi.org/10.5061/dryad.m68q0 [40].

Authors' contributions. M.M., P.R., J.L.L., P.B. and E.B. conceived, designed and developed the handgrips, tasks and mobile rehabilitation solution. C.U. and P.R. collected the data. M.M. performed the data analysis. The manuscript was written by M.M., P.B. and E.B., with all authors reading and approving the final manuscript.

Competing interests. We declare we have no competing interests.

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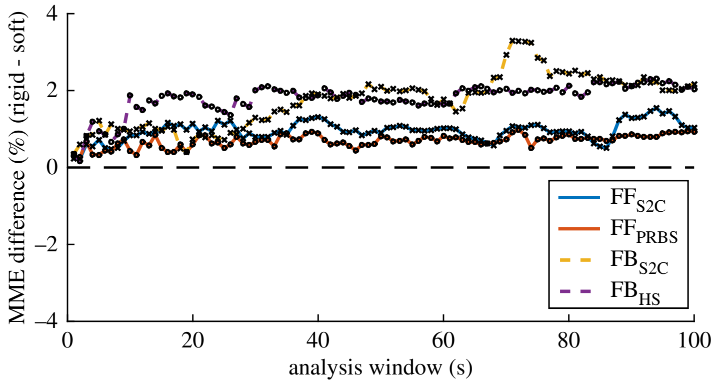

Figure 8. Relative MME difference between elastic and rigid handgrip interactions across different window sizes.

Appendix A. Sensitivity analysis

Sensitivity to the analysis window (W in equation (2.1)) was examined to check that its choice would not affect interpretation of the results. As the main outcome is the (paired) MME differences between soft and rigid handgrip control, this was tested against increasing W. Figure 8 shows the median error difference for the four trajectories (FF_{S2C}, FF_{PRBS}, FB_{S2C} and FB_{HS}) across all subjects as a function of W (computed at 1 s intervals). It can be seen that for any choice of W the error difference remains in favour of the soft handgrip and that after 10 s these differences are relatively stable. Therefore, W is chosen as 30 s providing a good compromise between length and rejection of spurious events. An additional benefit of performing this type of analysis is that the effects that duration (and time) have on the error differences can be seen. For example, between 70 and 80 s, there seems to be a relatively big jump in the FB_{S2C} error difference which could be caused by incorporating the transition of the reference path from a regular sinusoid to a time-dependent chirp signal. The instantaneous error estimation at this transition is more likely to be higher due to a change in the required control and lack of motion planning capabilities for the FB tasks, and (on average) seems to be accommodated better using soft handgrip control.

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GRIPABLE ‘ELASTICITY’ IMPROVES HANDGRIP PERFORMANCE AND USER EXPERIENCE

GripAble ‘elasticity’ Improves Handgrip Performance and User Experience: Results suggest that device compliance (not rigid) is an important design consideration for visuomotor control training devices.

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.

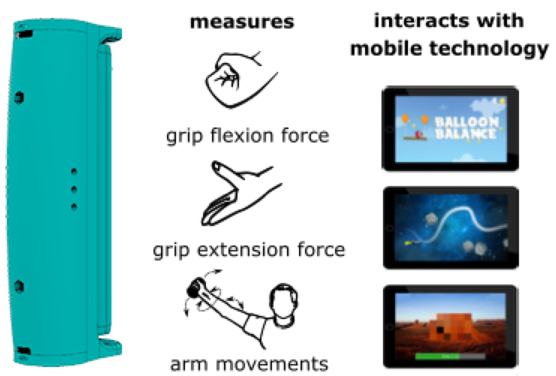

Fig. 1. GripAble hand-grip device and rehabilitation apps. The device is capable of measuring both finger flexion and extension force and wrist/arm motion depending on experimental protocol. Extension force is measured with the use of Velcro-straps that affix around the wrist and over the fingers.

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 TR 1 POS 1	PRE 2 TR 3 POS 3	PRE 4 TR 5 POS 5
Afternoon:	PRE 1 TR 2 POS 2	PRE 3 TR 4 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.

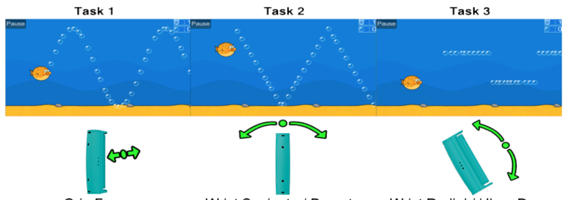

Fig. 2. Game and task design. Tasks 1, 2 and 3 are represented as unique trajectories and GripAble movement patterns. For each trial, the background scrolls from right to left with an animated fish character, giving the perception of player propagation through the trial. A cue of the GripAble movement 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 ϵ_{s-1}^{pos} and ϵ_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.

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

where t is a trial, k is a task, D is the difficulty for a given trial, α 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.

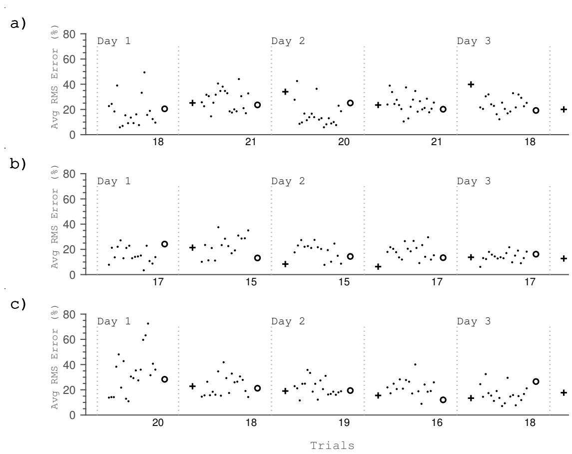

Fig. 3. Participant pt010 training trial errors over three days, where figures a-c) represent finger flexion/extension, wrist supination/pronation, and wrist radial/ulnar deviation. The dotted vertical lines represent morning or afternoon sessions. Each point on this graph is a trial, each circle and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

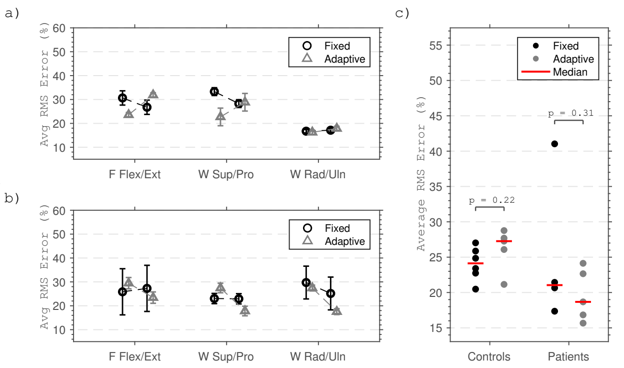

Fig. 4. a,b) Average RMSE and standard error for baseline and the delayed retention test on day 3 for each task and each condition, where a) is the control cohort and b) is the patient cohort. For each task shown, average baseline is the left point and performance on day 3 delayed retention test is the 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.

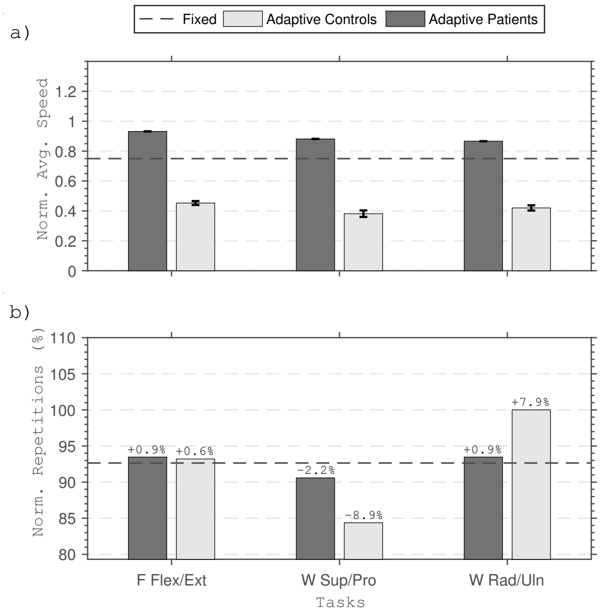

Fig. 5. a) Normalized average speed (difficulty) and standard error over all training sessions for each task and each condition. Normalizing scalar was the maximum difficulty. b) Normalized total repetitions over all training sessions for each task and each condition. Normalizing each task by total training 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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