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RESEARCH

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# Clinical validation of an individualized auto-adaptative serious game for combined cognitive and upper limb motor robotic rehabilitation after stroke

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## Abstract

**Background** Intensive rehabilitation through challenging and individualized tasks are recommended to enhance upper limb recovery after stroke. Robot-assisted therapy (RAT) and serious games could be used to enhance functional recovery by providing simultaneous motor and cognitive rehabilitation.

**Objective** The aim of this study is to clinically validate the dynamic difficulty adjustment (DDA) mechanism of ROB*i*GAME, a robot serious game designed for simultaneous rehabilitation of motor impairments and hemispatial neglect.

**Methods** A proof of concept, with 24 participants in subacute and chronic stroke, was conducted using a 5-day protocol (two days were dedicated to assessment and three days to consecutive training sessions). Participants performed three consecutive ROB*i*GAME sessions during which overall task difficulty was determined through simultaneous DDA of motor and attentional parameters. Relationships between clinical and robotic assessment scores with respective task-difficulty parameters were analyzed using a multivariate regression model and a principal component analysis.

**Results** Game difficulty rapidly (within approximately thirty minutes) auto-adapted to match individual impairment levels. The relationship between task-difficulty parameters with motor (Fugl Meyer Assessment: $r = 0.84$ $p < 0.05$) and with attentional impairments (Bells test total omissions: $r = 0.617$ $p < 0.05$) showed that task-difficulty during RAT adapted to each participant's degree of impairment. Principal component analysis identified two data subsets determining overall task-difficulty, one subset for motor and the other for cognitive functional evaluation scores with respective task-difficulty parameters.

**Conclusions** This proof of concept clinically validated a DDA mechanism and showed how task-difficulty adequately adapted to match individual degrees of impairment during RAT after stroke. ROB*i*GAME provided simultaneous motor and attentional exercises with parameters determining task-difficulty strongly related with respective clinical and robotic evaluation scores. Individualized levels of game difficulty and rapid adjustment of the system suggest implementation in clinical practice.

*Registry number* This study was registered at ClinicalTrials.gov (NCT02543424).

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**Keywords** Neurorehabilitation, Stroke, Cognitive rehabilitation, Robot-assisted therapy, Motor learning, Serious games

## Background

### Context

Each year more than 13 million people worldwide have a stroke, with approximately two-thirds having persistent upper limb paresis and one-third presenting with hemispatial neglect [1, 2]. Intensive rehabilitation using challenging and individualized tasks enhance functional recovery after stroke [3]. Emerging techniques promote intensive rehabilitation and allow simultaneous motor and cognitive training, complementing conventional approaches.

### Task difficulty adaptation during robotic rehabilitation

Recent guidelines recommend robot-assisted therapy (RAT) to improve upper limb strength, function and activities of daily living after stroke [4]. A review on control strategies, presented various types of task-difficulty adaptation mechanisms described in scientific literature for robotic neurorehabilitation [5]. Among these adaptive mechanisms, some are configured to automatically adjust task-difficulty using data derived from the robotic device as input to system decision-making [6]. Most commonly used computerized systems often rely on "assist-as-needed" guidance algorithms to adjust motor task-difficulty [5]. However, the way these systems' effectiveness is validated varies in scientific literature and remains vaguely described in many cases [7, 8]. More specifically, it would be worthwhile to assess the pertinence of the decisions made by the system during training. Are the parameters determining task-difficulty during RAT well adapted to the functional profiles of subjects after a stroke?

### Dynamic difficulty adjustment (DDA) during serious games training

Serious games also constitute an effective approach to stimulate upper limb recovery after stroke [9]. RAT can be combined to serious games to continuously and automatically adapt task-difficulty to match individual participants' impairments and immediate performance during training [10]. Depending on device and game characteristics, different types of task-difficulty adaptation mechanisms have been previously described for serious games in stroke rehabilitation [11]. For example, serious games implemented on virtual reality systems can adapt game difficulty using preestablished increments, configured at the beginning of each session by a therapist [12]. Other virtual reality tools allow progressive difficulty adjustment based on individual performance [13]. This type of difficulty regulation mechanism, known as dynamic difficulty adjustment (DDA), has also been described for serious games implemented on robotic systems [14]. The objective of DDA mechanisms is to adjust task-difficulty automatically, in real time, according to user performance, creating feasible, yet challenging tasks, keeping the game in constant balance [13, 14].

DDA mechanisms present two main advantages. First, game characteristics dynamically adjust to match participants' individual degree of impairment and performance in order to maintain an optimal challenge according to neurorehabilitation principle of increasing difficulty [15]. Secondly, DDA mechanisms lead to individualised levels of task-difficulty which could enhance human performance by maintaining a balance between motivation and learning. According to the concept of flow, in order to preserve motivation during training, task-difficulty should match participants' skill levels and should avoid extremes (i.e. exercise through tasks that are not too easy nor too difficult) [14]. Our team developed ROB*i*GAME [16], a serious game implemented on an end-effector rehabilitation robot using a DDA mechanism, detailed below.

### Combining motor and cognitive rehabilitation after stroke using robotic devices

In research and clinical practice, motor and cognitive impairments are usually addressed separately by different therapists. Additionally, most robotic devices are designed to solely target motor rehabilitation (i.e., not additionally including cognitive exercises) [17].

It has been suggested that combined cognitive-motor rehabilitation after stroke could lead to better improvements in motor function when compared with time-matched conventional approaches [18]. Although cognitive training constitutes an essential part of adult stroke rehabilitation, a recent systematic review underlined that cognitive exercises are insufficiently incorporated into robotic devices for combined rehabilitation in the stroke population [19]. Another systematic review identified only one study for robot-assisted cognitive training after stroke [20]. This review also highlighted that one of the main challenges of robotic rehabilitation for cognitive training remains personalisation of task-difficulty using RAT systems [20]. Indeed, participants' impairment severity and functional deficits vary widely after stroke, leading to differences concerning rehabilitation needs and objectives.

In this proof of concept, we study the DDA mechanism of ROB*i*GAME, a novel robotic gamified approach, that allows combined upper limb motor and cognitive rehabilitation for attentional impairments following stroke.

### Objectives and hypothesis

The primary objective of this proof of concept was to clinically validate ROB*i*GAME's DDA mechanism. We evaluated whether parameters determining task-difficulty during gameplay adapted to individually match participants' degree of motor impairments and/or hemispatial neglect following stroke. We hypothesized that ROB*i*GAME's DDA mechanism would lead to a different level of difficulty corresponding to each participant's degree of impairment.

Secondary objectives examined whether characteristics during gameplay (i.e., number of targets, number and position of visual distractors presented on screen, etc.), defining task difficulty, would rapidly adapt to reach an individualized level of difficulty.

## Methods

### Ethics committee

This proof of concept was approved by the clinical ethics committee of UCLouvain (Belgium). The study protocol was registered at ClinicalTrials.gov (NCT02543424). Participants signed an informed consent form before testing.

### Study design

This study was conducted using a 5-day experimental protocol. During the first two days, neurological impairments were evaluated using standardized clinical and robotic assessments. Then, on the three remaining days, each participant completed a daily 45-min session of RAT playing ROB*i*GAME. All sessions were performed at the Cliniques universitaires Saint-Luc (Brussels, Belgium).

### Participants

Recruitment took place during inpatient and outpatient rehabilitation. Participants were enrolled according to the following inclusion criteria: a first stroke diagnosis confirmed by computed tomography or magnetic resonance imaging, clinical stability, participants in subacute or chronic phase after stroke [21], presence of upper limb hemiparesis with preserved ability to voluntarily move the robot's end-effector, an ability to understand instructions and carry out tests. Ability to understand instructions was evaluated in collaboration with the clinical rehabilitation team in charge of therapy for each participant. Participants were excluded when they had a stroke located in the brain stem or cerebellum or presented with any other associated neurological or orthopaedic illness limiting upper limb function.

### Data collection

#### *Motor and cognitive clinical evaluation*

Participants' cognitive status regarding presence of hemispatial neglect was assessed using the Bells and Apples tests, two paper-and-pencil tests commonly used in clinical practice [22]. Upper limb motor impairments were clinically assessed using standardized rating scales according to recent recommendations for neurorehabilitation trials [23]. Upper limb motor control was evaluated with the computerized and adaptive testing system of the Fugl-Meyer Assessment for the Upper Extremity (FMA-UE) [24]. Gross manual dexterity was assessed using the Box and Block test [25]. Activity limitations were evaluated with the Action Research Arm Test (ARAT) [26]. When applicable, degrees of participants impairments and limitations were categorised as mild, moderate and severe.

#### *The REAplan® robot*

The REAplan® (Axinesis, Wavre, Belgium), illustrated in Fig. 1A, is a distal end-effector robot that was used in this study to conduct robotic assessments and to play ROB*i*GAME sessions. REAplan allows movements of the upper limb by mobilization of the hand in the horizontal plane, in different modes (active, active-assisted, passive, resistive) [27]. This robot, equipped with force and position sensors, recorded the position of the handle and the force exerted on the handle, with a frequency of 125 Hz. During training, the robot can provide motor assistance to help the participant complete the desired movement or can apply resistive force to disturb the participants' movements, according to a predetermined set of rules described in previous work [28]. All study participants were positioned in a standardised way during evaluation and sessions. A gutter was used to stabilize the participant's paretic wrist and forearm (Fig. 1B). If necessary, the participant's hand was attached with a glove to the distal end-effector (Fig. 1B).

#### *Motor and cognitive robotic evaluation*

In addition to clinical evaluation, motor and attentional impairments were assessed using the REAplan® robot. Upper limb kinematic indexes (straightness and smoothness) and isometric, pushing and pulling, forces with elbow extended at 90° were retained. Straightness index corresponded to the ratio between movement amplitude and path length covered by the participant. Smoothness index was the ratio between the mean and peak velocities of participant's movements, with a ratio closer to 1 indicating rectilinear paths and smoother movements [27].

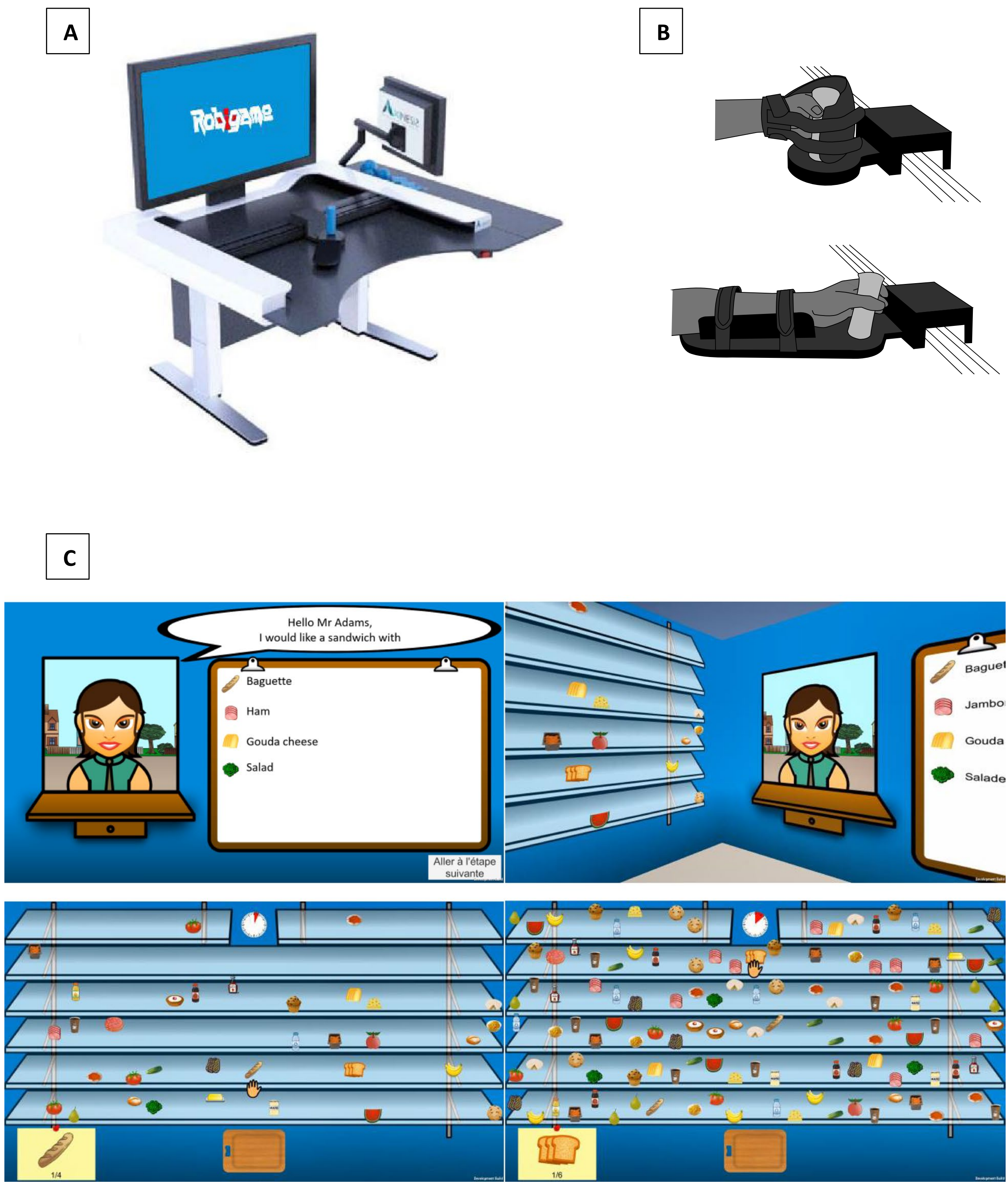



**Fig. 1** Illustration of the REAplan® robot [27], ROB*i*GAME's display [28] and schematic diagram of ROB*i*GAME's Dynamic Difficulty Adjustment mechanism. **A** Illustration of the REAplan® robot (Axinesis, Wavre, Belgium). **B** Positioning of the hand in the glove and the forearm in the gutter. **C** Four examples of the robotic interface, through the LCD screen illustration, during a ROB*i*GAME session corresponding to the environment and configuration of the game at different time points. **D** Schematic diagram of ROB*i*GAME's Dynamic Difficulty Adjustment mechanism

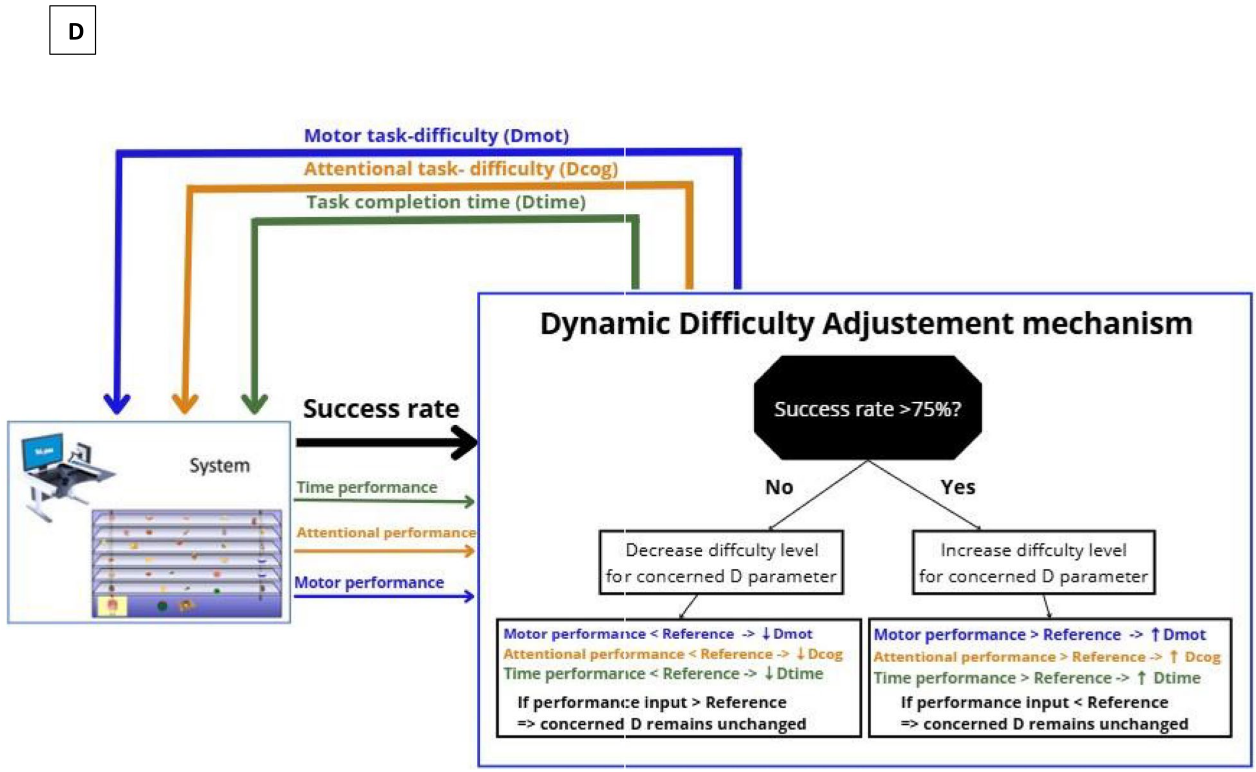



**Fig. 1** continued

In line with a recent systematic review suggesting the use of multi-test methods to detect hemispatial neglect [2], a robotic test was also performed in addition to the two paper-and-pencil tests described above. The MonAmour test was developed and validated on the REAplan® device for evaluation of allocentric and egocentric hemispatial neglect [29]. The MonAmour test gives access to various parameters including total mean reaction time, difference in reaction time between contralesional and ipsilesional space, number of total omissions and differences in total omissions between contralesional and ipsilesional space.

### *ROBiGAME*

ROB*i*GAME is a serious game implemented on the REAplan® robot that allows simultaneous rehabilitation of motor and attentional impairments after stroke [16]. Our team developed a DDA mechanism that allows this serious game to adjust task difficulty in real time, on a trial per trial basis, by automatically modifying game parameters during training.

During the game scenario (Fig. 1C), a series of planar reaching movements were performed to complete tasks. For each task, the level of difficulty was defined by exercise/game characteristics, such as target position, level of robot assistance/resistance and the number of visual distractors presented on the screen (Fig. 1C). These characteristics continuously adjusted, using a DDA mechanism described below, to match participant's performance during game play. The objective was to successfully complete as many tasks as possible by reaching a specified number of targets within a desired time frame.

The DDA uses a preestablished set of rules to adjust task-difficulty to the level of individual participant performance and impairment by modifying the parameters presented in Table 1. Each parameter varies independently and determines motor task-difficulty ($D_{mot}$), attentional task-difficulty ($D_{cog}$) and task completion time ($D_{time}$). In order to challenge the player, overall task-difficulty is continuously modified during gameplay without reaching a constant value. Task-difficulty parameters (D) oscillate from 0 to 1. A 'D score' closer to 1 indicates a higher level of difficulty. Each task-difficulty parameter (D) is respectively paired with participants' performance parameters (output of the game). Performance parameters are compared in real-time to predefined normative data obtained in an age-matched stroke population [28]. Game task-difficulty is adapted according to the game success rate. Success rate is measured by averaging results over the ten most recently performed tasks (using a dynamic sampling window for each subsequent performed task). If an exercise is completed within the desired timeframe, it

**Table 1** ROB*i*GAME's parameters

| Task-difficulty parameters (D) | *Game characteristics* that vary to adapt task-difficulty |
|---|---|
| $D_{mot}$ = motor task-difficulty | • Longitudinal assistance or resistance force provided by the robot |
| $D_{cog}$ = cognitive task-difficulty | • Total number of targets<br>• Target position<br>• Attentional load = number of distractors<br>• Number of cognitive cues provided |
| $D_{time}$ = task completion time difficulty parameter | • Total time available to complete a series of tasks |
| Participants' performance parameters | |
| Motor performance = reflects velocity (cm.s$^{-1}$) of movements performed by the patient in the horizontal plane | |
| Attentional performance = reflects the patients' reaction times by taking into consideration attentional load and salience of the cognitive cues | |
| Time performance = reflects the total time needed for task completion | |
| Game success rate: the game success rate varies from 0 to 100% | |

*D* task-difficulty parameters

is considered as a successful completion of the task. For example, if over the last 10 tasks, a patient succeeded on 7 tasks, then the success rate is determined as 70% (indicating that the individualised task-difficulty parameters allowed the player to successfully complete 7/10 tasks). In accordance with scientific literature, the 10 task success rate is compared to a target reference success rate set at 75% [30, 31]. It is suggested that keeping success rates within an optimal range at approximately 75% enhances human performance by maintaining a balance between motivation and learning [32]. The comparison between the success rate during training and the reference success rate determines whether the difficulty level of the game should be increased or decreased. If the success rate over the previous 10 tasks is higher than 75%, it indicates that task-difficulty of corresponding parameters is too low (too easy) and difficulty is increased. On the other hand, if the success rate over the previous 10 tasks is below 75%, it indicates that the task-difficulty of corresponding parameters is too high (too difficult), and the difficulty level is decreased. By modifying these parameters and the related game characteristics described in Table 1, ROB*i*GAME regulates difficulty of tasks performed during training. A detailed scheme of ROB*i*GAME's DDA mechanism is presented in Fig. 1D.

For this study, all task-difficulty parameters were set at the lowest value (0) at the beginning of the first session. Then, throughout sessions, adaptation of each parameter occurred automatically. For each participant, evolution of values of different parameters was recorded during all sessions.

### Primary and secondary objectives and outcomes

The primary objective of this work was to study the relationship between clinical evaluation scores and the level of task-difficulty reached at the end of three game sessions (mean of the last 10 performed tasks), for motor and attentional parameters ($D_{mot}$ and $D_{cog}$). We investigated whether parameters determining task-difficulty (D) correlated to participant's degree of impairment as a primary outcome. We hypothesized a negative relationship showing that with reduced degree of impairment (relative to norms), the level of game difficulty would increase for corresponding parameters, making the game more difficult. Also, we studied which clinical evaluation scores explain the level of task-difficulty reached at the end of all sessions (mean of the last 10 performed tasks) for corresponding motor and attentional parameters.

Secondary objective was to examine whether characteristics during gameplay rapidly reach an individualized level of difficulty corresponding to each participants' degree of impairment. We considered adjustment to be rapid when it occurred after approximately thirty-minutes, corresponding to completion of 15–20 tasks. As a secondary outcome, we studied the correlation between the reached motor task-difficulty after completion of 20 tasks (mean of the first 20 performed tasks) with the motor task-difficulty reached at the end of all sessions (mean of the last 10 performed tasks).

### Data analysis

Statistical analyses were performed using the SPSS Statistics software (IBM, version 27). The normality and equality of variances were checked by QQ-Plot graphic representation and Levene's test respectively [33]. Statistical significance level was set at $P < 0.05$ for all analyses.

To explore the structure of our data regarding functional assessment scores and levels of difficulty reached during the game, a principal component analysis was performed [34]. Principal component analysis included clinical and robotic (motor and attentional) evaluation scores and mean levels of task-difficulty ($D_{mot}$, $D_{cog}$) at the end of the three sessions. The number of generated principal components was selected based on scree plot interpretation and Kaiser criterion [35].

Two multiple linear regression models were computed to study separately the relationship between level of motor or attentional task-difficulty reached at the end of all sessions (with $D_{mot}$ or $D_{cog}$ set as dependent variables) and respective clinical/robotic evaluation scores regarding motor or attentional impairments (as explanatory variables). A stepwise selection was performed in order to identify the most pertinent explanatory variables [36]. When applicable, additional simple linear regression analyses were performed to study the relationship between $D_{mot}$ or $D_{cog}$ and the remaining variables.

A repeated measures ANOVA was conducted to analyse whether levels of game motor difficulty reached after completion of 20 first tasks differed in comparison to the value reached at the end of all sessions (mean of the last 10 performed tasks). We estimated that a sample size of 21 participants would be needed for this analysis, using an a = 0.05 and b = 0.80 [37].

**Table 2** Characteristics of study participants

| n = 24 | μ ± SD or absolute value |
|---|---|
| Age (years) | 61 ± 12.1 |
| Sex (M/F) | 12/12 |
| Dominant arm (R/L) | 22/2 |
| Type of stroke (I/H) | 22/2 |
| Time since stroke (weeks) | 6 ± 4.1 |
| Affected arm (R/L) | 11/13 |
| Hemispatial neglect[a] | 11 |
| NIHSS[b] | 11 ± 6.1 |
| Exteroceptive sensitivity (P/A)[c] | 15/9 |
| Proprioceptive sensitivity (P/A)[c] | 16/8 |

*n* total number of participants in this study, *μ* mean value, *SD* Standard Deviation, *M* male, *F* female, *I* ischaemic, *H* haemorrhagic, *NIHSS* National Institute of Health Stroke Scale, *R* right, *L* left, *P* preserved, *A* altered

[a] Presence of hemispatial neglect according to MonAmour test

[b] Assessment at the day of admission in the neurology department

[c] According to NIHSS

## Results

All 24 participants recruited for this study successfully completed all evaluations and training sessions with full collaboration and no adverse events. Characteristics of participants are presented in Table 2. Approximately half of them presented with hemispatial neglect (11 out of 24), according to assessment scores on the MonAmour test [29].

Clinical and robotic evaluation scores for motor and attentional impairments are summarized in Table 3. Concerning motor aspects, mean FMA-UE scores were 67% (± 27.3%) and mean ARAT scores were 35 (± 22.8), corresponding respectively to a moderate level of impairment and activity limitation according to the ICF-WHO model. Participants had FMA-UE scores ranging from 14 to 99% and ARAT scores ranging 0 to 57, covering a wide range of motor impairment severity and activity limitation (mild, moderate and severe). Concerning attentional impairments, number of omissions asymmetry ranged from 0 to 33 and mean reaction time asymmetry was of 380 ms (± 99) which corresponds to different participants profiles' regarding presence of hemispatial neglect (i.e., number of omissions asymmetry). The heterogeneity of our sample in terms of types and severity of motor and attentional impairments is further illustrated in supplementary Fig. 1A–C.

Main results of the principal component analysis are illustrated in Fig. 2. A total of 2 components were retained after scree plot interpretation (supplementary Fig. 2) and application of Kaiser criterion (supplementary Table 1). Aspects related to attentional impairments were retained on the first principal component and aspects related to motor impairments on the second. Attentional difficulty ($D_{cog}$) and task completion time parameter ($D_{time}$) reached at the end of all training sessions, along with total mean reaction time asymmetry in the MonAmour test, inversely correlated with principal component 1. Also, the level of attentional difficulty ($D_{cog}$) and the task completion time parameter ($D_{time}$) were negatively related to attentional impairments evaluation scores on principal component 1. Motor task-difficulty reached at the end of all training sessions along with motor evaluation scores highly correlated with principal component 2.

Results of the two multiple linear regression models, computed separately for motor and attentional aspects, are respectively illustrated in supplementary Tables 2 and 3. After removal of non-essential explanatory variables, using a stepwise selection process and co-linearity verification, only one explanatory variable was selected in each model. FMA-UE score was retained for the multiple linear regression model regarding motor aspects ($R^2 = 0.710$; $p < 0.05$) and Bells test total omissions regarding the multiple linear regression model for attentional aspects ($R^2 = 0.387$; $p < 0.05$). An additional simple linear regression was then separately computed with each one of the remaining variables, one motor and one attentional, to further study the relationship between evaluation scores and levels of game difficulty. These relationships are graphically illustrated in Fig. 3 (graph B for motor aspects and graph D for aspects related to cognition).

**Table 3** Clinical & robotic functional assessments of participants and ROB*i*GAME difficulty scores

| **n = 24** | **Motor aspects** | | **Attentional aspects** | |
|---|---|---|---|---|
| Clinical assessments | | *μ ± SD* | Bells Test | *M [min.–max.]* |
| | FMA-UE (%) | 67 ± 27.3 | Total omissions (n) | 2 [0–27] |
| | ARAT (/57) | 35 ± 22.8 | Omissions asymmetry (n) | 0 [– 2–8] |
| | Box and Block Test (block/min) | 20 ± 19.1 | Apples Test | |
| | | | Total omissions (n) | 2 [0–42] |
| | | | False positive asymmetry (n) | 2 [– 3–34] |
| Robotic assessments | | *μ ± SD* | MonAmour Test [] | *M [min.–max.]* |
| | Force (N) pulling (flexion) | 100 ± 48.0 | Total omissions (n) | 0 [0–67] |
| | Force (N) pushing (extension) | 88 ± 55.0 | Omissions asymmetry (n) | 0 [0–33] |
| | Kinematic indexes | | False positive asymmetry (n) | 0 [– 3–2] |
| | Velocity ($m.s^{-1}$) | 9.4 ± 6.3 | | *μ ± SD* |
| | Straightness | 0.92 ± 0.1 | Total Mean reaction time (ms) | 2313 ± 96 |
| | Smoothness | 0.45 ± 0.2 | Mean reaction time asymmetry (ms) | 380 ± 99 |
| ROB*i*GAME's difficulty parameters and success rate | | *μ ± SD* | | *μ ± SD* |
| | $D_{mot}$ *after one game session* | 0.69 ± 0.3 | $D_{cog}$ *after one game session* | 0.42 ± 0.4 |
| | *after three game sessions* | 0.76 ± 0.3 | *after three game sessions* | 0.61 ± 0.4 |
| | $D_{time}$ | | *after one game session* | 0.71 ± 0.2 |
| | | | *after three game sessions* | 0.73 ± 0.2 |
| | Success rate | | *after three game sessions* | 0.76 ± 0.1 |

*n* total number of participants in this study, *μ ± SD* mean value ± Standard Deviation, *Median [minimum – maximum or range]*, *FMA-UE* Upper Extremity subscale of the Fugl-Meyer Assessment, % score expressed in percentage, *ARAT* Action Research Arm Test, *N* Newtons, ms milliseconds, $m.s^{-1}$ m per seconds, $D_{mot}$ motor task-difficulty parameters, $D_{cog}$ attentional task-difficulty parameters, $D_{time}$ task completion time parameter

The way motor and attentional task-difficulty parameters evolved during three consecutive ROB*i*GAME sessions were graphically represented for all participants in Fig. 3 (graph A for $D_{mot}$ and graph C for $D_{cog}$). As illustrated, participants with a higher FMA-UE score reached a higher level of motor task-difficulty and participants with hemispatial neglect reached on average lower attentional task-difficulty levels than participants without hemispatial neglect. Also, in most cases, levels of difficulty progressively increased until a certain level and reached a plateau as illustrated on Fig. 3, graphs A and C.

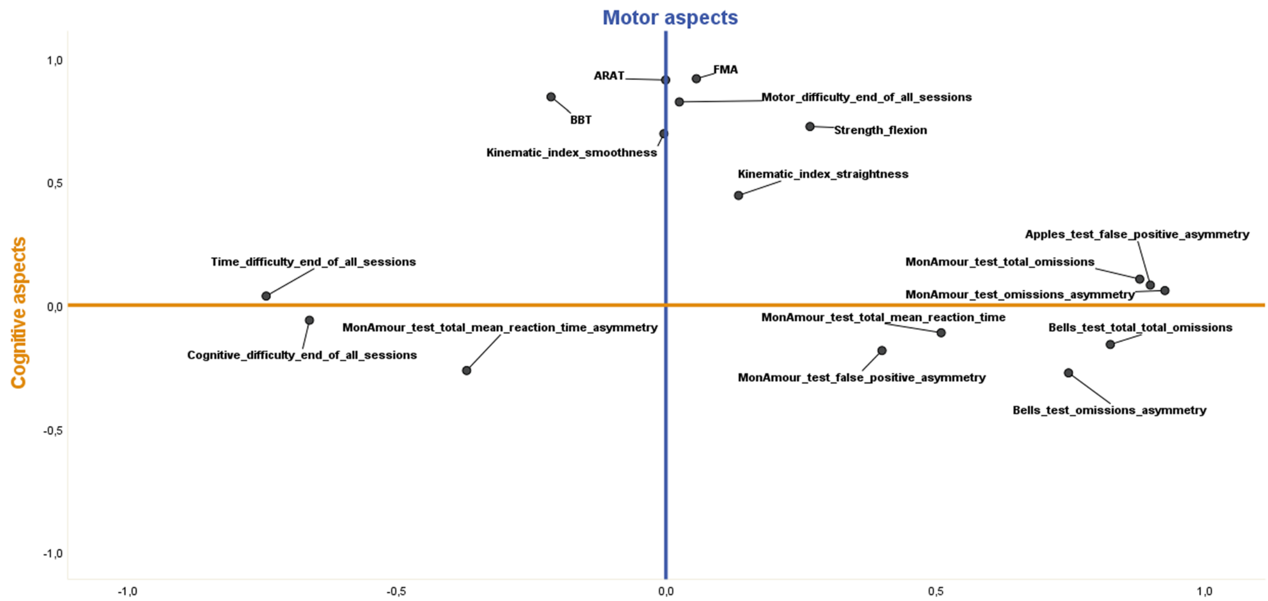
Supplementary Fig. 3 constitutes a typical trace of ROB*i*GAME's DDA mechanism in action. Specifically, it illustrates how motor (Figure S3A for $D_{mot}$) and attentional (Figure S3B for $D_{cog}$) difficulty evolved over the course of the three sessions for one participant (participant 11). On average, 15–20 tasks are performed per session. The dots on the graphs represent the value of the corresponding task-difficulty parameter after the completion of each task. The dotted line in each graph corresponds to the average value of the task-difficulty parameter for the last 10 performed tasks. As shown in these graphs, beyond completion of approximately 15–20 tasks, task-difficulty parameters dynamically fluctuate around an individualized plateau value.

A repeated measures ANOVA showed no significant differences between levels of motor task-difficulty reached after completion of the first 20 tasks and mean value of motor task-difficulty reached at the end of all sessions (mean of the last 10 performed tasks). This confirms that individualized levels of task-difficulty were reached after approximately thirty minutes of training, corresponding to completion of 15–20 tasks, which indicates a rapid adjustment of task-difficulty to each participants' individual degree of impairment. Finally, the mean success rate of participants was of 76% in all sessions.

## Discussion

### Main findings

This work demonstrated how task-difficulty adequately adapted to match individual degrees of impairment during serious game robotic training for combined rehabilitation of motor and attentional impairments after stroke. Additionally, by studying relationships between functional evaluation scores of both motor and attentional impairments and respective task-difficulty parameters, we suggest a novel way to perform clinical validation of a DDA mechanism. Principal component analysis illustrated that overall difficulty regulation of the system was dictated by two subsets of parameters, one subset




| | Component 1<br>Cognitive aspects | Component 2<br>Motor aspects |
|---|---|---|
| Fugl Meyer Assessment - Upper Extremity | | 0,917 |
| Action Research Arm Test | | 0,912 |
| Box and Block test | | 0,844 |
| Motor difficulty reached at the end of all sessions | | 0,823 |
| Arm flexion strength | | 0,724 |
| Kinematic index smoothness | | 0,695 |
| Kinematic index straightness | | 0,445 |
| MonAmour test omissions asymmetry | 0,925 | |
| Apples test false positive asymmetry | 0,898 | |
| MonAmour test total omissions | 0,878 | |
| Bells test total omissions | 0,824 | |
| Bells test omissions asymmetry | 0,746 | |
| MonAmour test total mean reaction time | 0,510 | |
| MonAmour test false positive asymmetry | 0,400 | |
| MonAmour test total mean reaction time asymmetry | -0,371 | |
| Cognitive difficulty reached at the end of all sessions | -0,663 | |
| Time difficulty reached at the end of all sessions | -0,743 | |

**Fig. 2** Principal component analysis illustrated in graphic and table form. Two components were retained: data regarding cognitive aspects were retained on component 1 (horizontal) represented in orange, data regarding motor aspects were retained on component 2 (vertical) represented in blue. Correlation coefficients of each variable with respective component are also annotated

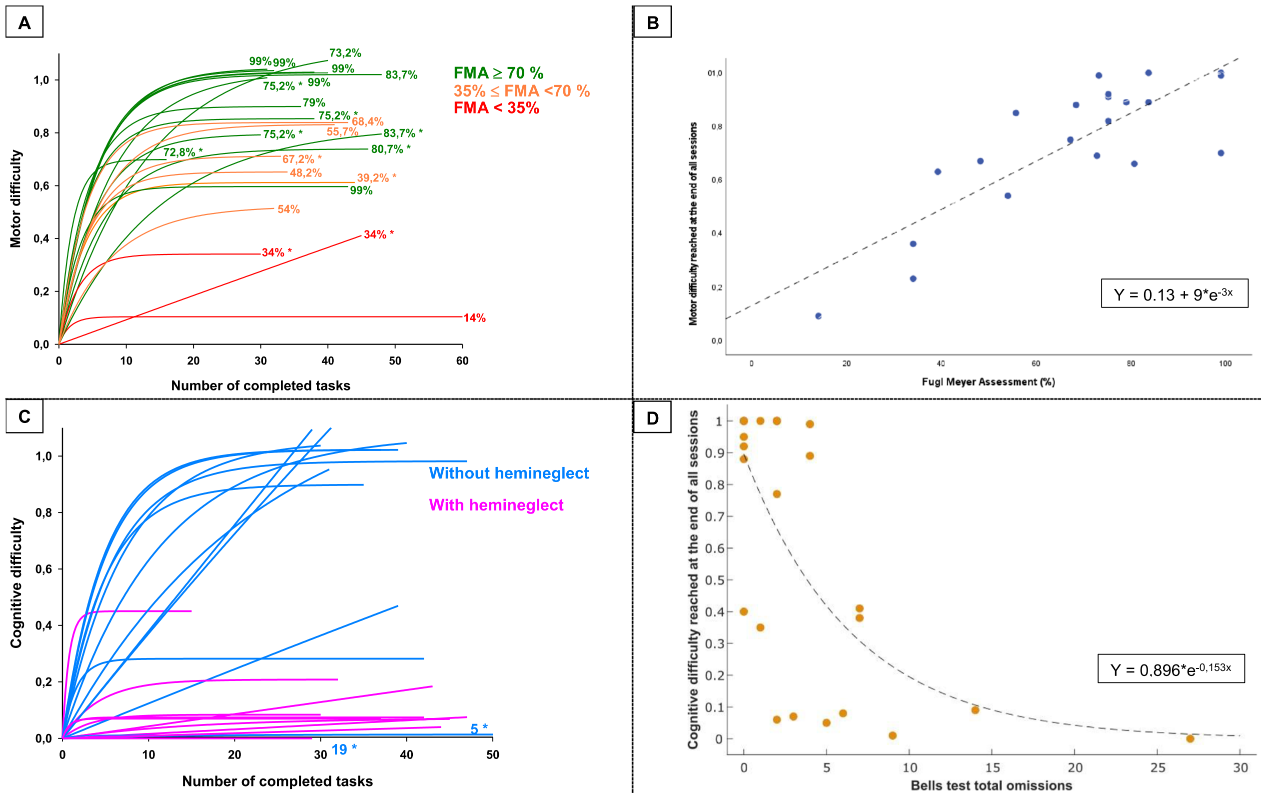



**Fig. 3** Evolution of game difficulty parameters and relationship with functional assessment scores. **A** Evolution of motor task-difficulty parameters ($D_{mot}$) during three ROB*i*GAME sessions. Each line represents one participant. Participants with hemispatial neglect are annotated with an asterisk (*) symbol. **B** Relationship between FMA-UE with respective motor difficulty scores reached at the end of three ROB*i*GAME sessions. General tendency of data is illustrated through dotted function and equation. **C** Evolution of attentional task-difficulty parameters ($D_{cog}$) during three ROB*i*GAME sessions. Each line represents one participant (participants numbers' 5 and 19 are annotated to improve readability). **D** Relationship between Bells Test total omissions score with respective attentional difficulty scores reached at the end of three ROB*i*GAME sessions. General tendency of data is illustrated through dotted function and equation. *FMA-UE* upper extremity subscale of the Fugl Meyer Assessment, $D_{mot}$ motor task-difficulty parameters, $D_{cog}$ attentional task-difficulty parameters

concerning motor impairments and the other subset concerning attentional impairments. Our findings recommend that adaptation of parameters determining motor and attentional task-difficulty can be adequately performed simultaneously, allowing combined rehabilitation with individualized levels of difficulty.

### Task-difficulty adjustment mechanisms during RAT and serious games: a common validation methodology?

Patients after stroke present various profiles in terms of types and severity of impairments, activity limitations and recovery trajectories [38]. Consequently, their rehabilitation and functional objectives vary widely, evolve over time and thus should be assessed individually and dynamically. In robotic and gamified rehabilitation, various ways to appropriately adjust task-difficulty during training have been described in scientific literature [5, 8, 11, 13]. A strategy for task-difficulty selection is to perform adaptation manually through direct therapist intervention, using the Wizard-of-Oz paradigm [6, 8]. However, when using this method, the selection of task-difficulty relies on subjective assessment and necessitates validation via an experienced therapist, who is usually physically present before or during training. Other adaptive mechanisms were configured, using objective data-driven approaches, to automatically adjust task-difficulty during training and optimize therapists' time [5]. For example, task-difficulty adaptation can be performed according to heuristic parameter increments based on pre-assessment [31] or using partially observable Markov decision process models [39].

Following their development, automated mechanisms should undergo validation in order to confirm that task-difficulty adaptation is performed adequately by the system and corresponds to the patient' rehabilitation needs. Indeed, the way task-difficulty is initially selected and then adapted during therapy is important because this choice could influence efficacy of the intervention and most importantly performance and motivation of the participants during treatment [40]. Interestingly, serious games using a DDA mechanism, like the one developed by our team for ROB*i*GAME, seem to offer various benefits compared to random, incremental or no difficulty regulation [11]. It is suggested that serious games using DDA mechanisms lead to a higher number of completed tasks per session, an optimal success rate in total number of completed tasks and a better modulation of training induced fatigability and motivation [11, 13]. Consequently, having the possibility to rapidly offer RAT or serious games with individualized difficulty, adjustable in real-time, could presumably outperform fixed difficulty algorithms in motor learning [41]. Additionally, based on our findings, task difficulty during RAT could be set to the appropriate level of difficulty at the beginning of training, according to the patients' functional assessment scores.

To the best of our knowledge, there is a lack of consensus in scientific literature on a validation methodology for automated mechanisms adjusting task-difficulty, during RAT or serious games training. This may be due to the underlying complexity of defining a common validation methodology for various types of previously described mechanisms. Previous works in literature have described different ways to perform validation of such mechanisms aiming to balance exercise difficulty during training [31, 39, 41]. For example, performance of the system could be validated according to a human therapist's agreement to the decisions made by the system [39]. Other studies conducted validation through participants' perceived performance to different levels of difficulty, through questionnaires [11]. However, these methods rely on an individual expert's judgement or patient-reported measures and hence present limitations. Other described ways to perform validation is to study how changes in difficulty conditions (easy, balanced, hard) lead to differences in the number of successful trials and other performance metrics (i.e. more successful trials and better performance metrics for easier difficulty levels and vice versa for harder difficulty levels) [42]. Although a data-driven assessment is included in this method, the individual patient's degree of impairment is not taken into direct consideration. Finally, it has been suggested that studying the relationship between difficulty level progression and functional impairment scales constitutes a way to evaluate whether difficulty adaptation is optimally performed during RAT [31]. Our study puts this validation approach into implementation and encourages further integration of functional evaluations, using clinical and robotic tests, when performing validation of DDA mechanisms.

### Challenges for DDA during combined motor and cognitive rehabilitation after stroke

A meta-analysis focusing on tasks performed in virtual environments after stroke suggested that combined training approaches may lead to better recovery outcomes, especially regarding motor function and activities of daily living [43]. Another recent study has suggested that combining cognitive exercises to motor rehabilitation using RAT could lead to improvements in cognitive impairments beyond motor function [44]. Data made available through serious games, implemented on robotic devices, could help differentiate profiles and thus target specific cognitive improvements in addition to motor recovery [45]. In line with literature, our work showcases that incorporating cognitive exercises into motor tasks on a robotic device could allow simultaneous training, with individualized levels of difficulty.

Based on our results, motor task-difficulty ($R^2 = 0.710$; $p < 0.05$) appears to be mainly influenced by the severity of the motor impairment. On the other hand, attentional task-difficulty ($R^2 = 0.387$; $p < 0.05$) seems to be affected by additional factors, other than simply the presence or absence of hemispatial neglect. This may be due to concurrent presence in our sample of cognitive impairments beyond hemispatial neglect or broader attentional deficits, such as executive or memory impairments. Additionally, contrary to motor evaluation tests, the clinical and robotic evaluation tests used in our work for hemispatial neglect are simple binary classifiers, meaning they allow to detect the presence or confirm the absence of hemispatial neglect [22, 29]. This means that, these tests do not allow an established classification concerning the severity of attentional impairment. This could also explain the attribution of similar attentional task-difficulty by the system in some cases where impairment severity seems to be different, as illustrated in Fig. 3C, D. A recent scoping review highlighted the lack of robotic assessment tools for categorisation of hemispatial neglect, based on subtypes and degrees of severity [2]. It is therefore indicated that there is a contrast in terms of precision and standardisation of tools when comparing evaluation of motor and cognitive functions. Consequently, this may explain why our results suggest a more straightforward task-difficulty adaptation for motor impairments and a more challenging one for attentional impairments.

Finally, standardized evaluation for motor impairments is performed at specific time points after stroke (day 7, 6 weeks, 3 months, 6 months, etc.) [23], not on a daily or weekly basis. Task-difficulty parameters defined during RAT, such as those described in the present study, could complement existing methods to assess patients and track recovery using regular time points. Being easily accessible, in real time during training, acquisition of such parameters would not require therapists to dedicate additional effort.

### Strengths and limitations

Using a novel approach, this proof of concept demonstrated ROB*i*GAME's ability to adapt task-difficulty to varying levels of impairment after stroke. Previous studies have showed how difficulty adapted to patients that presented with motor impairments of moderate severity [31, 39, 40]. This clinical validation was performed on a sample presenting a wide spectrum of types of impairments (motor and/or attentional) and severity (mild, moderate, severe). Moreover, heterogeneity of our sample indicates that ROB*i*GAME has an intuitive interface and is appropriate for use with a large population of patients after stroke.

In addition to clinical functional scales, we performed evaluation using quantitative data, acquired through the robotic device, of both motor and attentional impairments. However, cognitive evaluation of participants focused on hemispatial neglect since ROB*i*GAME was specifically developed to address this impairment. Therefore, evaluation of other types of cognition which could additionally influence performance during training, such as executive functions or memory, was not conducted. Also, sensory deficits were not thoroughly evaluated. Measures regarding motivational aspects or patient enjoyability, which could impact long term adherence, were also not evaluated in this work.

Finally, the DDA mechanism, validated in this study, is not bound to ROB*i*GAME and could potentially be implemented on other devices or other serious games, broadening potential applicability.

### Areas for future study

Recovery after stroke is usually a long process and future investigations should track evolution of task-difficulty parameters over longer periods of time than three consecutive days of training, as described in this proof of concept. This could help determine the added value of additional evaluation time points in comparison to current guidelines (7 days, 6 weeks, 3 months, 6 months) regarding prognostic prediction models and recovery trajectories [47]. In addition to functional outcomes and task-difficulty parameters, motivation during sessions should be further assessed. Some serious games use reward systems, such as the collection of points during the game scenario, modulating motivation [13]. Whether motivation in stroke recovery is influenced by modulation of task-difficulty over time or reward systems during gameplay should be further studied [48]. Additionally, future trials should investigate whether systems using a DDA mechanism like the one described in our work could lead to better rehabilitation outcomes compared to non-adaptive approaches.

Finally, validation of ROB*i*GAME's DDA mechanism opens perspectives in terms of self- and tele- evaluation and home rehabilitation. Indeed, after a period of initial guided training and familiarization, evaluation and serious game training could be performed autonomously, with no or distant supervision. Accustomed participants could receive extrinsic feedback between sessions to autonomously track their progress on a more regular basis. In the era of personalized medicine, these data collected through serious games, such as task-difficulty parameters described in ROB*i*GAME, could feed existing prediction models. ARAT or SAFE score are already available on the internet for prediction models concerning motor impairments [47]. Future models could further include other parameters for prediction of recovery regarding cognitive impairments.

## Conclusions

This proof of concept clinically validated a DDA mechanism for RAT after stroke. ROB*i*GAME provides simultaneous motor and cognitive exercises with task-difficulty parameters strongly related with respective clinical and robotic evaluation scores. Thus, tasks performed during training were individualized to each participant's impairments, suggesting an optimal level of challenge which could enhance rehabilitation efficacy and help achieve functional goals. Also, an individualized level of game difficulty matching the participants' degree of impairment was rapidly reached after only one RAT session (approximately thirty minutes). This rapid adjustment of the system ensures efficiency and facilitates implementation in clinical practice.

#### Abbreviations

| | |
|---|---|
| DDA | Dynamic difficulty adjustment |
| RAT | Robot-assisted therapy |
| FMA-UE | Fugl meyer assessment upper extremity |
| ARAT | Action research arm test |
| D | Task-difficulty parameters |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12984-025-01551-w.

Additional file 1.
Additional file 2.
Additional file 3.
Additional file 4.
Additional file 5.
Additional file 6.

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**Author contributions**
I.D. performed data acquisition, wrote the main manuscript text and prepared Tables 1, 2, 3, Figs. 1, 2, 3, additional tables and figures. T.L. contributed to data analyses and interpretation. M.E. contributed to data analyses and interpretation. G.S. contributed to data analyses and interpretation. Y.V. contributed to data analyses and interpretation. B.D. contributed to data analyses and interpretation. S.D contributed to data acquisition, data analyses and interpretation. All authors reviewed the manuscript.

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**Availability of data and materials**
Data is provided within the manuscript or supplementary information files.

## Declarations

**Ethics approval and consent to participate**
This study was approved by the clinical ethics committee of UCLouvain (Belgium). The study protocol was registered at ClinicalTrials.gov (NCT02543424). Participants signed an informed consent form before testing.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare no competing interests.

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