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RESEARCH ARTICLE

Feasibility of a theory-driven dynamic difficulty adjustment algorithm integrating individual performance and normative data for adaptive modulation of spatial and distractor inhibition attention in a non-immersive virtual reality task: Evidence from individuals following stroke

[version 1; peer review: 2 not approved]

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v1 **First published:** 30 Apr 2026, **6**:137
https://doi.org/10.12688/openreseurope.23432.1
Latest published: 30 Apr 2026, **6**:137
https://doi.org/10.12688/openreseurope.23432.1

Abstract

Background

Post-stroke attentional deficits are heterogeneous and may involve both spatial attention impairments, such as unilateral spatial neglect, and non-spatial deficits, including distractor inhibition. Conventional cognitive neurorehabilitation tasks often rely on fixed or manually adjusted difficulty levels to match the level of the patient, which may not adequately accommodate individual variability. Dynamic Difficulty Adjustment (DDA) algorithms offer a performance-driven approach to modulating task demands. The present study examined the feasibility of a theory-driven DDA algorithm integrating individual performance and normative data within a non-immersive virtual reality environment task.

Methods

Open Peer Review

Approval Status ✗ ✗

	1	2
version 1 30 Apr 2026	✗ view	✗ view

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A single-group repeated-measures feasibility study was conducted in inpatient and outpatient rehabilitation settings. Ten individuals with stroke completed three 15-minute sessions of DDA-REAsmash. The multi-parameter DDA algorithm continuously adjusted stimulus presentation time, distractor inhibition demands, and spatial configuration based on real-time individual performance, aiming to maintain an optimal engagement range of 65–85% success rate. Normative reaction-time percentiles derived from an independent mean age-matched sample were implemented as lower algorithmic constraints. Feasibility was defined as stabilization of performance within predefined engagement boundaries, and adaptive behavior was examined in relation to baseline attentional profiles.

Results

All participants completed the protocol without adverse events. Across sessions, performance converged toward the target engagement range.

Conclusions

These findings indicate the feasibility of a theory-driven multi-parameter DDA algorithm integrating individual performance and normative data to maintain individualized engagement in a heterogeneous post-stroke sample. Further controlled studies are required to determine clinical efficacy and functional outcomes.

Plain Language summary

After a stroke, many people experience attention problems. Some may fail to notice objects on one side of space, while others have difficulty ignoring distracting information. These problems can interfere with everyday activities such as moving around in complex environments, or interacting with objects.

Computer-based tasks are increasingly used for rehabilitation, but many provide the same level of difficulty to all users. Because stroke survivors differ widely in their abilities, a fixed level of difficulty may be too easy for some people and too difficult for others.

In this study, we tested the feasibility of a new digital assessment task called DDA-REAsmash, presented on a large interactive touchscreen. Participants played a visual search game in which they had to find target items while ignoring distracting ones.

A key feature of the system is a dynamic difficulty adjustment algorithm. The algorithm continuously analyzes the participant's performance and automatically adjusts the difficulty of the task. As a result, each participant encountered customized game levels tailored to their individual abilities.

Ten people who had experienced a stroke completed three sessions of the task. The results suggest that the system can successfully adapt task difficulty and maintain an appropriate level of challenge, supporting the feasibility of personalized digital rehabilitation tools for attention after stroke.

Keywords
Stroke, Unilateral Spatial Neglect, Distractor Inhibition, Dynamic Difficulty Adjustment, Serious Games, Virtual Reality, Neurorehabilitation.

This article is included in the COST Actions gateway.

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Author roles: Sorrentino G: Conceptualization, Data Curation, Formal Analysis, Methodology, Writing – Original Draft Preparation; **Everard G**: Formal Analysis, Software, Writing – Review & Editing; **Lejeune T**: Formal Analysis, Software, Writing – Review & Editing; **Edwards M**: Formal Analysis, Software, Supervision, Writing – Review & Editing

Competing interests: No competing interests were disclosed.

Grant information: This project has received funding from the European Union's Framework Programme for Research & Innovation as part of the COST Action [CA24123 - Extended Reality Neurorehabilitation of Spatial Neglect and Related Disorders After Brain Injury (neuroXRehab)], as supported by COST (European Cooperation in Science and Technology).

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How to cite this article: Sorrentino G, Everard G, Lejeune T and Edwards M. **Feasibility of a theory-driven dynamic difficulty adjustment algorithm integrating individual performance and normative data for adaptive modulation of spatial and distractor inhibition attention in a non-immersive virtual reality task: Evidence from individuals following stroke [version 1; peer review: 2 not approved]** Open Research Europe 2026, **6**:137 https://doi.org/10.12688/openreseurope.23432.1

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Introduction

Despite increasing awareness of the importance of cognitive rehabilitation after stroke, visuospatial attention deficits, such as unilateral spatial neglect (USN),[1] are frequently underdiagnosed and often not targeted effectively in rehabilitation programs.[2] Furthermore, key cognitive functions, such as distractor inhibition, lack in validated assessment and rehabilitation tools.[2] This under-diagnosis and under-treatment is often linked to limited resources, time constraints, and the shortage of trained neuropsychologists within rehabilitation settings.[3] Stroke rehabilitation requires regular and intensive sessions conducted by trained professionals to support functional recovery.[4]

Psychological factors such as reduced motivation, depression and anxiety, along with fatigue, can further complicate the rehabilitation process.[5] It is therefore essential to not only guarantee access to high-quality rehabilitation, ensuring adequate treatment intensity, but also to offer engaging and individualized sessions sustaining motivation and preventing dropout.[6,7]

Digital technologies such as Virtual Reality (VR) Serious Games (SG) have gained growing interest in neurorehabilitation.[4,8] VR provides structured, interactive, and repeatable environments,[9] with non-immersive VR configurations enabling task execution through screens or touch-based interaction without requiring full sensory immersion.[10,11] SG consists of entertaining educational training[12] that can facilitate patient-centered assessment and rehabilitation by encouraging participants to complete challenging and enjoyable tasks.[13] Research shows that VR SG enhances motivation and increases therapy intensity, further improving sensitivity and standardization in outcome measurement and rehabilitation.[4,8,14] Like other computerized technologies, VR SG enables the collection of diverse objective and quantitative data, such as behavioral and performance-based outcomes, increasing quantitative measurement sensitivity and specificity.[4,8,15]

Despite positive evidence in stroke survivors,[16] the clinical adoption of VR SG for cognitive rehabilitation remains limited.[17] One major barrier is the heterogeneity of post-stroke cognitive profiles, with multiple cognitive functions typically affected.[18,19] This variability makes personalization of rehabilitation particularly challenging, as patients require task demands to be continuously tailored to their individual cognitive abilities.[20] Conventional VR SG often rely on manual, operator-dependent adjustment of task parameters, usually carried out at the beginning of the session, and with subsequent changes in task difficulty following fixed rules that do not allow for further customization.[21] Fixed-difficulty tasks often fail to maintain patient engagement, particularly because difficulty is not tailored to the individual's varying abilities. Overly simple tasks reduce motivation through being too easy, while overly difficult tasks cause frustration and dropout.[22,23]

Conventional VR SG for cognitive rehabilitation entails two major practical limitations: (i) it requires trained personnel with sufficient expertise to accurately assess an individual's cognitive deficits and select appropriate task difficulty parameters and (ii), it demands specific training in the use of VR SG software (difficulty adjustment), increasing personnel burden.

To address this limitation, DDA SG have emerged as a promising approach.[24] DDA SG use algorithms to adjust task difficulty based on user performance,[25,26] aiming to provide challenging yet achievable levels that maintain optimal engagement, typically associated with success rates around 75% (not too easy and not too difficult).[25,27–29] Implementing DDA in cognitive rehabilitation requires finely tuned algorithms that are theory-driven and sensitive to latent constructs.[30]

Within this framework, we developed REAsmash, a modular VR SG grounded in Feature Integration Theory (FIT).[31] The assessment module of the REAsmash has demonstrated replicable FIT effects, providing an assessment of spatial and non-spatial (distractor inhibition) visual-attention, and motor control in post-stroke and healthy populations in both immersive and non-immersive VR versions.[32–35] Here, we present a new REAsmash module implementing a DDA algorithm designed to provide individualized, theory-driven cognitive rehabilitation. A fully immersive VR version of DDA-REAsmash was recently used by Everard et al.[36] to study motor learning in healthy older adults (with the DDA algorithm specifically designed to support motor learning). In this study, task difficulty was continuously adjusted to individual performance across training sessions, resulting in improvements in response speed, accuracy, movement smoothness, and manual dexterity, with retention and transfer to untrained tasks. In contrast, the present study introduces a novel, theory-driven DDA algorithm tailored to post-stroke cognitive rehabilitation, targeting spatial and non-spatial attentional deficits in a non-immersive VR setting. This new module introduces an additional innovation in DDA-SG design by integrating normative performance data from age-matched healthy controls within the DDA update rules, extending standard DDA approaches that rely solely on individual performance.[37]

Based on previous findings and FIT, three hypotheses were formulated.

(i) Feasibility: The DDA-REAsmash will maintain performance within an optimal engagement range of 65–85% success rate (i.e., centered around the mean of 75%).

(ii) Adaptability: To maintain the optimal success rate, the DDA algorithm will modulate task difficulty as a function of individual participant performance.

(iii) We expect DDA-REAsmash to modulate task parameter difficulty to each participant's cognitive profile, leading to a progressive stabilization of cognitive demand, reflecting clinically interpretable parameters. We expect longer stimulus presentation durations in individuals presenting impaired distractor inhibition, and we expect spatial configuration adjustment in individuals presenting lateralized visuospatial deficits.

Materials and methods

Study design

This study employed a prospective single-group repeated-measures feasibility design. The objective was to examine the short-term behavior of a theory-driven DDA algorithm integrating individual and normative data within a non-immersive virtual reality environment. The study was conducted in accordance with the STROBE guidelines[38] for observational studies, and the intervention description followed the TIDieR framework.[39]

The study is part of a broader research program registered on ClinicalTrials.gov (NCT04694833); the registry reflects the overall study timeline, while recruitment for the present feasibility phase evaluating the DDA-REAsmash module took place between November 2024 and June 2025.

Participants

Given the feasibility design of this study, no formal *a priori* sample size computation was performed. Sample size was instead informed by previous work on the FIT interaction underlying the DDA algorithm. *A prior* study using the non-immersive REAsmash assessment module[35] reported a large within-participant FIT effect ($\eta^2 = 0.487$; Cohen's $f \approx 0.97$). Based on this effect size, a power estimate suggested that nine participants would be sufficient to detect the effect with 80% power at $\alpha = 0.05$. To account for potential dropouts, ten participants were recruited.

Participants were recruited from the physical medicine and rehabilitation department of the *Cliniques universitaires Saint-Luc* in Brussels and were either currently hospitalized or already discharged. Recruitment took place from November 2024 to June 2025. The post-stroke participants were selected using the following inclusion criteria: (1) adult participants (i.e., minimum age of 18 years old); (2) presence of an ischemic or hemorrhagic first cortical and/or sub-cortical stroke, diagnosed by CT or magnetic resonance imaging; and (3) a good understanding of the task instructions. The exclusion criteria were: (1) uncorrected vision deficiencies; (2) presence of other neurological conditions (e.g., major neurocognitive disorder or extrapyramidal disorders) that could bias the outcomes; (3) medication-resistant epilepsy; (4) orthopedic dysfunction that could influence upper extremity function; and (5) too poor trunk control to sustain the trial.

All participants were screened for visual USN. The assessment included a standardized battery of gold-standard tests: the Bells Test,[40] the Broken Hearts Test,[41] and Visual Field and Visual Scanning subtests from the computerized Test for Attentional Performance (TAP) battery.[42] The complete gold-standard assessment session also included the Go/NoGo subtest of the TAP and the Montreal Cognitive Assessment (MoCA)[43] and lasted approximately 40–60 minutes. All participants also completed one session of the non-immersive REAsmash assessment module to estimate individual distractor inhibition deficits.

Assessment time windows were chosen *a priori* to balance clinical feasibility with the need to ensure that baseline assessments reflected participants' current functional status. Participants in the subacute phase underwent the assessment within 10 days prior to the DDA-REAsmash sessions to minimize confounding effects of rapid spontaneous recovery and clinical fluctuations that are most prominent in the early post-stroke period,[44] participants in the chronic phase were assessed within up to 30 days.

Materials

The DDA-REAsmash runs on the REAtouch® (Axinesis®), a non-immersive VR medical device. The REAtouch® consists of a 43″ interactive touch-sensitive screen (95 × 53 cm) mounted on a motorized structure that allows for customizable height adjustment and screen inclination (Figure 1).



Figure 1. The non-immersive VR device. The REAtouch® system consists of a 43-inch interactive touchscreen mounted on an adjustable support structure allowing customization of height and inclination. In the present study, the screen was positioned horizontally (0° inclination). Participants interacted directly with the touchscreen to perform the visual search task. Photograph taken by the authors.

The DDA-REAsmash module maintains the graphical design of the REAsmash assessment module. It features a cartoon-style visual display and an active playing area measuring 95 × 45 cm. The playing field can present up to 24 molehills arranged in a 6 × 4 grid, with moles simultaneously emerging from different molehills. Each mole and molehill covers an area of 8 × 8 cm. The target mole is identified by a red miner's helmet, while distractor moles have blue miner, blue horned, or red horned helmets.

The DDA task parameters included (i) the number and distribution of the molehills (i.e., the active playing field), (ii) distractor salience and number, (iii) stimuli presentation time, and (iv) cues designed to attract attention to the target (i.e., spatial auditory cues, and visual cues, each progressively simplifying the task difficulty relative to the no-cue condition). The first 12 trials served as a baseline block presenting an 'easy' starting point. The presented stimuli had minimal task demands, with a reduced active playing field consisting of eight molehills arranged in a 4 × 2 grid centered close to the participant. In this initial phase, only the target mole was presented (requiring no distractor inhibition), and the target remained visible for 10 seconds (maximum duration), with cues set at maximum intensity (helping the participant to find the target).

All DDA parameters were then updated after each block of 12 consecutive trials, enabling the system to adjust task difficulty at regular intervals based on mean individual performance across the previous 12 trials. Each parameter was designed to stabilize a specific performance dimension corresponding to the individual's profile, and together these adaptive mechanisms aimed to maintain an overall success rate of approximately 75% (i.e., with difficulty specific to the individual's profile and allowing the individual to find the target on 75% of trials). For the active playing field, the DDA algorithm dynamically adjusted the spatial configuration of the molehills based on the participant's spatial performance profile. Specifically, the algorithm used the spatial distribution of omissions to reshape the active playing field, progressively modifying its size and lateral balance in order to maintain an optimal challenge level while targeting individual visuospatial limitations. Targets were presented in a semi-randomized manner, appearing at least twice in each active column per block and never twice in the same molehill (except when a column contained a single molehill). This procedure ensured spatial unpredictability while allowing the detection of systematic lateralized response biases, such as increased omissions when targets appeared in the contra-lesional hemifield relative to the brain lesion. When such lateralized omissions are detected, the DDA is expected to adjust the shape of the playing field by reducing target density in the most impaired spatial regions while maintaining a limited number of molehills within the neglected hemifield. This spatial manipulation was designed to challenge participants with a playing area slightly exceeding their current visuospatial and/or motor range, rather than fully excluding the impaired space.

For example, in individuals with unilateral spatial neglect, the DDA progressively shifted the active playing field toward the ipsi-lesional side while preserving a small proportion of targets in the contra-lesional hemifield. This configuration allowed the system to maintain the target success rate around 75% while simultaneously promoting engagement with the neglected space, thereby directly targeting the participant's spatial attentional bias.

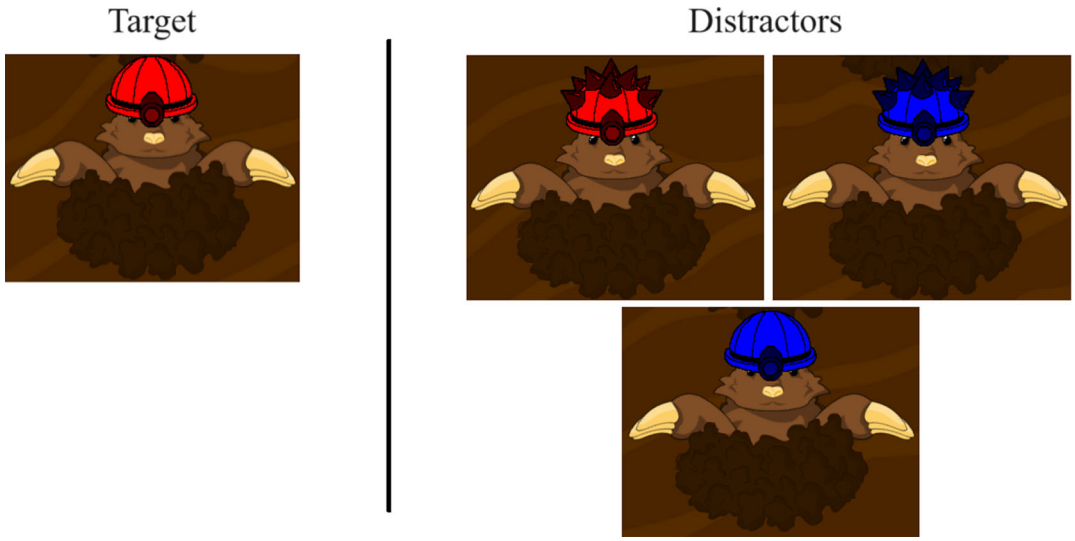


Figure 2. The different stimuli of the DDA-REAsmash. The target mole is identified by a red miner's helmet. Distractor moles wore blue miner's helmets, blue horned helmets, or red horned helmets. The presentation of the target with only distractor moles wearing blue helmets created high salience conditions with low inhibition demands. The presentation of the target with distractor moles wearing red and blue helmets created low target-distractor salience conditions, requiring greater inhibition demands relative to the high salience conditions.

The number and type of distractors were chosen based on the FIT effect. The FIT effect relies on a contrast between high versus low target-distractor salience and the number of distractors. The red-helmet distractors create low target-distractor salience with the red-helmet target (differing by the shape of the helmet) and evoke serial visual search when searching for the target's spatial location amongst distractors. In low target-distractor salience conditions, increased numbers of distractors progressively increase cognitive load and increase the need for distractor inhibition.[32–34] In contrast, the high target-distractor salience conditions (red-helmet target amongst blue-helmet distractors) require little distractor inhibition and are not influenced by increasing distractor number (Figure 2).

By manipulating target-distractor salience (features) and distractor number, the DDA algorithm can modulate distractor inhibition demands (difficulty). After an initial presentation with an incremental number of high-salience distractors, low-salience distractors were progressively introduced to increase the cognitive load through distractor inhibition. If a participant already showed reduced accuracy with high target-distractor salience conditions (i.e., only blue distractors), red distractors were not introduced by the DDA to prevent overload due to low target-distractor salience (i.e., too much difficulty). Conversely, when the overall success rate dropped below the target range, the algorithm analyzed the type of distractor most frequently associated with errors and progressively reduced their occurrence, maintaining an adaptive balance between challenge and performance stability.

To ensure the task remained appropriately challenging, especially under high distractor inhibition demands, stimuli presentation times were calibrated by the DDA using normative response time data from healthy controls tested with the non-immersive VR assessment module.[35] Specifically, lower bounds were derived from the 75th percentile of response times observed in low-salience levels of the assessment version. The 75th percentile of response times represents the minimum duration required for individuals without distractor inhibition deficits to correctly find the target in 75% of trials. These bounds were then estimated for different conditions varying in the number of red distractors. The full DDA algorithm description is provided as Extended Data 1 ("Full DDA algorithm description"), including step-by-step mathematical specifications of the computation of minimum stimulus presentation times, the derivation of normative performance constraints, and the explicit rule-based update equations governing all DDA parameters, enabling independent replication of the adaptive procedure.

At the end of each block, a 10-second pause was provided. During this pause, the touch-sensitive screen displayed feedback scores related to the completed block, including success rate, number of errors, and number of omissions. At the end of each session, an animation provided rewarding feedback with festive music and the achievement of a new personal best or a virtual medal linked to the number of levels played.

Procedure

The study was conducted in a clinical testing room at the *Cliniques universitaires Saint-Luc*, Brussels. All sessions were conducted by the first author of the study (PMR specialist), who was the intervention provider for the project. Participants

were seated either on a standard four-legged office chair or in their own wheelchair. They were positioned in front of the REAtouch® and aligned with the sagittal axis of the interactive screen. The inclination and height of the interactive screen was set at 0° and 74 cm.

Prior to the first 12 trials block, participants were instructed to "smash" the target mole as quickly and accurately as possible using their less impaired hand. Before the task, the examiner provided oral instructions supported by a standardized visual presentation illustrating task instructions and stimulus examples. Immediately before the session, a short-written sentence and an audio prompt appeared on the touch-sensitive screen, inviting the participant to find and respond to the mole as quickly as possible. At the start of each trial, participants had to place their response hand on an "X" super imposed at the center-lower edge of the screen, ensuring a consistent starting position. The "X" disappeared immediately after touching it and the trial began.

Omissions referred to missed targets (i.e., the participant was unable to hit the target within the presentation time). Errors were recorded when participants responded to and touched a distractor. Different types of auditive feedback were associated with positive or negative responses. Each session lasted 15 minutes. Participants completed three training sessions over one week.

Outcomes

The primary outcome testing the feasibility hypothesis was the success rate per 12-trial block, defined as the percentage of targets correctly found within each block. This measure was used to assess whether DDA-REAsmash could adjust task difficulty in order to maintain individual participant performance success within the optimal engagement range of 65–85%[25,27–29] (mean 75%).

Adaptability was evaluated using a Composite Difficulty Index. The Composite Difficulty Index provides a quantitative measure of task difficulty by integrating the three dimensions most relevant to cognitive load modulation in DDA-REAsmash. Specifically, it combined stimuli presentation time, the number of low-salience distractors, and the size of the active playing field. Shorter presentation times, a higher number of red distractors, and larger playing fields contributed to increased composite difficulty. Each component was normalized relative to its predefined theoretical or observed range, yielding Composite Difficulty Index values between 0 and 1, with higher values indicating greater difficulty. The index reflects how the DDA algorithm balances visual search load, inhibition demands, and spatial complexity across successive blocks, representing each participant's individualized task difficulty trajectory. A detailed explanation and operational description of the Composite Difficulty Index is provided as Extended Data 2 ("Composite Difficulty Index formalization").

A further assessment of adaptability was assessed by analyzing stimuli presentation time and active playing field configuration across blocks to examine whether adaptive adjustments aligned with individual participant clinical profiles for distractor inhibition and visuospatial attention impairments (i.e., to examine whether adaptive parameter adjustments corresponded to attentional profiles).

Data analysis

Statistical analyses were conducted in R (version 4.4.0). All derived metrics and modeling procedures were implemented using reproducible R scripts. No proprietary statistical software was required.

Success rates were calculated per 12-trial block and per participant. The feasibility of the DDA-REAsmash algorithm was assessed using two analyses. Firstly, Chi-square goodness-of-fit tests were performed on the total counts of successes versus non-successes (errors and omissions) for each participant across blocks. Secondly, one-sample t-tests ($\alpha = 0.05$, two-tailed) were applied to block-wise success rates to verify deviations from the expected 75% target, thereby allowing the identification of stabilization around the target range of 75% (early blocks with significant deviations and later blocks showing stabilization).

Adaptability was evaluated using the Composite Difficulty Index score. For each participant, block-wise Composite Difficulty Index scores were computed to track the evolution of task difficulty over time on a continuous scale from 0 (minimum difficulty) to 1 (maximum difficulty). To characterize how difficulty changed across successive blocks, Composite Difficulty Index trajectories were modeled using an asymptotic growth function:

$$\gamma(x) = a + b(1 - e^{-c \cdot x})$$

where a represents the initial difficulty level, b the gain from baseline to plateau, and c the adaptation rate. Model parameters were estimated using nonlinear least squares fitting implemented in R. This modeling approach enables the

identification of potential plateaus in the difficulty curves, providing model-based estimates of each participant's task difficulty stabilization level. Plateau stabilization was interpreted as consistent with algorithmic convergence toward individualized engagement bounds.

Analysis of individualized adaptability used two separate analyses. These analyses explored patterns in the adaptive responses of DDA-REAsmash in relation to two distinct cognitive deficits: (i) distractor inhibition impairment and (ii) USN-related lateral bias. The first analysis assessed whether participants with distractor inhibition difficulties required longer stimulus presentation durations. To detect impairments in distractor inhibition, participants were classified according to the number of omissions across the three low-salience levels of the REAsmash assessment module. Because omissions may also result from attentional lateral bias, for participants identified with USN using gold-standard tests, omissions were attributed to pure attentional lateral bias when they occurred exclusively in the contra-lesional field. Accordingly, these participants were considered not to exhibit distractor inhibition deficits (i.e., zero omissions attributed to distractor inhibition impairment). Participants with USN were considered to have concurrent distractor inhibition difficulties if omissions occurred in the ipsi-lesional field were more than one and accounted for over 25% of total omissions. Participants with USN and less than 25% of omissions, or only one omission, in the ipsi-lesional field were not included in this analysis.

To characterize adaptation over time, stimuli presentation durations for each participant were analyzed using asymptotic growth functions. A Spearman rank correlation analysis was then conducted between distractor inhibition impairment (i.e., omission count in the assessment module) and the stabilized stimulus presentation time in the DDA-REAsmash.

The second analysis explored whether participants with USN-related lateral bias specifically exhibited asymmetric adjustments of the active playing field, quantified as the percentage of molehills displayed in the contra-lesional hemifield relative to the total. For this analysis, participants were classified based on gold-standard USN assessments and omission lateralization at the assessment module into three groups: individuals with USN at the gold standard tests and no omissions in the ipsi-lesional hemifield, individuals with USN and concurrent omissions in the ipsi-lesional hemifield, and participants without USN. Temporal changes in the percentages of molehills displayed in the contra-lesional hemifield were analyzed using asymptotic growth functions.

Results

None of the participants asked to interrupt the session or withdraw from the project. The sessions were well tolerated and overall described as non-stressful and engaging. No participants asked to stop the experiment prematurely or to extend the rest periods.

The participants consisted of 7 males and 3 females, with a mean age of 56 years (SD = 12.0). All participants were VR naïve and 6 reported that the less impaired hand (i.e., the response hand) was their pre-stroke dominant hand. The average time since stroke was 14 months (SD = 15.0 months), with 4 participants in sub-acute phase (i.e., within 6 months from the stroke) and 6 in chronic phase, and 8 with ischemic stroke, 1 with hemorrhagic stroke, and 1 with ischemic stroke complicated by hemorrhagic transformation. Lesions primarily affected the Sylvian regions in all participants and were located in the right hemisphere in 6 participants. The mean MoCA score was 25.7 (SD = 1.6). Rehabilitation status varied, with all participants still undergoing neuropsychological, occupational, and/or physical therapy at the time of testing. In the REAsmash assessment module, omission rates ranged from 0 to 5 in the low target-distractor saliency levels, with higher omission rates indicating more severe deficits in distractor inhibition. Three participants exhibited signs of USN on the gold-standard tests. See Table 1 for demographic and clinical characteristics of the participants. Detailed results of the gold-standard assessments for spatial attention are provided as Extended Data 3.

All participants completed the training sessions without adverse events.

Feasibility

Participants completed an average of 48.5 (SD = 7.12) blocks across the three sessions. Participants required 5.4 (SD = 1.07) blocks on average to reach the 65–85% target range (hereon labelled as pre-target range blocks). Chi-square goodness-of-fit tests on overall success versus non-success counts across all blocks showed a significant deviation from the expected 75% success rate for one participant ($\chi^2 = 16.79$, $p < .001$), while the other nine participants aligned with the expected distribution. When analyses were restricted to blocks following the first in-range block (i.e., pre-target range blocks exclusion), this same participant continued to show a significant deviation ($\chi^2 = 6.92$, $p = .009$), whereas no significant deviations were observed for the remaining participants ($p \geq .22$).

Table 1. **Demographic and clinical characteristics of participants (de-identified).**

ID	Sex	Age (years)	The response was made with the pre-stroke dominant hand?	Stroke phase	Stroke type	Brain lesion side	Omission count in the assessment module	Current spatial attention impairment	Rehabilitation status
P1	M	60–69	No	Chronic	Hemorrhagic	Left	2	No	Ongoing rehabilitation
P2	M	50–59	Yes	Chronic	Ischemic	Right	3	Yes	No rehabilitation
P3	M	50–59	Yes	Chronic	Ischemic	Right	5	Yes	Ongoing rehabilitation
P4	F	50–59	No	Chronic	Ischemic	Left	0	No	Ongoing rehabilitation
P5	M	50–59	Yes	Chronic	Ischemic	Right	0	No	Ongoing rehabilitation
P6	F	70–79	Yes	Chronic	Ischemic	Right	1	No	Ongoing rehabilitation
P7	M	60–69	Yes	Subacute	Ischemic	Right	1	No	Ongoing rehabilitation
P8	M	50–59	No	Subacute	Mixed	Left	1	No	Ongoing rehabilitation
P9	M	60–69	No	Subacute	Ischemic	Left	5	No	Ongoing rehabilitation
P10	F	20–39	Yes	Subacute	Ischemic	Right	3	Yes	Ongoing rehabilitation

F = Female; M = Male.

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Table 2. Mean success rates and inferential statistics relative to the 75% target performance.

ID	Mean success rate	SD	t-test	t-test p-value	Chi-square	Chi-square p-value
P1	74.8%	0.196	−0.061	0.951	0.009	0.923
P2	75.0%	0.180	0.000	1.000	0.000	1.000
P3	79.5%	0.140	2.350	0.023	6.922	0.009
P4	73.6%	0.240	−0.375	0.709	0.519	0.471
P5	73.4%	0.154	−0.676	0.503	0.694	0.405
P6	72.7%	0.218	−0.691	0.493	1.455	0.228
P7	73.0%	0.222	−0.556	0.582	0.973	0.324
P8	76.1%	0.127	0.643	0.523	0.427	0.513
P9	74.2%	0.139	−0.317	0.753	0.125	0.724
P10	73.1%	0.153	−0.725	0.473	0.790	0.374

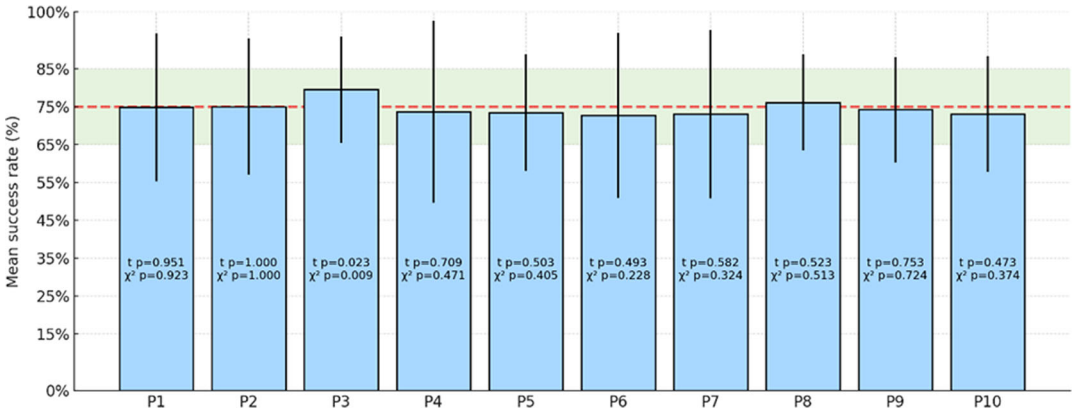


Figure 3. Individual block-wise success rates, excluding warm-up blocks, across participants. Each bar represents the mean success rate across blocks after exclusion of initial blocks required to reach the target engagement range. The dashed horizontal line indicates the 75% target success rate, and the shaded area represents the predefined engagement range (65–85%). Error bars denote standard deviation.

One-sample t tests comparing observed success rates to the 75% target across blocks showed that pre-target range blocks exceeded the target range, with mean success rates of 100% for blocks 1 and 2 and 94–99% for blocks 3 and 4 ($p < .001$). One-sample t tests on blocks following the pre-target range blocks indicated a significant deviation for a single participant, ($t(53) = 2.35$, $p = .023$), with all others non-significant ($p > .05$) (see Table 2 and Figure 3).

Adaptability

Composite Difficulty Index trajectories showed, in all participants, a rapid early change in difficulty adjustment followed by stabilization over successive blocks. Plateau values ranged between 0.7 and 0.9, indicating individual task difficulty levels (i.e., the difficulty level required for the individual to successfully find the target on 75% of trials). These difficulty levels depend on the performance profiles of each individual. The fitted curves suggest similar adaptation patterns across participants, with consistent stabilization patterns observed across trajectories (Figure 4).

Individualized adaptability

DDA-REAsmash for distractor inhibition rehabilitation

For the estimation of distractor inhibition impairment, participants were classified according to the number of omissions across the three low-salience levels of the REAsmash assessment module: no omissions (2 participants), one (3 participants), two (1 participant) three (2 participants), and five omissions (2 participants).

In participants with USN, omissions were examined with respect to their spatial distribution, since contra-lesional omissions are typically attributed to lateralized attentional bias. One of the three participants with USN showed three omissions, all confined to the contra-lesional hemifield, consistent with pure attentional lateral bias. This participant was

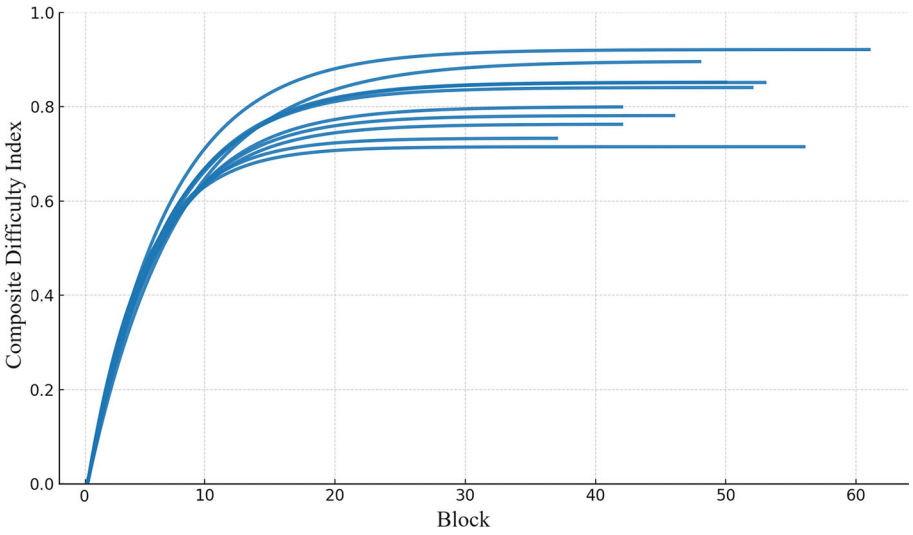


Figure 4. Composite Difficulty Index trajectories across participants. The X-axis represents the block number (i.e., progression over successive blocks), and the Y-axis represents the Composite Difficulty Index, ranging from 0 (minimum difficulty) to 1 (maximum difficulty). Each curve shows the evolution of task difficulty over time in one participant. The duration of the study was fixed (i.e., 15 minutes per session), causing the number of blocks completed by the individual to vary depending on their speed of performance.

therefore considered as not showing distractor inhibition deficits (i.e., zero omissions attributed to distractor inhibition). In the remaining two participants with USN, omissions occurred in both hemifields. However, in only one, the omissions in the contra-lesional hemifield accounted for less than 75% of the total omissions (i.e., 1 out of 3 total omissions), meeting the criterion for concurrent spatial and distractor inhibition difficulties. The third participant showed four omissions in the contra-lesional hemifield and only one in the ipsi-lesional hemifield and was therefore excluded from this distractor inhibition analysis.

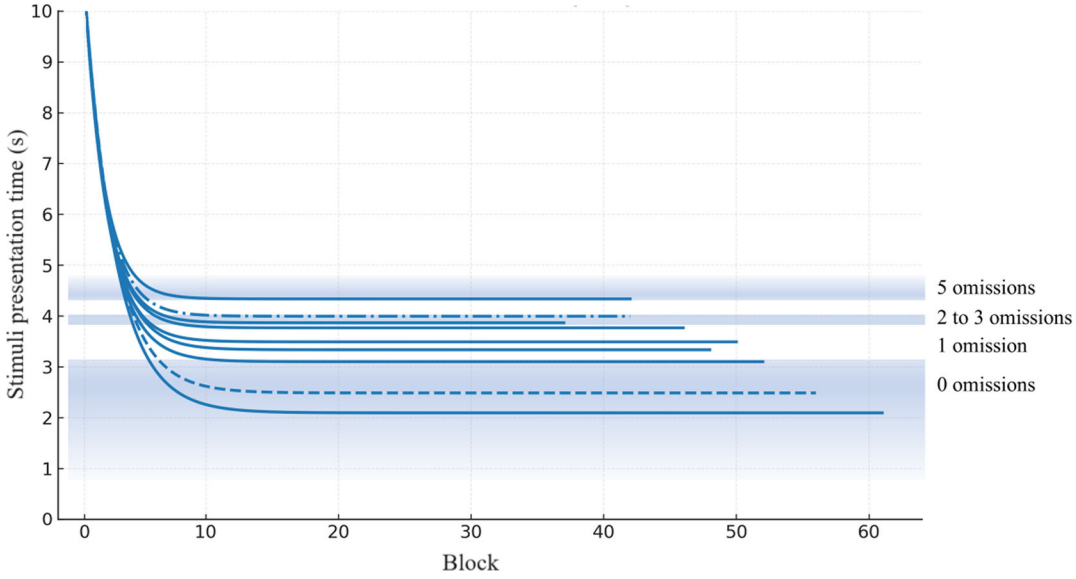


Figure 5. Relationship between stabilized stimuli presentation time and omission number. The figure illustrates the evolution of stimuli presentation time across successive blocks for each of the 9 participants included in this analysis. The X-axis presents the block number, and the Y-axis presents the stimulus presentation time (in seconds) determined by the DDA. The shaded horizontal bands highlight clusters of stabilized presentation times corresponding to different omissions obtained in the REAsmash assessment module (values shown on the right). The dash-dotted line presents the participant who exhibited both USN and distractor inhibition impairment, while the dashed line corresponds to the participant with USN only, whose omissions were not related to distractor inhibition.

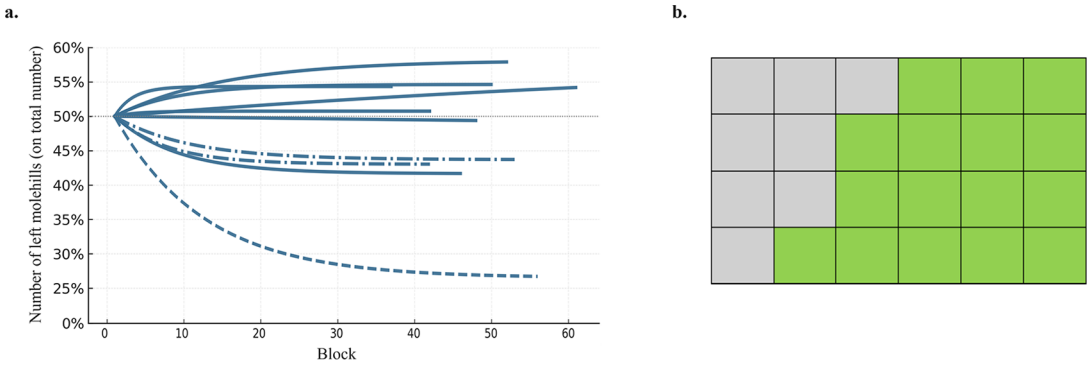


Figure 6. Adaptation of the active playing field in relation to attentional lateral bias. (a) Percentage of molehills presented in the left hemifield relative to the total, plotted across blocks. The X-axis presents block number, and the Y-axis presents the proportion of molehills displayed on the left side of the playing field relative to the total number of molehills. The dashed line corresponds to the participant with USN and no concurrent omissions in the ipsi-lesional hemifield. The two dash-dotted lines represent participants with USN and concurrent spatial and distractor inhibition difficulties. Continuous solid lines correspond to participants without USN. (b) Schematic representation of the active playing field of the participant with USN and no concurrent distractor-inhibition deficits. Green rectangles indicate the molehills selected by DDA-REAsmash as the configuration to challenge the participant's attentional lateral bias, whereas grey rectangles represent inactive areas of the playing field in which no molehills were presented.

A strong positive correlation was observed between the number of omissions in the assessment module and the stabilized stimulus presentation time in the DDA-REAsmash (Spearman's $\rho = 0.97$, $p < 0.001$). Participants with higher omission rates required longer presentation durations (to obtain 75% correct performance) (Figure 5).

DDA-REAsmash for attentional lateral bias rehabilitation

For the analysis examining the algorithm's ability to detect and target attentional lateral bias, participants were categorized into three groups: (i) pure USN-related lateral bias based on gold-standard tests, with no concurrent omissions in the ipsi-lesional hemifield (1 participant); (ii) USN with omissions in both the contra- and ipsi-lesional hemifields (2 participants); and (iii) no USN (7 participants).

The DDA algorithm for the participant with pure USN lateral bias adapted to the active playing field, and showed less targets in the contra-lesional space, showing a lateralized adaptation pattern. The percentage of molehills in the contra-lesional (left) hemifield stabilized slightly above 25% of the total. In contrast, the remaining participants showed values close to symmetry between the two hemifields (Figure 6).

Discussion

The present study evaluated the feasibility and adaptive behavior of DDA-REAsmash, a non-immersive VR SG implementing a theory-driven multi-parameter DDA algorithm integrating individual and normative performance data within a heterogeneous group of post-stroke individuals. All participants completed the protocol without adverse events, indicating good tolerability.

Concerning feasibility, individual- and group-level performance data showed rapid stabilization of success rates within the predefined optimal engagement range (65–85%). Success rates converged toward the 75% target after an average of 5.4 blocks, corresponding to approximately 2.5 minutes of gameplay. Although one participant showed a statistically significant deviation in inferential analyses, the observed mean success rate remained within the predefined engagement range. Overall, these findings are consistent with algorithmic convergence toward predefined engagement bounds.

Analyses of adaptability using the Composite Difficulty Index showed a rapid early increase in task difficulty followed by individualized plateau stabilization across participants. All participants began at minimal task demand, and the DDA progressively modulated stimulus presentation time, distractor inhibition load, and spatial configuration of the active playing field. The plateau levels were consistent with the level of difficulty required to maintain approximately 75% correct performance.

A central characteristic of the present implementation was the integration of normative performance from an independent sample of healthy participants within the DDA difficulty moderation rules. Lower limits for stimulus presentation time

were derived from the 75th percentile of response times observed in the mean age-matched healthy controls and implemented as algorithmic constraints. This integration anchored parameter modulation to empirically derived performance distributions and was designed to constrain parameter drift driven solely by intra-individual variability.

The relationship observed between omission counts in the assessment module and stabilized stimulus presentation times further illustrated individualized adaptive modulation. Participants with higher omission rates in low-salience conditions stabilized at longer presentation times, whereas participants with fewer omissions stabilized at shorter durations. These findings suggest that stimulus presentation time was modulated in relation to individual distractor inhibition characteristics during serial visual search.

With regard to spatial attention, most participants showed that the DDA maintained symmetrical configurations of the active playing field across blocks. In contrast, the participant presenting pure USN showed that the DDA made a progressive ipsi-lesional lateralization of the active playing field. Early blocks began with symmetrical presentation, but contra-lesional lateralized omissions (typical for USN) influenced subsequent spatial parameter adjustments, leading to a stimuli configuration having most stimuli presented in ipsi-lesional hemifield, and only a few stimuli presented in the contra-lesional hemifield, thereby to maintaining performance within engagement bounds (i.e., only the right molehills proximal to the playing field midline were displayed). In this case, spatial modulation allowed difficulty stabilization under lateralized attentional constraints.

In participants presenting concurrent spatial and distractor-inhibition impairments, adaptive adjustments involved multiple task parameters without a predominant spatial shift. Stimulus presentation time modulation appeared sufficient to stabilize performance, reducing the need for marked spatial reconfiguration. This pattern is consistent with parallel modulation across multiple attentional dimensions rather than isolated adjustment of a single domain.

Taken together, these results describe a multi-parameter adaptive mechanism capable of modulating visual search load, inhibitory demand, and spatial configuration in parallel. Unlike fixed-difficulty implementations or manually preset session-level adjustments, the DDA-REAsmash continuously updated task parameters according to explicit algorithmic rules integrating both real-time performance and normative constraints. The primary contribution of this study lies in the characterization of these algorithmic trajectories within a feasibility framework.

From a translational perspective, stabilized adaptive parameters such as stimulus presentation time and spatial field distribution provide quantitative descriptors of attentional processing during controlled task performance. Further investigation is required to determine whether changes in these parameters reflect learning, recovery processes, or task-specific adaptation. The adaptive framework described here may provide a methodological basis for future adaptive serious games targeting heterogeneous cognitive deficits in neurorehabilitation.

Limitations and directions for future research

The study was not designed to evaluate clinical efficacy, transfer effects, or long-term learning. No comparison with fixed-difficulty training was performed. The small sample size limits precision of effect estimates and generalizability. Future randomized controlled trials with larger cohorts will test the efficacy of DDA-REAsmash against fixed-difficulty training. Planned protocols will extend to three sessions per week over four weeks, with follow-up to assess retention, transfer, and functional impact. Further studies will explore multimodal rehabilitation (e.g., cognitive-motor coupling) and performance using the more impaired hand as response hand.

The non-immersive setting was chosen based on prior REAsmash (assessment module) findings[35] showing that immersive VR increases extraneous load in patients with attentional deficits. Direct comparisons between immersive and non-immersive DDA-REAsmash versions are needed to clarify how sensory load and user experience influence rehabilitation outcomes.

Conclusions

This study demonstrates the feasibility of a theory-driven multi-parameter DDA algorithm integrating individual performance normative data in a heterogeneous post-stroke sample. The algorithm maintained performance within predefined engagement bounds and generated individualized adaptive trajectories coherent with baseline attentional profiles. These findings describe algorithmic behavior within a feasibility framework. Controlled studies are required to assess clinical efficacy and functional outcomes.

Ethics approval and ethical compliance
The study received approval from the Saint Luc UCLouvain Clinical Ethics Committee (reference: 2015/10FEV/053) and was conducted in accordance with the principles of the Declaration of Helsinki and its later amendments. The protocol was prospectively registered on ClinicalTrials.gov (Identifier: NCT04694833).

Informed consent
All participants volunteered to participate in the study providing written informed consent prior to enrollment. Participants received detailed written and oral information regarding study objectives, procedures, potential risks, and their rights, including the right to withdraw at any time without impact on their clinical care.

Consent for publication
Not applicable, as no identifiable individual data are included in the manuscript or associated materials.

Data availability
Underlying data
Underlying data are openly available from the UCLouvain Dataverse repository:

Sorrentino, Gregorio, 2026. Replication Data for: Feasibility of a theory-driven dynamic difficulty adjustment algorithm. Open Data @ UCLouvain. https://doi.org/10.14428/DVN/EZR1JX

Data are available under the Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) license.

The repository contains fully de-identified participant-level and trial-level data supporting the analyses presented in this study. All data were de-identified in accordance with the Safe Harbor method (U.S. Department of Health & Human Services),[45] and indirect identifiers were generalized to minimize re-identification risk.

For further information regarding the dataset, readers may contact the corresponding author.

Extended data
Extended methodological details and additional materials are available from the same repository: https://doi.org/10.14428/DVN/EZR1JX.[46]

All extended data are provided in de-identified form and are available under the Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) license.

This repository contains the following materials:

- Detailed description of the Dynamic Difficulty Adjustment (DDA) algorithm, including parameter update rules and computational procedures enabling independent replication.

- Formalization of the Composite Difficulty Index, including normalization procedures and mathematical definitions across temporal, spatial, and distractor-related dimensions.

- De-identified participant-level data from gold-standard neuropsychological assessments (e.g., MoCA, Bells Test, Broken Hearts Test, TAP subtests).

- Informed consent form (English version, de-identified template approved by the local ethics committee), provided for transparency purposes.

Software availability
The DDA-REAsmash framework is implemented within a research software platform developed at UCLouvain, tightly integrated with proprietary hardware (REAtouch®, Axinesis), and is therefore not distributed as standalone code. For this reason, the source code is not publicly available.

However, to ensure transparency and reproducibility, a complete description of the algorithm, including parameter definitions, update rules, and computational procedures, is provided in the manuscript and Extended Data. This level of detail enables independent replication of the adaptive algorithm without access to the proprietary implementation.

For further information, readers may contact the corresponding author.

Reporting guidelines

The STROBE and TIDieR reporting checklists have been completed and are available in the UCLouvain Dataverse repository.

Repository: UCLouvain Dataverse.

DOI: https://doi.org/10.14428/DVN/EZR1JX

Data are available under the terms of the Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) license.

Acknowledgments

We thank Julien Sapin (AXINESIS) for providing help and support with the REAtouch® device.

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Open Peer Review

Current Peer Review Status: ✗ ✗

Version 1

Reviewer Report 06 July 2026

https://doi.org/10.21956/openreseurope.25357.r75721

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✗ **Dario Cazzoli**
University of Lucerne, Lucerne, Switzerland

This manuscript presents a feasibility study that evaluates the implementation of a theory-driven Dynamic Difficulty Adjustment (DDA) algorithm within the non-immersive REAsmash virtual reality platform for post-stroke rehabilitation. The proposed algorithm adapts task difficulty continuously, using both individual performance and normative data, to maintain performance within a predefined range. Ten stroke survivors completed three sessions, and the authors demonstrate that the adaptive algorithm successfully stabilised task performance while producing adaptations tailored to each participant's attentional profile. The manuscript addresses an important challenge in neurorehabilitation: the personalisation of cognitive training for heterogeneous stroke populations. The work is original and well motivated by cognitive theory. The integration of normative constraints into the DDA algorithm is also an interesting methodological contribution. Overall, the manuscript is clearly written. However, I have several points that the authors may wish to consider:

- This may be just a terminological issue. The authors repeatedly state that the algorithm maintains an "optimal engagement range of a 65–85% success rate", and then define feasibility as maintaining participants within this range. In my understanding, performance refers to what the participants actually do (e.g. accuracy, reaction time, errors and omissions), whereas engagement reflects the participants' psychological state (e.g. motivation and willingness to continue the task, or 'flow'). It therefore seems that performance is being used as a proxy for engagement, but engagement itself is not being measured. Please clarify.
- The results section of the abstract is quite short. The authors could briefly state the results with respect to the three formulated hypotheses, for instance.
- In the main body of the text (introduction): DDA SG is used without the abbreviation being defined at first use.
- The third hypothesis (end of the introduction) is quite detailed compared to the other two and covers several different aspects. The authors may wish to divide these into different, more specific hypotheses.
- In the methods section, the authors state that participants were screened for neglect using "gold-standard tests". Although the tests used are valid, it is unclear whether the current

literature supports the use of the term 'gold standard'. Furthermore, it is unclear how many patients had neglect; Table 1 ('Current spatial attention impairment') suggests that patients with lesions in both the left and right hemispheres were included, and that three out of ten patients had left-sided neglect following a right-hemispheric lesion. How was this defined (e.g. lateralised impairment in any of the applied clinical tests, and according to which cut-off)? Perhaps a supplementary table with patient characteristics would clarify these aspects. Some of this information can be found in the results section; the corresponding reference could be moved for clarity.

- Somewhat related to the previous point, the authors state that "in individuals with unilateral spatial neglect, the DDA progressively shifted the active playing field toward the ipsi-lesional side while preserving a small proportion of targets in the contra-lesional hemifield". What size is this 'small portion' and how was its size determined? If I interpret Figure 6 correctly, the percentage of left-sided molehills decreases over blocks and then stabilises. This suggests that molehills from the unused part of the left active playing field are not transferred to the preserved "small portion" on the left but, are evenly distributed across the entire active playing field. Is this correct? What is the rationale behind this choice? Would it not be a therapeutic goal to engage (and perhaps enlarge) the left-sided 'small portion' by increasing target number within this space?
- The Composite Difficulty Index is central to the manuscript. Although its mathematical formulation is provided in the extended data, there is little discussion of whether equal weighting of the three adaptive components would be justified.
- Again, concerning Figure 6, one patient who is not supposed to have USN (solid line with development below 50%) behaves quite similarly to the three patients with USN (dashed and dash-dotted lines). Does this indicate that this patient did not exhibit USN in the standard assessment, but indeed an USN pattern in the VR SN?
- The number of patients (10) appears adequate for a feasibility study. However, the population seems to show certain heterogeneity (e.g. different lesion lateralisation, acute versus chronic and perhaps severity of cognitive impairment), and sometimes smaller subgroups are formed. The statistical analyses are generally appropriate, but they rely heavily on null-hypothesis significance testing, despite the small sample size and exploratory feasibility design. As the primary objective is to characterise individualised adaptation trajectories rather than test population-level hypotheses, alternative analytical approaches, such as single-case longitudinal analyses, nonlinear mixed-effects models or descriptive estimation of convergence parameters, may be more informative. In particular, repeated one-sample t-tests and goodness-of-fit tests comparing performance with the predefined 75% target may not provide much additional insight beyond that already offered by the descriptive adaptation curves.

Is the work clearly and accurately presented and does it cite the current literature?

Yes

Is the study design appropriate and does the work have academic merit?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?

Partly

If applicable, is the statistical analysis and its interpretation appropriate?

Partly

Are all the source data underlying the results available to ensure full reproducibility?
Partly

Are the conclusions drawn adequately supported by the results?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Neuropsychology, cognitive neuroscience

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

Reviewer Report 02 June 2026

https://doi.org/10.21956/openreseurope.25357.r73666

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The report is dense starting from the title. The title is way too long. I was lost after the first 7 words. Was an assessment or treatment being developed through some algorithm? Please revise the title and shorten it by half or more. The manuscript in general gives the impression: There's a lot of information but no clear message emerged. See more specific comments as follows.

1. The Results section of the Abstract contains no information. At this point, readers should be informed what was tested exactly and what was found specifically. I suggest you move some content from the Methods section, if the word limit is a concern, to describe engagement and feasibility-related results.

2. Page 4: DDA, the abbreviation, was introduced without being spelled out full.

3. Page 5: The definition of feasibility is convoluted, especially this part "an optimal engagement rate of X success rate." Was feasibility measured by engagement or success?

4. Page 5: The third hypothesis was formatted differently than the first or second. Was it a hypothesis? The word "expect" was used 3 times in this very dense "hypothesis" statement. Please break it down and clarify. This "iii" statement may be re-written as its own paragraph as exploratory objectives, rather than hypotheses.

5. Before page 5, the Introduction was well-written, leading to the anticipated complexity of DDA-REAsmash. And the hypothesis statement suggested that the algorithm considered each person's "cognitive profile". However, later in the Methods section, the cognitive profile was not revealed. That is, it is unclear what factors were included in a "cognitive profile" which determined the algorithm. Please explain at a higher level in the Introduction and provide details in the Methods section.

6. Page 5: Participants were assessed using "gold-standard tests". There are no gold-standard tests for USN. Please revise the paragraph by stating what USN tests were used and what criterion was used for operationally identifying a patient with USN in the present study. For the rest of the manuscript, please remove "gold-standard assessment" or "gold-standard tests" entirely.

7. Page 9: Unpack and rewrite the paragraph describing distractor inhibition difficulties. The word "analysis" was used 3 times in the first line of the paragraph. Was the goal to understand the ability of the algorithm in individualized adaptability? Or to examine specific cognitive deficits using the algorithm?

8. Pages 9 and 10: Feasibility and adaptability results were reported. Please restate what was feasibility in the present study and what was adaptability. It is not directly apparent that the definitions described in the Introduction section were used here.

9. Page 13: What do Figure 6 and the related text (i.e., the section of DDA-REAsmash for attentional lateral bias rehabilitation) demonstrate? It seems to me that the DDA adapted to patients' behavior over time/blocks such that patients with USN played the game mostly in their non-neglected side (i.e., right side) toward the end of the study. This finding suggests the DDA-REAsmash is an assessment tool, rather than a treatment program.
Also, the group sizes (1, 2, and 7) were so uneven. What kind of analysis methods did you use? Were any permutation-based analyses performed? Please clarify.

Is the work clearly and accurately presented and does it cite the current literature?
Yes

Is the study design appropriate and does the work have academic merit?
Yes

Are sufficient details of methods and analysis provided to allow replication by others?
No

If applicable, is the statistical analysis and its interpretation appropriate?
Partly

Are all the source data underlying the results available to ensure full reproducibility?
Partly

Are the conclusions drawn adequately supported by the results?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: spatial neglect

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.