A Novel Multidimensional Dynamic Difficulty Adjustment Algorithm: Use Case in a Cognitive Training Video Game

Abstract

This study introduces a novel methodological framework for cognitive control training, embedded in a video game that incorporates action-based gameplay and a multidimensional Dynamic Difficulty Adjustment (DDA) system. This system adapts to individual player performance in real-time, ensuring a personalized and engaging experience. The game architecture is modular, including a configurable set of cognitive training modules which are tailored according to one's training goals. Transitioning between modules occurs through an action-based central hub following the literature on action video games and their positive impact on brain plasticity. Analysis of data from 34 players demonstrates how they progress through each module, with most players reaching their zone of proximal development after approximately 30-45 minutes of playing a module. Once players stabilize in their skill progression, the DDA system maintains variability in gameplay, a feature that has been suggested to promote the transfer of skills to novel situations. This analysis also highlights how our novel multidimensional DDA system accommodates to a wide range of skill levels, offering a seamless on-boarding experience across a variety of players. Together, this novel architecture and DDA framework provide a new, rigorous methodological blueprint for the design of computerized cognitive training tools.

Keywords: Dynamic Difficulty Adjustment; Skill Progression; Personalized Learning; Video games

A Novel Multidimensional Dynamic Difficulty Adjustment Algorithm: The Case of a Cognitive Training Video Game

Video games are an interactive medium with great potential to engage and entertain players. The ascent of video games over the past few decades has not only captivated a global audience but also piqued the interest of the scientific community. Researchers have delved into the multifaceted effects of video games on players, investigating both the positive impacts and the challenges they present (Gee, 2005; Schell, 2014). Video games are more than mere entertainment; they are now recognized as a dynamic and interactive medium with substantial potential for education and skill learning (Blumberg et al., 2024; de Freitas, 2018).

Amidst this recognition, there has been a surge in the development of video games with a deliberate focus on teaching or training players. These games aim to combine the inherent engagement and fun of traditional video games with learning objectives, creating an interactive learning experience that is both effective and enjoyable. However, crafting such games introduces several challenges, notably in designing experiences that align playful game activities with both learning objectives and the player's skill levels (Gee, 2005; Mayer, 2020). Drawing parallels with educational theory, the content and difficulty of these games must adapt to the player’s competencies, ensuring an optimal learning curve (Hunicke, 2005; Paraschos & Koulouriotis, 2023; Plass & Pawar, 2020). This adaptive challenge can be met through various approaches: manual difficulty adjustment by the player, structural game design elements like boss battles that test player skills or through adaptive algorithms that adjust the game’s difficulty based on the player’s ongoing performance (Bogost, 2007; Zohaib, 2018). The latter approach, employing dynamic difficulty adjustment (DDA) algorithms, offer a sophisticated way to tailor the gaming experience to a player’s skill level (Lopes & Lopes, 2022; Mortazavi et al., 2024). This approach aligns with Vygotsky's Zone of Proximal Development (ZPD), which posits that the most effective learning occurs when tasks fall within a zone that surpasses what learners can do without assistance but is attainable with help (Chaiklin, 2003; Vygotsky & Cole, 1978). In video games, this support can come through game mechanics like hints, adjustable difficulty, or feedback that helps players gauge their performance (Plass et al., 2015). An advantage of DDA is that it operationalizes the concept of ZPD by continuously adapting game difficulty in response to the player's performance, keeping them at the edge of their abilities and facilitating continuous learning and cognitive development (Plass et al., 2019).

In this context, we introduce Legend of Hoa’manu (LoH), a video game designed to enhance cognition through a variety of dynamically-adjusted game modules. Each module targets specific cognitive skills, utilizing a DDA algorithm to facilitate continuous learning and cognitive development. By recording and analyzing player metrics over time, this study aims to demonstrate how each game module’s difficulty calibration effectively supports skill progression. This analysis not only underscores the effectiveness of variable training and DDA in supporting learning but also offers detailed insights into how video games can be strategically designed to train and enhance cognitive functions.

Theoretical background

Attentional control training through video games

In the quest for effective methods to train and enhance cognitive skills, action video games (AVGs) have emerged as a significant tool. In the scientific literature, distinct from gaming industry nomenclature, the term "action video games" refers primarily to first- and third-person shooters. More recently, recognizing that other genres also encompass action elements, action-role playing games, real-time strategy, and racing sports games have been added (Bowman et al., 2024). Although still an active area of research, action elements have been hypothesized to include the combination of precise actions under time pressure, divided attention as well as swift shifts between divided and focused attention (Cardoso-Leite et al., 2020; Joessel, 2022). Indeed, AVG share in common to heavily load on divided attention as the player navigates the environment on the lookout for enemies; they require to make decisions under time pressure, whether shooting or picking up health packs, and also demand to refocus attention at a precise time and location as when aiming at an enemy, in essence requiring switches between divided and focused attention on an on-demand basis. Such requirements closely mimic the cognitive demands of many real-world tasks, making AVGs a compelling medium for cognitive training (Bavelier & Green, 2019).

Recent meta-analyses provide quantitative evidence supporting the cognitive benefits of AVG play (Bediou et al., 2018, 2023, but see Sala et al., 2018). Bediou et al. (2023) conducted an extensive review, analyzing data from 105 cross-sectional studies and 28 intervention studies with active control groups. Their findings reveal an overall advantage in cognitive skills for action video game players over non-players in the cross-sectional meta-analysis, with a large effect size (g = 0.64, 95% CI [0.53, 0.74]). Furthermore, the intervention meta-analysis demonstrated that action video gameplay was causally related to improvements in cognitive skills, with a small-to-medium effect size (g = 0.30, 95% CI [0.11, 0.50]). These results underscore the potential of AVGs to enhance cognitive function, reinforcing the need for further research into the mechanisms underpinning these benefits.

Tailoring video game-based programs for "learning to learn"

Effective learning necessitates deep, repetitive, and consistent engagement, as highlighted by studies that emphasize the importance of commitment to a training regimen (Hardy et al., 2015). The intrinsic motivation to engage, also essential for maintaining interest over time, can be fostered through feedback, clear objectives, and a judicious balance between directive gameplay and the freedom to explore (Mayer, 2020; Plass et al., 2020). Yet, such extended practice known to improve performance on specific tasks, often fails to transfer to new tasks (Bjork & Bjork, 2011; von Bastian et al., 2022). The issue of transfer is a recurrent one in education and in rehabilitation where the stated goal is to ensure everyday benefits of the training received (Barnett & Ceci, 2002; Deveau et al., 2015; Klahr & Chen, 2011).

Recent work points to two complementary ways to facilitate transfer. First, by introducing structured discovery within the domain of acquisition to scaffold a better understanding of more complex concepts within that domain, a mechanism also termed preparation for future learning, one can ensure broader generalization (Schwartz et al., 2011). By nature, such scaffolding remains however domain-specific. Other design factors associated with facilitating transfer, concerns variability of training context, such as interleaving practice (rather than blocking in line with short, distributed practice); providing intermittent rather than continuous feedback and introducing different variations of the task to be learnt, rather than keeping it constant (Baddeley & Longman, 1978; Raviv et al., 2022; Schmidt & Bjork, 1992). A third rather different means to facilitating transfer is through augmenting resource-limited processing, such as attentional control, working memory or other forms of executive functions (Jaeggi et al., 2011). Recently, we and others have shown that AVG playing enhances not only attentional control, but also in turn learning to learn as better attention facilitates the identification of task-relevant statistics (Bejjanki et al., 2014; Gozli et al., 2014; Zhang et al., 2021).

Video games naturally offer a conducive environment for learning as they build on repetitive activities while maintaining high engagement. Yet, a lesson from the video game literature is that not all games are created equal when it comes to transfer. In particular, mini-games modeled after specific psychology tasks with little to no variations may improve performance on those tasks but show minimal transfer

(Baniqued et al., 2014; Martincevic & Vranic, 2020; Owen et al., 2010; Stojanoski et al., 2021). In contrast, complex games like AVG lead to broader cognitive enhancements, highlighting the importance of training that encompasses a variety of activities while challenging attention and cognitive control. Finally, similar to any learning environment, games that implement distributed practice, intermittent feedback and carefully scaffolded task variations appear best at optimizing the delicate balance between fast learning of the game specifics and broad transfer beyond the game environment (Stafford & Dewar, 2014; Bavelier & Cochrane, 2024).

Closed-loop Algorithms in Dynamic Difficulty Adjustment

While commercial video games excel at difficulty adjustment, games for impact often only offer discrete options like easy, medium, or hard, which can fail to adapt to a player's evolving skill level, potentially leading to boredom or frustration. Addressing these challenges necessitates the deployment of a control system designed to dynamically adjust game difficulty in real-time. Central to this adaptive approach is the provision of real-time feedback on the player’s performance, paired with the flexibility to modulate game parameters (Chaiklin, 2003). This ensures that the game's difficulty level is directly tuned to the player's skill level, promoting a seamless gaming experience that evolves with the player’s performance (Madigan, 2015; Mishra et al., 2016; Mishra & Gazzaley, 2014).

The literature on DDA presents multiple strategies for modifying game difficulty, but most focus on the adjustment of a single 'difficulty' parameter in response to player performance (Hagelback & Johansson, 2009; Rao Fernandes & Levieux, 2019; Silva et al., 2015; Sutoyo et al., 2015). This method may fail to pinpoint an individual player's strengths or weaknesses—a critical consideration in games designed for cognitive training as several different cognitive constructs may be at play within the same game. To adequately address the multifaceted nature of cognitive skills, DDA systems must evolve beyond conventional single-parameter adjustments. Multidimensional DDA (Dziedzic & Włodarczyk, 2018) systems introduce a paradigm where difficulty adjustment is granular, offering the potential for simultaneous modulation across various task dimensions, such as presentation speed, number of targets/distractors, and more. This complexity requires a meticulously calibrated game design that incorporates separate yet combined adjustments of the varieties of parameters based on player performance to ensure overall progression (Guo et al., 2024; Madigan, 2015).

Recent advancements in DDA methods include reinforcement learning, dynamic scripting, PID control systems (which use Proportional, Integral, and Derivative calculations to maintain desired output), Bayesian or probabilistic graphs, deep learning, and other discrete optimization techniques (Mortazavi et al., 2024). These innovative approaches enable a more efficient adaptation of individual game parameters by creating detailed player models. This contributes to a more immersive and tailored gaming environment, highlighting the transformative potential of personalized gaming experiences to enhance player engagement and facilitate cognitive enhancement through tailored challenges (Chopin, 2022; Pato & Delgado-Mata, 2013; Sekhavat, 2017; Spronck et al., 2006; Xue et al., 2017; Zook & Riedl, 2012). Here, we take stock of these advances to present a multidimensional DDA specially designed for cognitive training.

The present study

In this study, we showcase our multidimensional DDA system using *Legends of Hoa'Manu* (LoH), a video game designed to integrate action-based mechanics and address challenges commonly encountered in educational and therapeutic game design (Pasqualotto et al., 2023). A short demo is available online on YouTube (https://www.youtube.com/watch?v=el9Spu-iez0). The game serves as a demonstrative platform to test how the DDA system adapts in real-time to individual player performance, optimizing the learning experience. With the view that enhanced cognitive control may strengthen the individual capacity to overcome mental health issues such as depression (Choi et al., 2022; Joormann & Gotlib, 2010; Pizzagalli & Roberts, 2022; Shimony et al., 2021), we present here user data from LoH from two different pre-registered clinical trials for Major Depression Disorder (MDD).

Game Architecture – LoH builds on a novel game architecture that links, via an action video game module, different satellite game modules built to train more targeted attentional and cognitive control functions. This game architecture is inspired of that of "Skies of Manawak", a game developed over a 2-year period through an iterative process that involved game designers and artists, domain experts in cognitive and clinical sciences, and players (Menestrina et al., 2021).

“Skies of Manawak” successfully improved attentional control and reading skills in 8 to 12 years old children after 12 hours of training over 6 weeks, with benefits maintained at a 6-month follow-up (Pasqualotto et al., 2022).

Adaptive Game Training Path – LoH has been designed to allow personalized trajectories among the satellite game modules presented. In this way, players who need more support with a given cognitive skill encounter activities demanding that cognitive skill more often.

Multi-dimensional DDA – A third feature of LoH is to implement for each game module a DDA system that exploits the fact that cognitive tasks can be made more difficult in multiple ways including task precision, display duration, inter-stimulus interval, or distractor load to cite a few. This multi-dimensional DDA system ensures that the player is presented with gameplay exercises that vary in how similar levels of difficulty are attained, avoiding boredom or frustration. It is also aligned with the action gameplay characteristics of reinforcing the capacity to perform under time pressure and under different modes of attention.

The goal of the present paper is to detail the three primary design elements of LoH and assess the proper implementation of our innovative DDA systems. In doing so, we will evaluate how effectively LoH facilitates game progression, both across various players and individually within each player's experience.

Methods

Dataset

Game progression is reported based on data collected from two different randomized controlled trials (RCT) with adult patients diagnosed with clinical depression: the DiSCoVeR trial (Dechantsreiter et al., 2023 for more details) and the Beer Yakov study (MOH_2020-06-30_009090). In the DiSCoVeR trial, the gameplay was paired with transcranial direct current stimulation (tDCS), a non-invasive brain stimulation (NIBS) method, for treatment at home. In both studies, participants were asked to play 30 game sessions of 30 minutes each. at home, for a total of 15 hours, distributed over a period of 6 weeks. We refer the reader to Supplementary Information (SI) section 1 for information on the participants included in the study (as well as those excluded due to a software bug) and to SI sections 2 and 3 for more information on the study protocols. We illustrate below gameplay behavior using the 34 players who completed at least 20 sessions out of the 30 from these two data sets.

LoH Design – Game Architecture

A first distinguishing feature of this architecture (Figure 1) is its fusion of cognitive training principles with AVG mechanics, optimizing the enhancement of attentional control and related executive processes (Anguera & Gazzaley, 2015; Bavelier & Green, 2019; Pasqualotto et al., 2023). Secondly, LoH introduces novel multi-dimensional DDA systems across its architecture to facilitate smoother progression and personalized experiences for players. Thirdly, other novel aspects of this training tool include (i) its modular architecture, where an expandable bank of satellite game modules enables the training of different skills, and (ii) the use of an AVG activity to link these satellite modules.

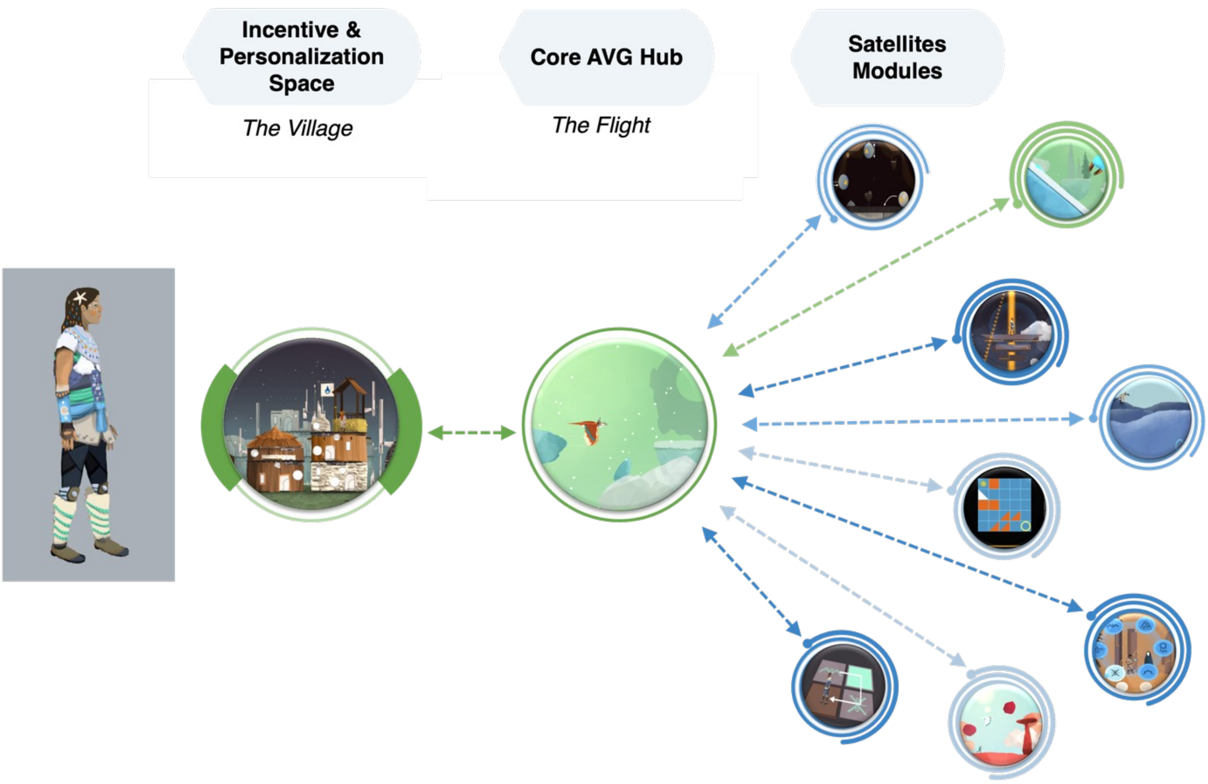
- ***Core Action Video Game Hub****:* This AVG hub bears key characteristics of action video games, including the need to make decisions under time pressure as well as the necessity to shift between divided and focused attention at proper times. As such, this core game, called “*Flight", is* designed to enhance attentional control which in turn has been proposed to facilitate learning new skills and tasks such as those presented in the game modules (Bavelier et al., 2012). Importantly, this core game serves as a gateway for each satellite game module, meaning players transition from one satellite game module to another by playing a “Flight” sequence. This mechanic ensures time is systematically spent playing an AVG.

- ***Bank of Satellite Game Modules***: A modular game architecture has been built so that satellite game modules can be added at will. Moreover, which satellite game module is presented depends on (i) the cognitive processes targeted by the training (e.g., skills relevant for reading acquisition, for alleviating depression etc.) and (ii) players’ performance on each of the modules they play.

- ***Incentive and Personalization Space***: This third component of the game – called *The Village* – bears key characteristics of an incentive world, where the players discover how points earned during the rest of the gameplay can be redeemed and where opportunities are given to personalize his/her world. In the Village, players also discover the next quest they are assigned to, sending them back into the game to explore a new part of the game world.

Figure 1

LOH game architecture showing the core AVG hub linking to the satellite modules (right), and the incentive personalized space (left)



Note. Eight different satellite modules were available: a multiple object tracking task (MOT; "Fishing" game), a visual running memory span task (Running-span; "Uka"), a visual N-back task (N-back; "Elevator"), a spatial Corsi-like short-term memory task (Spatial-STM; "Security System"), a Flanker task (Flanker; "Gate"), an emotional Go/No-Go task (Go/No-Go; "Falling Islands"), a divided attention task (DivAttent; "Meteors and Islands"), and a deductive reasoning task (Reasoning; "Energy Panel").

DDA Detailed Specification

The LoH video game places players in a virtual world filled with tasks that are systematically organized into game modules (Figure 1). At the start of each 30-minute session, the system selects a subset of these modules from a larger, pre-defined bank. Of note, the core AVG Hub (Flight) is a mandatory activity between each satellite game module, as well as between the incentive space (the Village) and the satellite game modules. The duration of one core action Hub sequence is approximately 120 seconds, and it recurs several times per session.

Training Path Adaptation

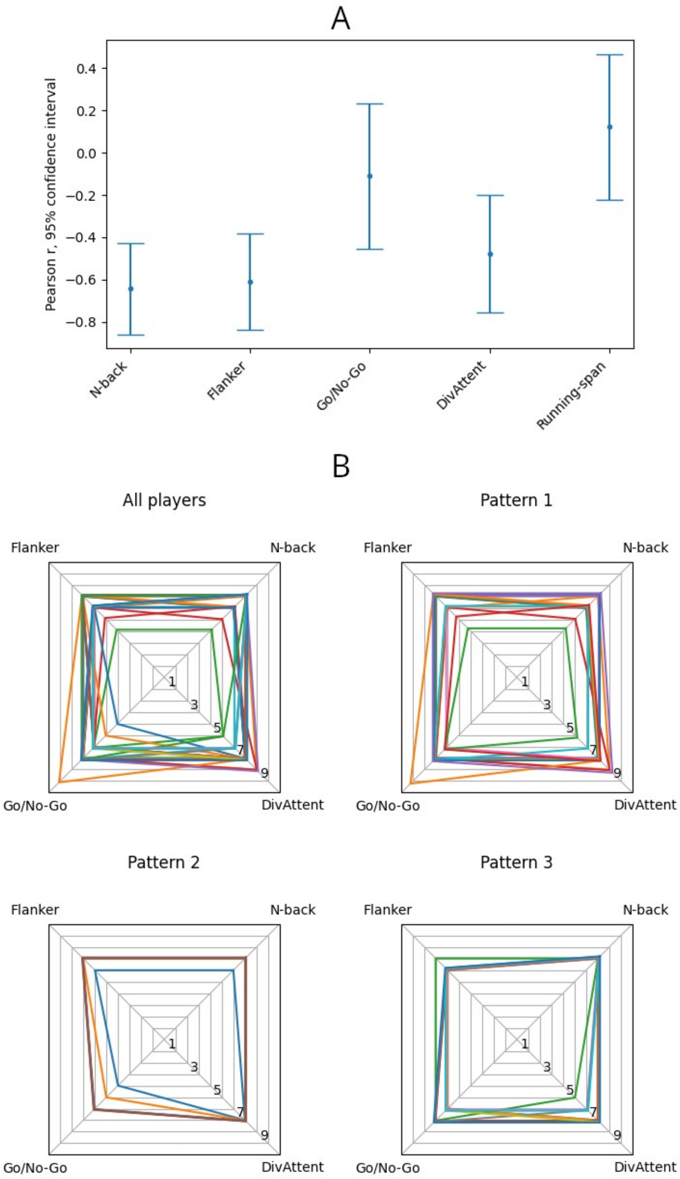
Across each 30-minute session, our system dynamically adjusts which satellite modules are presented, based on the player's past performance. For example, if a player demonstrates lower performance in a module designed to train inhibitory control, the algorithm is more likely to include this module in future sessions. Conversely, significant improvement in a cognitive domain such as working memory (WM) will decrease the frequency of related modules in future sessions. This adaptive path procedure directly controls the frequency of 5 out of 8 satellite game modules: N-back (Elevator), Flanker (Gate), Go/No-Go (Falling islands), DivAttent (Meteors and islands), and Running memory span task (Uka – due to a software bug the adaptive procedure was faulty for the latter).

The MOT game is always presented as the penultimate module (in addition to being called from within the core AVG hub when the player struggles), while the final module is randomly chosen between either the Reasoning (Energy panel) module, which lacks adaptive sub-parameters, or the spatial-STM (Security System) module, which features long trials that can become cumbersome if played too frequently. Lastly, the duration of each satellite module is fine-tuned to ensure that the total session length is 30 minutes. For further details on the training path, please refer to SI section 2.

As expected, the frequency of experiencing a satellite module is predicated upon success rate of the previous sessions (Figure 2A; again, except for the Running span task, Uka, which was affected by a software bug). Note that the Go/No-Go module shows only a small negative correlation most likely due, as we will see below, to this task remaining too easy most of the time for most participants. The negative correlation between performance in and number of times a satellite game was presented (seen for N back, Flanker, DivAttention) is in line with our adaptive path algorithm. Figure 2B illustrates the result of that training path adaptation across players illustrating that different players did experience each satellite module with different frequencies as expected given our path training algorithm.

Figure 2

Panel A. *Correlations between overall performance (success rate from the beginning of the training until the 10th session) and number of sessions a game module was presented (in these same first 10 sessions).*
Panel B. *Illustration of different training paths across different users. Each colored line represents a single player's data. The top left plot includes all selected players, while the remaining plots group players into 3 types.*



Note. Only the modules that were varied as part of the adaptive training path are included in these plots: N-back, Flanker, Go/No-Go, and DivAttention (Running memory span not shown due to a software bug in its adaptive training path – see SI section 7).

Multi-dimensional DDA

The LoH game implements 4 different variations of DDA. The primary multi-dimensional DDA algorithm applies to the MOT (Fishing), N-back (Elevator), Flanker (Gate), Go/No-Go (Falling Islands), and Running memory span (Uka), modules. The fast-paced DDA algorithm, a slight modification of the primary DDA algorithm, applies to the DivAttention (Meteors and Islands) module. A simplified DDA algorithm had to be used for games without explorable sub-level parameters, like the Corsi-like WM (Security System) module. Finally, a stratified DDA algorithm was implemented for the Core AVG hub which presents the player with challenges (waves) specific to each sub-level dimension.

Our primary multi-dimensional DDA algorithm and its variations ensure that each player is sufficiently challenged by adapting not just one, but several different parameters within each game module. The algorithm updates the game module parameters after a set of trials has been completed. The number of trials over which game module parameters are updated depends on the duration of a trial within each task - the specific *update period* for each game module is defined in the respective module's section. All variations of our DDA algorithm share several core elements to ensure a uniform gameplay experience. We describe the exact DDA first for one of our satellite game modules and then for the AVG Hub.

Satellite Game modules DDA

We illustrate below the principles underlying our DDAs through one specific example from the MOT game module. For a detailed review of the DDA for the remaining satellite modules, please refer to SI section 5.

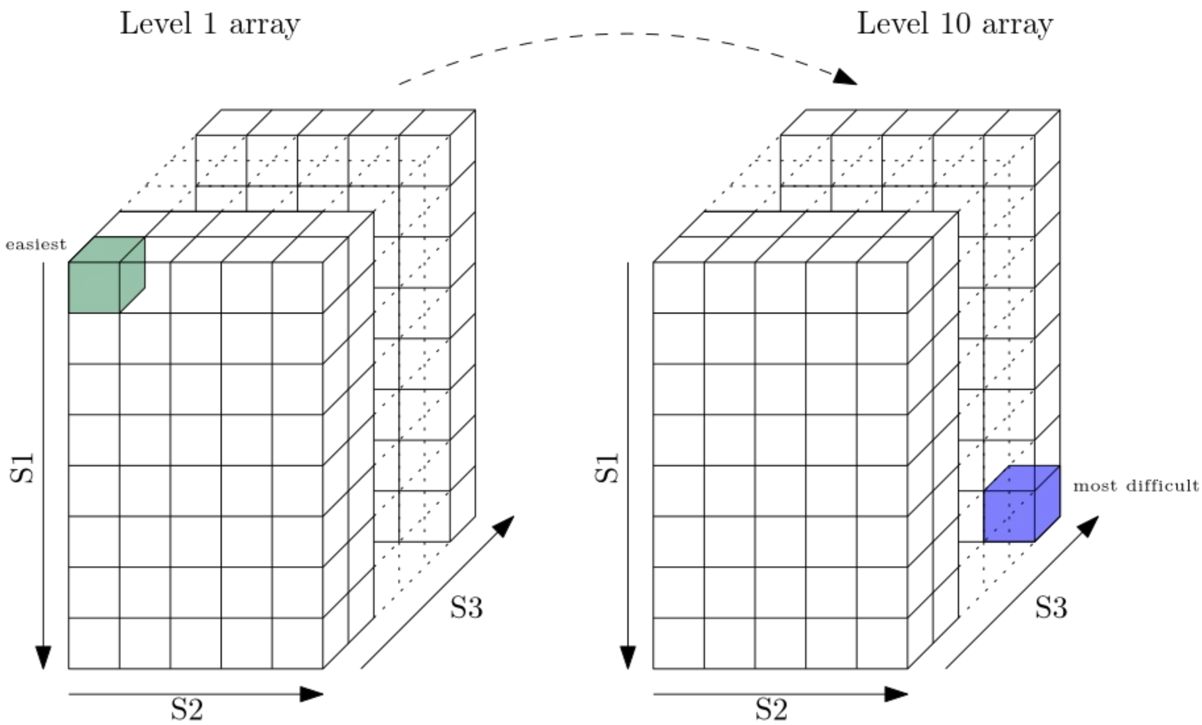
MOT task (Fishing Satellite Module). The MOT task requires participants to track moving objects amongst similar looking, and moving, distractors (Pylyshyn & Storm, 1998). In our adaptation of the MOT task (Figure S5), the procedure is structured into two distinct phases. During the initial phase, the target objects are exclusively highlighted by a glowing circle, ensuring clear visibility and differentiation from any potential distractors in the initially static and then moving object scene. Transitioning into the second phase, the glowing circles disappear forcing attentional tracking. The trial concludes when all objects cease movement. At this point, participants are required to identify all objects that were initially marked as targets—referred to as "fish" in our game context. A trial is judged successful if, and only if, the participant accurately selects all and only the initially-designated target objects.

The update period for this module is 4 trials. Thus, every 4 trials, mean success rate is computed, and the difficulty level is adjusted. We describe below the structure of the difficulty levels which includes 10 main levels, each one made of sub-levels. The 10 difficulty levels are defined by the number of objects to track (1 to 10 objects to track). Each level comprises of 3 sub-levels determined by the number of distractors (S1), the motion speed of the objects (S2). and the tracking duration (S3).

In this module as in the others, the levels typically provide a coarse difficulty adjustment while the sub-levels facilitate a more fine-grained adaptation of difficulty for a smoother player experience (Figure 3). The levels and sub-levels can be represented in the form of a stack of arrays for simplicity. Each difficulty setting in the game module can then be represented as a position in one of the level arrays in the stack. Note that the sublevel parameter values at a position in one level array may be different than the same position in a different level array; in other words, the sub-levels can be level specific.

Figure 3

Example of the logical organization of levels and sub-levels in the MOT satellite module.



Note. For illustration, Sub-level 1 (S1 – number of distractors) has 8 options, S2 (object speed) has 5, and S3 (tracking duration) has 20.

Level and Sublevel Probabilistic Path. From the current position in the array stack, the path across levels and sublevels depends on the performance of the player as defined by the ratio of correct trials every update period (4 trials for the MOT module). With high performance (e.g., 3 or more correct trials out of 4), the system moves up in one sub-level difficulty with a 70% probability, stays at the same position with 15% probability, or moves down one sub-level difficulty with a 15% probability. In case of low performance (e.g., 0 or 1 correct trial out of 4), the system will move up in difficulty with a 15% probability, stay at the same position with 15% probability, and move down in one sub-level with a 70% probability. Finally, for medium performance (e.g., 2 correct trials out of 4), the sub-level difficulty stays the same. This strategy is aimed at providing a suitable experience, limiting boredom and frustration.

In addition, the choice of which specific sub-level is increased in the next trial is also determined probabilistically according to the following equation:

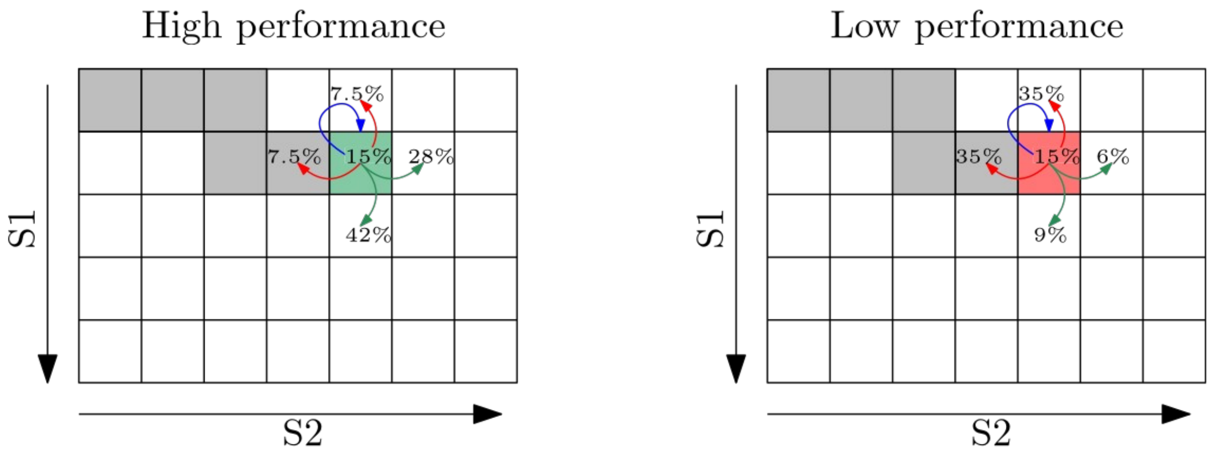
Where is the size of sub-level s, is the position in the sub-level at the current trial , and is the set of all sub-levels of the module.

This equation increases the likelihood that the player will advance in a sub-level that is currently low in difficulty, while simultaneously decreasing the likelihood for sub-levels that are currently high in difficulty. In this way, the difficulty is advanced in a balanced manner across the sub-levels. To illustrate this, we consider a two-dimensional array with sub-levels S1 and S2, which we set to sizes 5 and 7 respectively, for the purpose of illustration (Figure 4). If the player is currently in the 2^{nd} position of S1 and the 5^{th} position of S2, then applying the above equation results in probabilities of 60% and 40% for moving up in S1 and S2, respectively. When combined with the probability of advancing in a sub-level in a high-performance scenario (70%), this leads to joint probabilities of 42% and 28% for moving up in S1 and S2, respectively. In the case of the low performance scenario (15% probability to move up), the joint probabilities would be 9% and 6% to move up in S1 and S2, respectively. With this logic, it is possible for players to re-experience levels that they have cleared and are comfortable with – but in small doses.

For moving down in sub-levels, the choice of the dimension to move down in was uniformly random among the sub-level dimensions. In our two-dimensional example in Figure 6, an overall 15% probability of moving down would be evenly split to 7.5% for each dimension in the high-performance scenario, and the overall 70% probability would be split to 35% for each dimension in the low performance scenario. This enforces further exploration of the parameter space while still allowing players to revisit previous locations in the level array.

Figure 4

Next step probabilities as per our DDA in a two sublevels system (S1, S2). ***A****. probabilities of moving up a sub-level, of remaining on the same sub-level, or of going down to a previous sub-level after high performance in the latest update period;* ***B.*** *Similar probabilities but after low performance in the latest update period.*



Finally for game modules with an update period of 4 trials, like the MOT task (and only for those), in case of extreme performance (all 4 trials are either correct or incorrect), the algorithm is applied not just once but two times consecutively, enforcing larger steps either up or down. In doing so, we aim at limiting extreme boredom in excelling players or frustration in struggling ones.

Winning streak and losing streak. A winning streak is defined by the performance of the player being consistently high (e.g., 4 correct trials out of 4) for a series of update periods (e.g. 5 update periods or in other words, 20 consecutively correct trials). In these cases, the likelihood of difficulty increase is set to a higher value as compared to the likelihood mentioned above. More specifically, after a winning streak, there is a 90% probability of increasing one of the sub-levels, 5% probability of staying, and 5% probability of going down in a sub-level.

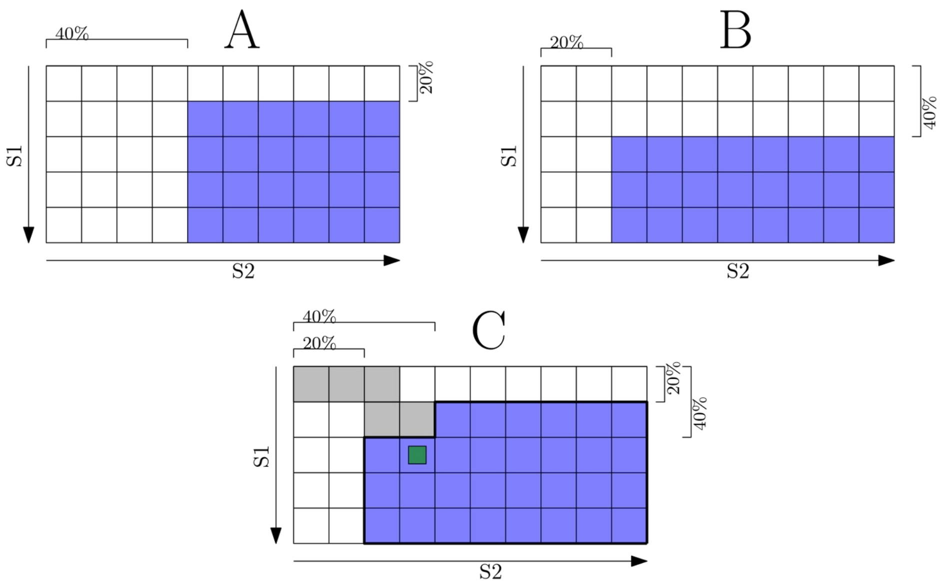
Similarly, a losing streak is defined by the performance of the player being consistently low (e.g., 1 correct trial or less out of 4) for a series of 5 update periods (e.g., no more than 5 correct trials over the past 20 trials). In these cases, the likelihood of going down in sub-level or level is higher as compared to the likelihood mentioned above. More specifically, after a losing streak, there is a 90% probability of going to a lower sub-level, 5% probability of staying, and 5% probability of going up in one sub-level.

Leveling up and down. For each level, regions in the level array are defined where there can be a transition to the next level up, as for example, when the game difficulty switches from 3 to 4 objects to track in the MOT. Again, this is done probabilistically, at each update period, when reaching one of these regions. When that region is reached, there is a 25% probability of going to the next level up, 65% probability of increasing one of the sub-levels, 5% probability of staying, and 5% probability of going to a lower sub-level.

These regions are defined by being within a certain % of the most difficult positions in the level array concerned. A distinctive feature of our level-up region is that it is defined by a set of thresholds in a dimension-blind manner. We illustrate below the example of a 20-40% set for a two-dimensional sub-level array (Figure 5).

Figure 5

Computation of level-up region



Note. **A.** Region where the player has crossed the 20% thresholds in S1 and the 40% thresholds in S2. **B.** Region where the player has crossed the 40% thresholds in S1 and the 20% thresholds in S2. **C.** Combining the two regions illustrated in panels A and B gives the complete level-up region (in blue) assuming we have only two dimensions. A possible player progression is shown in grey; when the player enters the blue region as shown by the green overlay, the player may level up (from 3 to 4 "fish" to track) at the next update with a probability of 25% (see text above).

In the MOT game, the % thresholds for our 3 sub-levels are set to allow for a large level-up region, at 25%, 35% and 45%, for the most easy, initial level 1 (1 object to track). These percentages are initially low by design to allow good players to level up fast and avoid boredom. Yet, as players progress in levels (and thus number of objects to track), the % thresholds grow restricting the level-up region: 32%, 41%, and 51% for level 2, 39%, 48%, and 57% for level 3, up to 80%, 87%, and 93% for level

9. These stricter values ensure players gain enough expertise before they graduate to a more difficult level.

When the difficulty system calls for a level-up (i.e., going to the next level array) the sub-level parameters in the new array are *not* set to the easiest position (top left in our example above) but rather to an intermediate position approximately 30% from the easiest position relative to the size of each sub-level dimension of that new level.

Level-down can also occur, but a level is only decreased when all the sub-levels have reached their minimal values (i.e., the current position in the array level is the lowest across all sub-level dimensions) and the system selects the action of decreasing the difficulty. Level-downs ensure that struggling players are brought down one level, while still pushing players to experience the level that is challenging for them.

Rollback. At the end of every trial, the system randomly decides to temporarily pause the main algorithm and instead explore sub-levels of lower levels that have not been visited yet; such events are called "Rollback". The probability of a trial being a rollback trial is dynamic and depends on when the last rollback trial happened. On average, there are 2 to 3 rollback trials every 16 trials. When the system calls for a rollback, the difficulty is set to an unexplored set of sub-levels in one of the lower-level arrays (constrained to be within the 3 levels lower to the current one). Rollbacks can occur at any point in time and allow the player to explore unvisited sub-levels at easier levels of play, that might otherwise never be visited by the action selection system. In doing so, rollbacks increase the gameplay variability, while allowing for a period of either less or differently challenging play.

Core Action Video Game Hub (Flight)

We now turn to the AVG hub which serves as a gateway for the satellite game modules we just described. This module employs a platformer style of gameplay, where the player navigates his/her flying companion, the Raku, through a two-dimensional space, collecting valuable items like coins—which can be exchanged for upgrades and cores (later in the Village)—and evading a barrage of obstacles such as meteors, boulders, and enemy projectiles which appear in waves (Figure S6). Collisions with these reduce Raku’s strength, while the Raku’s own ability to fire projectiles enables the player to neutralize threats. In this game module, a trial is defined as a continuous play section, lasting approximately 120 seconds, which can be composed of between 3 to 5 waves. The first wave is always a wave of enemy sentinels; for the other waves, meteors, boulders, or sentinels are randomly chosen with the only restriction being that there cannot be two waves of the same type in a row.

Unlike other satellite game modules that employ multiple levels and sub-level parameters, this game operates within one unique level and 3 sub-level, one for each wave type: (i) the difficulty level of meteors, (ii) the difficulty level of boulders, and (iii) the difficulty level of the enemies known as sentinels. Each of these 3 sub-levels influences several aspects of their respective waves.

The Meteors difficulty sub-level can take 12 possible values corresponding to the frequency and velocity of the meteors, introducing a complexity to the gameplay that challenges the player's reaction time and attentional focus. The frequency and velocity are low (easy) at level 1 and gradually become more difficult in a yoked manner at each subsequent level. The Boulders difficulty sub-level can also take 12 possible values, conjointly increasing the frequency and the velocity of the boulders.

The Sentinels difficulty sub-level has 12 possible values as well. Each of these 12 values corresponds to a pre-set class and strength of enemy sentinels presented during the sentinel waves. As for Boulder and Sentinel difficulty, these two dimensions increase in difficulty in a yoked manner at each value step. The sentinel wave classes range across three macro-groups—Rust, Silver, and Gold—with each successive group demanding more firepower to defeat. Within these groups are various sentinel types, each possessing unique movement patterns and abilities, such as firing at the player or deploying shields.

The DDA mechanism for the AVG hub is *stratified* according to each sub-level. During a trial, after each wave, the wave-specific sub-level is updated, creating an experience that is responsive to the player's skill progression. If the player does not receive any damage during the wave, then the difficulty of the relevant sub-level is increased by one. If the player is hit 2 or more times during the wave, then the difficulty of the sub-level is decreased by one. If there is only 1 hit, then there is no change in difficulty level. This is the case for all wave types: meteor, boulder, and sentinel.

Multi-dimensional DDA Analyses

The previous sections cover how the difficulty of each game module was adapted as players experienced the game. We now described how gameplay data were analyzed to derive a representative measure of gameplay progression for the MOT satellite game module and for the Core AVG Hub. Analysis of the remaining satellite modules can be found in the SI section 7.

Ensuring a continuous measure of game difficulty

As described in the sections above, game difficulty in our main DDA algorithm can be conceived of several multi-dimensional arrays, with one array per level. To track players' progression, we rank the difficulty of each position in the level arrays across all levels.

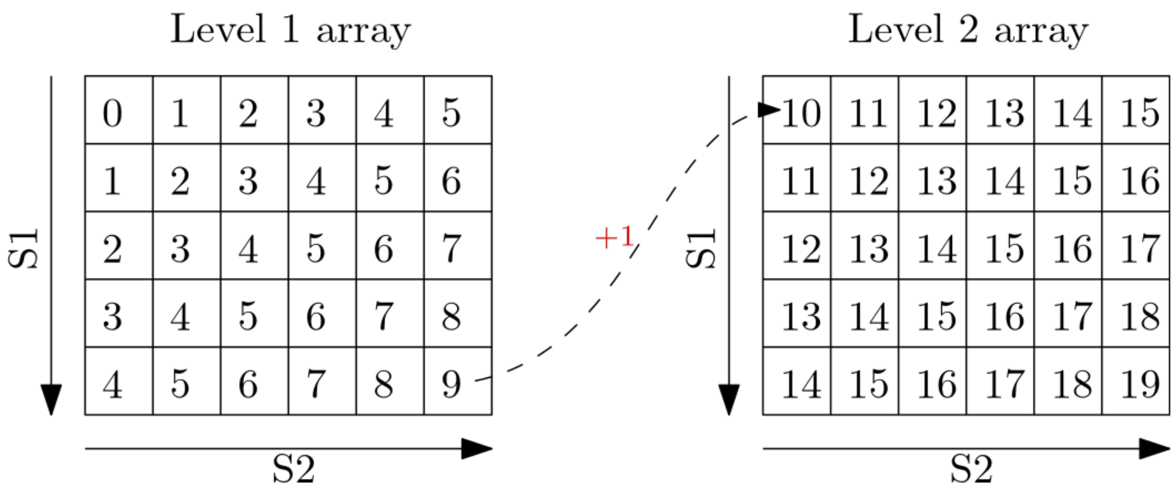
The difficulty of each trial is ranked based on the respective game module's parameters as:

The first term computes the rank offset of the current level while the second term computes the rank within the current level array (i.e., the Manhattan/city-block distance in the level array; Deza et al., 2009). is referring to the level at trial , is the set of all sub-level dimensions of the game module at level , are all the settings of sub-level at level ordered by difficulty, is the specific setting in the sub-level at trial , so that is the position of in the ordered list .

Finally, to allow comparison between modules, the difficulty ranking is normalized from 0 to 1 based on the lowest and highest ranking possible for each game module. In the following sections, we refer to this normalized difficulty ranking simply as the game's difficulty; however, it is not an accurate measure of the actual difficulty experienced by players. Figure 6 illustrates a 2D example of the pre-normalized difficulty ranking at each position in the level arrays composed of two sub-level dimensions S1 and S2 of size 5 and 6, respectively.

Figure 6

A 2D example illustrating the pre-normalized difficulty rank at each position in the array for two consecutive levels



This ranking has the property of being monotonically increasing (i.e., if the level or sub-level is increased, the difficulty value will always increase) and a position in a lower-level array will always have lower ranking than the lowest ranking of a higher-level array. For example, level 1 with all sub-levels set at the highest difficulty will have lower overall difficulty than level 2 with all sub-levels set at the lowest difficulty.

Recall that a level-up region includes positions that are not at the maximum difficulty, and that when the difficulty system calls for a level-up (i.e., going to the next level array) the sub-level parameters in the new array are *not* set to the easiest position (top left in our example above) but rather to an intermediate position. Thus, even though the difficulty space is not in itself discontinuous, these elements can result in rather abrupt changes in the difficulty when a level-up occurs. In this way, players get clear feedback about their progression.

Satellite Game Module Performance

For most satellite game modules, the performance during a trial could be flagged as 1 or 0 depending on whether the trial was successful or not. For modules with relatively few trials per session, performance was computed over each update period (1 *trial* for the DivAttent and Reasoning satellite modules, and 4 *trials* for the MOT, Running memory span, and spatial STM satellite modules). For modules with many trials in each session, performance was computed over 4 *update periods* (16 *trials* for the N-back, Go/No-Go, and Flanker satellite modules). Refer to SI Section 6 for the Satellite Module DDA Performance Analysis, including the Difficulty-Weighted performance and progression index. The performance of the DivAttent and Reasoning tasks were computed based on other module-specific measures which are detailed in the SI section 7.

MOT task (Fishing Satellite Module)

As above, we will illustrate our game performance analyses on the

MOT game module. Figure 7 illustrates an example of a player who is proficient and another who is less proficient. The less proficient player (Panel A) is already struggling to perform at the first jump in difficulty around session 4, and mostly remained at this difficulty level on the main level trials for the remainder of the intervention. In contrast, the more proficient player (Panel B) maintains a success rate (blue line) above approximately 0.75 until session 13 where they advance to a level that is at their limit. At this point their success rate oscillates around 0.5. Importantly, players’ asymptotic performance is reached quickly enough during the intervention to keep each at a challenging, yet doable, difficulty level, in line with their zone of proximal development. Specifically, this point is typically attained by the 15th session, equating to approximately 45 minutes of gameplay.

Crucially, despite players reaching a plateau in terms of the main level of difficulty, in both cases as can be seen in the zoomed-in plots, the sub-level parameters during the main level trials (which fixes the number of dots to track) are constantly changing. This means players are presented with a variety of experience, with trials varying in terms of distractor numbers, tracking duration and object speeds even if fixed in terms of number of objects to track. Equally importantly, thanks to rollback trials, the difficulty of the sublevel parameters varies even more widely, with even possible changes in levels (Figure 8). This mechanic further ensures that the players keep training their skills through exposure to a variety of lower levels and sublevel parameters. The proficient player for example, shows a difficulty plateau starting at trial

182 (session 13) where they reach level 5 (5 objects to track); yet the player continues to explore other levels and sub-level difficulty until the very end of their training. More specifically, that player keeps advancing in all sublevels of the level 4 rollback trials until the end of the training; in the sublevels of the level 3 rollback trials, that player keeps advancing for 30% of the performance plateau region before maxing out the sublevels. For levels 1 and 2, that player shows no changes in sublevels since they were already at their maximum. Similarly, the less proficient player began their difficulty plateau when they reach level 3 (3 objects to track) at trial 153. They were able to keep advancing the sublevels of the lower levels (1 and 2) during the rollback trials until trial 268, accounting for 53% of the plateau region where they reached the maximum sublevel values and could no longer advance them; yet they still experienced variability in sub-levels at level 3. Overall, these patterns of progression highlight how our DDA implementation maintains play variability even as players are repeatedly presented with the same overall level of difficulty.

Figure 7. Trial-by-trial progression of a less (A) and a more (B) proficient player in the MOT (Fishing) game module. Each point in the plot corresponds to a trial; new sessions are indicated by the tick-marks on the x-axis along with the corresponding trial number. The blown-up panel shows the different sub-levels presented despite participants having reached their asymptotic performance in terms of number of objects to track. The paler orange line illustrates performance on the easier roll

backs. The enlarged area highlights the variability of play even when performance tends to plateau.

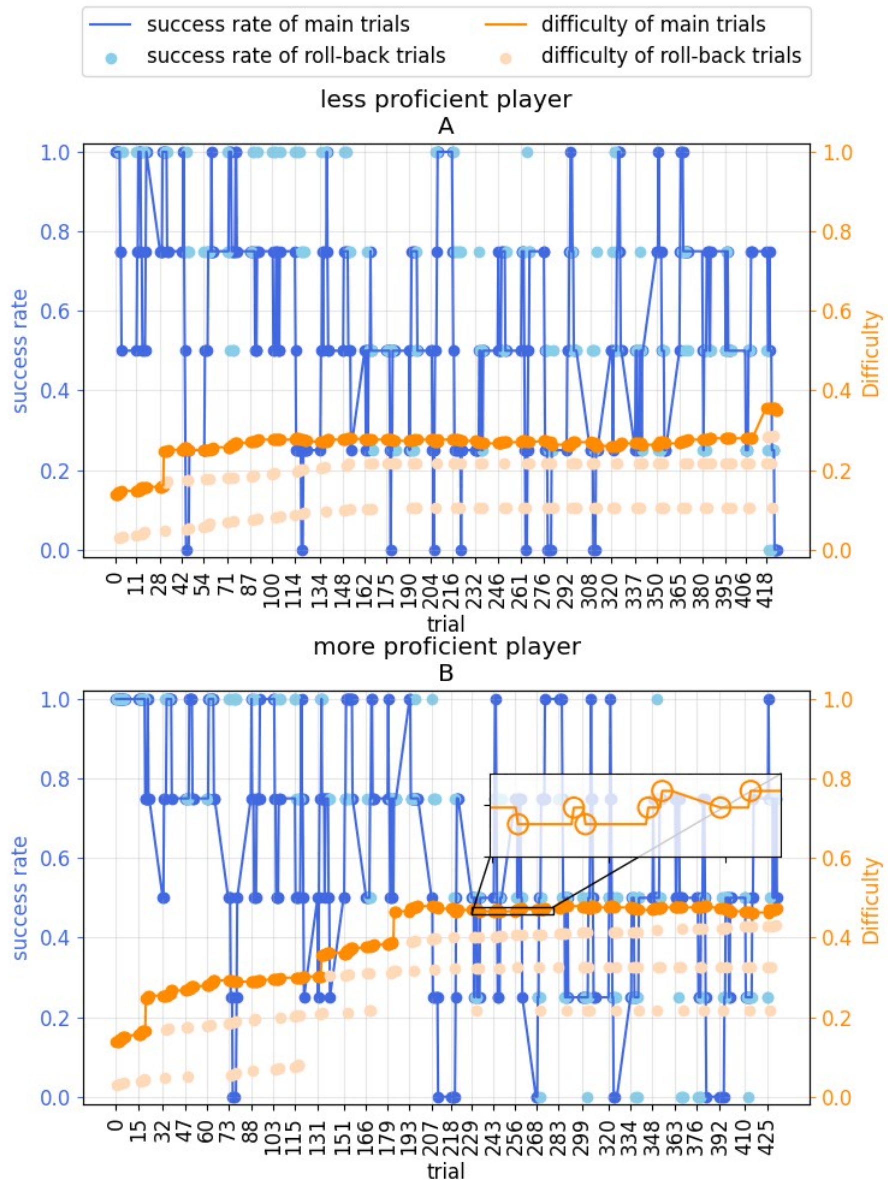
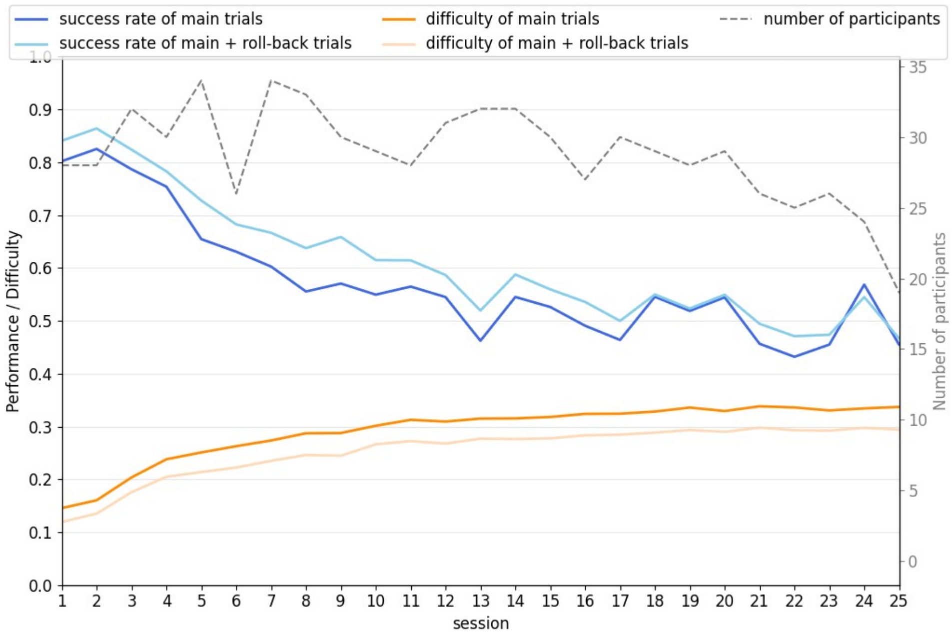


Figure 8 shows an aggregate across all participants of the same statistics. In general, the DDA algorithm successfully adapts the difficulty to a challenging level by session 13 (where the success rate reaches 0.5). The rollback trials help ensure that the overall success rate is slightly higher than when considering the main trials alone. Even after session 13, players make small improvements in the game difficulty until the end of the intervention. The highest level that players reached was level 5 (5 objects to track).

Figure 8

The normalized difficulty ranking and success rate as a function of session number for the MOT module aggregated across participants



Note. In orange, normalized ranking of the difficulty level for main trials; In paler orange, normalized ranking of the difficulty level for all trials (main and rollback as explained in section 4.4.1.); In light blue, the success rate across all trials (main and roll backs) in each session, and in darker blue success rate in main trials only. In gray (dashed line) the number of participants contributing to difficulty and success rate out of the 34 participants in the dataset is shown.

Core Action Video Game Hub (Flight)

For the Core AVG module, performance was defined as an inverted sigmoid function of the number of coins picked, number of cores picked, number of sentinels destroyed, and the total damage taken during the trial:

Where is the total damage that the player received during the trial, defines the damage value at the midpoint of the rapid decay section, and defines the damage value to the left of the midpoint where the performance value starts to decay rapidly. These parameters were set to 4 and 2 respectively for the core AVG module such that the midpoint coincides with an average of 1 hit per wave (recall that the difficulty remains the same with a single hit). The damage performance was weighted such that it contributed 3 /4 in performance value since it was the main driver for the difficulty updates, while the rest of the measures combined contributed only 1/4 in the performance value.

The Flight game module was the most complex in terms of visual elements and tasks (Figure 10). We see that on average, players quickly reached a challenging difficulty within about 45 minutes of being played (or 6 sessions), which may also be attributed to the higher dosage of this game compared to the satellites game modules. After this initial phase, there was a much slower progression throughout the remainder of the intervention. Unfortunately, the recorded data for this game only includes the difficulty values of each sub-level at the end of each 120 second trial, but not the number or types of waves, preventing more detailed analysis. Figure 11 presents trial by trial progression of a less and more proficient player in the Core Action Game module.

Figure 10

The normalized difficulty ranking and performance as a function of session number for the Core Action Game (flight) aggregated across participants. The average difficulty progression in each of the sub-levels (meteor, boulder and sentinel) is also shown.

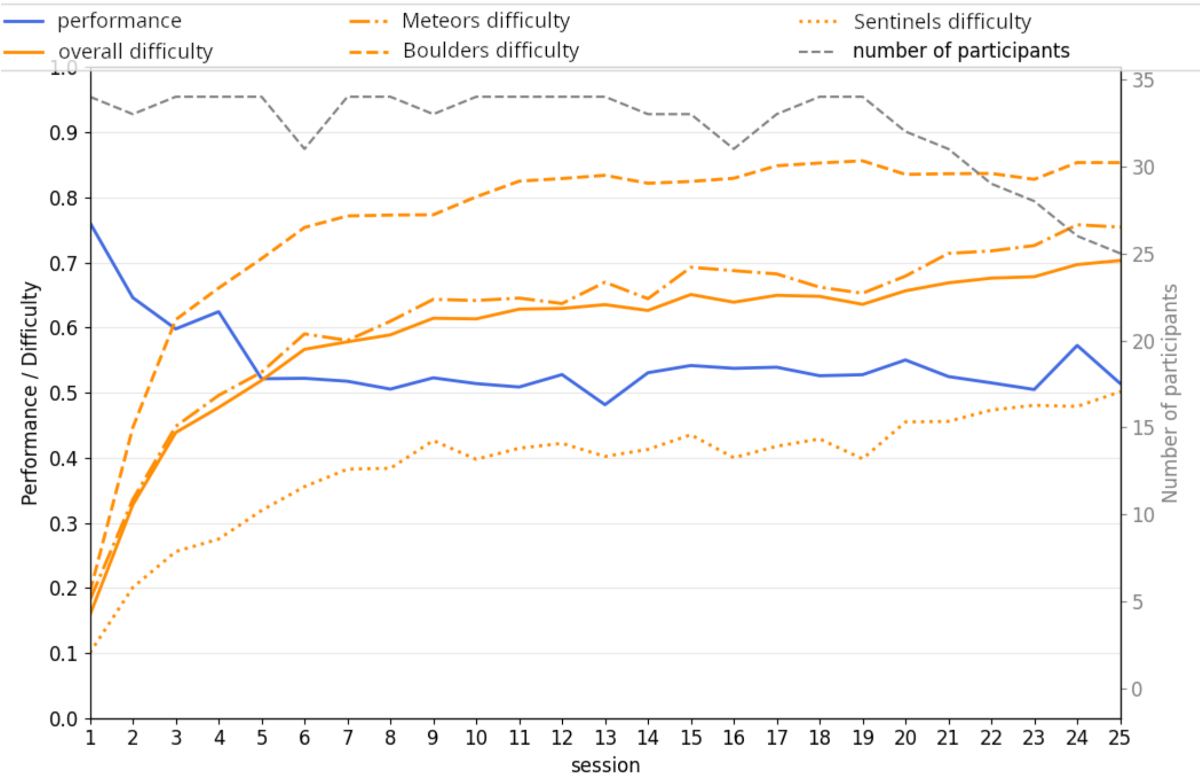
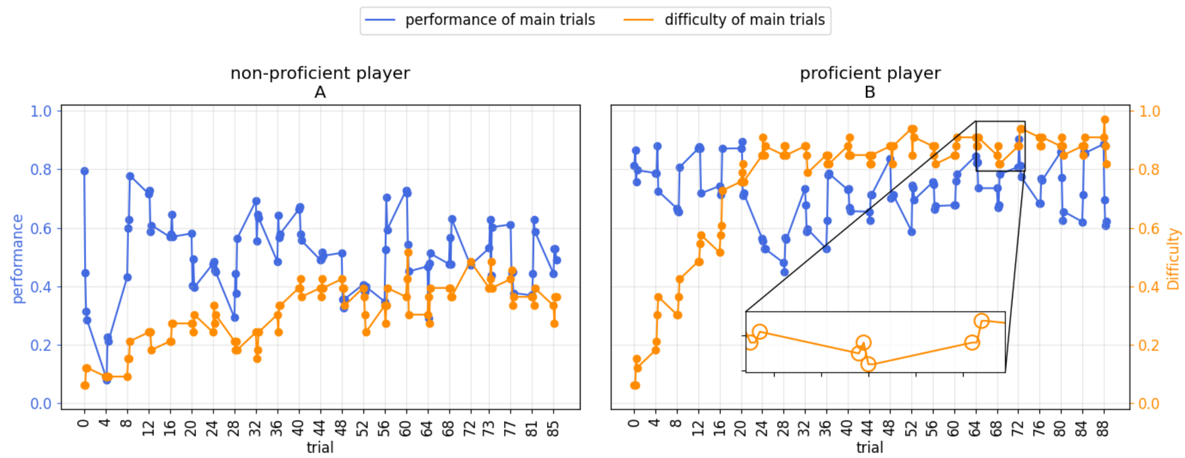


Figure 11

Trial by trial progression of a less and more proficient player in the Core AVG (flight) game module for a non-proficient (A) and a proficient (B) player. The enlarged area highlights the variability of play even when performance tends to plateau



Discussion

This study evaluates variations of novel multidimensional Dynamic Difficulty Adjustment (DDA) systems in the context of a novel game architecture. Our findings demonstrate adaptive and individualized learning paths across players, as well as variability of play experience within each player. A strength of the modular, adaptive design presented is that its game play is suitable for a wide variety of participants, from children to adults, from healthy individuals to those with cognitive impairments. We implemented four different versions of the same DDA system, which mostly worked well, though some performed better than others. Below, we discuss the lessons learnt.

Features Achieved

Modular architecture allowing the addition of new training modules

The game architecture of LoH leverages action mechanics to enhance attentional control, enhancing the ability to learn new tasks (Bavelier et al., 2012; Bavelier & Green, 2019). A key feature is its modular architecture with an expandable bank of game modules targeting a variety of cognitive skills. This design feature offers flexibility as training needs are likely to vary from one study to another, or even from one player to another. The presented instantiation of this modular architecture consisted of 8 cognitive training modules each linked to the other through a core action game hub.

The latter ('Flight') integrates essential action mechanics like decision-making under time pressure and attention shifting (Cardoso-Leite et al., 2020; Joessel, 2022). Each flight game lasts 120 seconds, with typically 4 or 5 games occurring every 30 minutes of gameplay, resulting in an average training duration of nearly 5 hours over 15 hours of training (30 sessions of 30min each). Importantly, the hub serves as a gateway for transitioning between the different cognitive training modules, ensuring that players regularly engage with action gameplay to reinforce their attentional control, and more generally cognitive control skills (Bavelier & Green, in Press).

The integration of the Core AVG action Hub amongst satellite game modules is designed to be seamless from the player's perspective. This was achieved by situating the gameplay in an adventure world akin to that of typical entertainment video games, unlike conventional cognitive training tools (Mishra et al., 2016). Engagement of the player is further facilitated by a third component of LoH, named the “Village”, which provides a safe space where players can personalize their gameplay experience by redeeming the accumulated wealth from other parts of LoH (Core AVG or Bank of satellite Game modules).

Adaptable Training Path and On-boarding

LoH demonstrated significant adaptability, addressing both variation in expertise across activities as well as large differences when initially on-boarding a player within an activity.

First, within each 30-minute session, our system dynamically adjusted the presentation of satellite modules based on the player's past performance ensuring an *Adaptive Game Training Path*. Specifically, our adaptive path procedure directly regulates the frequency of five out of the eight satellite game modules (see SI section 5 for task descriptions and SI section 7 for DDA results). For instance, lower performance in a Flanker or Go/No-Go modules increased their future frequency, while improvements in N-back decreased its frequency (Figure 3). By doing so in a probabilistic manner, and not in an all-or-none fashion, this mechanic ensures all activities are encountered, just with varied frequency.

Second, the DDA mechanics was designed such that players could enter the game at various skill levels, thanks to the DDA's ability to quickly adapt and allow players to progress at their own pace. This aligns with a prominent account of intrinsic motivation, which states that the motivational value of a task is proportional to the opportunity for changes in task performance (Oudeyer et al., 2007). In other words, effortful tasks are engaging if they provide an opportunity for performance improvement (Oudeyer et al., 2016; Sayalı et al., 2023). In LoH this was achieved through a stochastic procedure of *leveling up and down, augmented by the winning/loosing-streaks mechanic.* Indeed, more proficient players could progress faster thanks to the *winning-streaks* mechanic; similarly, less proficient players were not confronted for too long to their inability to perform thanks to the *losing-streak* mechanic. Winning streaks provide positive reinforcement that enhances self-regulation beyond a single victory (Rieger et al., 2014). Conversely, losing streaks might negatively impact mood and competence, especially following positive feedback. Limiting these by de-escalating the difficulty mitigates such negative consequences. In the present study, we observed varying frequencies of winning and losing streaks across different game modules.

Overall, most players reached the zone where the game module begins to match their skill level within the reasonable time frame of about 30 to 40 minutes of playing that module (about 12 sessions). This is of note as such balance between players' skill and the challenges they meet is well known to favor engagement, guaranteeing more time on task, an important determinant of learning (Ericsson, 2006; Ericsson & Harwell, 2019).

Personalized Progression

A key feature of our *multidimensional DDA algorithm* is to provide fine-grained adaptations at the sub-levels, but coarse difficulty adjustments along the main level of the activity (Figure 5). Progression at the sub-level was designed to be stochastic to limit large detectable gaps in difficulty, which could be jarring and break the play flow. In addition, this stochastic mechanism allowed players to explore more of the space of play possibilities, limiting any sense of grinding or repetitiveness. When considering adaptation in levels, high flexibility and personalization was ensured via a different set of mechanics. Here, new levels were presented when performance had reached the *level-up region*, which was determined as a multi-dimensional threshold region and thus could be accessed via many different paths (Figure 6). While changes in levels did introduce discontinuity in play difficulty, these remained rather rare events adding a possible element of either sense of achievement or surprise. Importantly, even after a level-up participants continued to be presented with lower levels regularly, as enforced by the *Rollback mechanism*.

Maintaining Variability in Play Experience

Maintaining high variability is key to engagement (Raviv et al., 2022). Our DDA system ensures varied experiences through a multidimensional and probabilistic framework.

This is ensured first by the multidimensional and stochastic nature of sub-level selection. The next activity within a module changes the dimension along which the difficulty is increased, ensuring the players do not dwell on just one dimension of progression (see Figures 7 and 11 – enlarged panels). Importantly, leveling-up and –down regions are defined by predefined thresholds that apply to any combinations of sub-levels, rather than rigidly requiring a given threshold on each sub-level. This additional mechanics allows for an extremely varied experience across the gameplay of each individual player. Moreover, high performance can be followed by a decrease in difficulty or vice versa. This ensures the play difficulty experienced is not deterministic and keeps an element of surprise in the overall game play.

Crucially, our *rollback mechanism* ensures that these challenging periods of gameplay are interspersed with more relaxed states (on average, there are 2 to 3 rollback trials every 16 trials). Of note, the rollback mechanism should have applied to all game modules except the Core AVG Hub (yet these will need to be added zo DivAttent and spatial-STM). The rollback mechanism is meant to reduce frustration and sustain engagement (Raviv et al., 2022).

Multi-dimensional and multi-activity DDAs

The use of DDA to bring learners within their zone of proximal development (ZPD) and maintain most of their experience in this fortuitous zone for learning is quite common in game design. DDA employing single-parameter adjustments in response to player performance have been widely used in commercial and in serious games. Examples include manual difficulty options (easy, medium, hard) or adaptive algorithms that automatically scale difficulty (Hagelback &

Johansson, 2009; Rao Fernandes & Levieux, 2019; Silva et al., 2015). However, most conventional DDAs fall short in the cognitive training context, where more complex, multi-dimensional adjustments are required. Recent advancements in DDA methods, such as multidimensional DDA (Dziedzic & Włodarczyk, 2018) or reinforcement learning-based algorithms (Mortazavi et al., 2024), offer more sophisticated adjustments by modulating multiple parameters simultaneously, ensuring a more precise alignment between player performance and task difficulty. The present work follows up in this vein by presenting different DDA implementations across multiple modules, offering a more granular and integrated approach to cognitive training.

In doing so, our game architecture uniquely combines both a rather high number of activities (8 modules and one action hub) and, within each activity, several different dimensions (levels and sub-levels) of progression. It is notable that all players successfully reached their plateau of performance, with most players doing so in 30-45 minutes (Running memory span-30min; MOT-40 minutes and Action Hub-45min). In this plateau performance regime, players are within their zone of proximal development whereby their skills are closely matched by the game challenges proposed. This slow phase of learning is desirable as it indexes the very training of the processes and representations that sustain enhanced task performance in the long run. This contrasts with the initial, fast phase of learning that reflects more learning about the task itself. Accordingly, while in the early phase of learning, the fast increase in performance has been linked to an expansion of the neural networks subtending task performance, during the slow phase of learning this expansion is thought to be followed by a pruning and selection phase that is a key step toward skill expertise (Dayan & Cohen, 2011; Yotsumoto et al., 2008).

A known challenge in the field of training is that, although critical to learning, the slow phase of learning is at risk of feeling repetitive and boring. This presents a design challenge. The negative feelings associated with grinding, or the impression of barely progressing as one stays on a plateau of performance, needs to be overcome (Bogost, 2016). To counteract the negative feelings associated with plateauing, our game introduces variability through a constant personalization of sub-levels. This ensures the experience of diverse challenges that reduce repetitiveness, despite grinding for a while at a set level. Additionally, our frequent rollback mechanics offer easier trials, introducing highly noticeable variability in game play. By allowing for more relaxed periods, these are thought to help sustain engagement (Hung & Seitz, 2014; Raviv et al., 2022).

Finally, several of our mechanics conspire to augment the generalizability of training to a wide array of cognitive skills. The use of an action hub which is over-represented compared to each module is one such mechanics. This builds on a growing body of research in cognitive neuroscience that highlights the role of action video games (as defined by Dale et al., 2020) in facilitating “learning to learn” (Bavelier & Green, in Press). Training across a wide range of difficulty levels, rather than just focusing on asymptotic performance, has been shown to promote future skill transfer and, consequently, generalized learning (Hung & Seitz, 2014). Although in need of further consideration this latter point is quite central to our aim of providing broad and generalizable cognitive enhancement.

Temporal Intervals and Metrics for DDA Progression

An important design feature of a DDA is the choice of the temporal interval and metrics used to evaluate progression. In the domain of cognition, accuracy tends to be the most common metric with the time scale set to a few trials following largely the use of staircase procedures to control which difficulty levels will be presented next. With the advance of computing power, however, it is easy to record reaction times and quite possible to use speed-based metrics rather than accuracy ones, over periods of time much longer or scaffolded in a more complex way.

In this view, our DDAs are rather standard always using accuracy as the performance metrics to assess progression. This was done over a rather short interval of a few to 30 seconds (see our 4 trial update period for most modules, even if a trial could vary in duration from under a second to up to 8 seconds). Accuracy was used even for game modules which heavily relied on reaction time such as the Flanker or the Go/No-Go modules. In these, reaction times were recorded and used as one of the sub-levels or dimensions of difficulty progression. One way to increase difficulty was to shorten the interstimulus interval pushing players to respond under time pressure (see SI section 5). Yet, accuracy of response, and not reaction times, guided whether the difficulty should be increased, decreased or stay the same. This design choice was in part motivated by the fact that participants are rarely able to recognize that they progress in reaction times unless they are given explicit feedback about their exact speed of processing. On the contrary, whether performance is correct or incorrect is readily available, with errors eliciting the well characterized Error-Related Negativity, a neural index documenting such almost automatic self-monitoring of performance (Gehring et al., 1993, 2018). In using accuracy to drive difficulty our design ensures clear feedback, a key ingredient to build a sense of competency (Rigby & Ryan, 2011; Sailer et al., 2017).

Future improvements

Four of our game modules that implemented the DDA system demonstrated areas for improvement, albeit for different reasons.

The first one concerns the Flanker module. Once players reached a certain proficiency, maintaining a challenging task became difficult (Figure S17). The satellite module DDA did not allow for difficult enough parameters with players reaching the maximum difficulty levels too quickly, well before the end of the intervention (Figure S18). This issue was likely due to the limited range of the level arrays used to adjust difficulty, where predefined limits on several sub-parameters (i.e., the number of distractors, the size of the symbols, the spacing between them, and the contrast between the symbols and the background) underestimated the players' capacity for improvement. This can be adrressed in future version by scaffolding to higher difficulty levels.

The second issue involves the Go/No-Go task, which uses success rate every 4 trials as a performance measure. In our task, Go trials are far more frequent than No-Go trials, comprising 90% or 70% of trials, depending on the case. This imbalance can lead to a 'trigger-happy' strategy, where players respond to every trial, thus inflating difficulty without accurately reflecting inhibitory control on No-Go trials. Most players quickly advanced in difficulty, reaching the maximum level within the first 10 sessions. For example, a proficient player reached the highest difficulty within 6 sessions and maintained a success rate above 0.9, while a less proficient player had a success rate slightly above 0.7, leading to similar difficulty progression. As shown in Figure S21, using the sensitivity measure d-prime (Green & Swets, 1966) over a broader range of trials—ensuring at least 4 No-Go trials per calculation—could provide a more accurate metric for guiding difficulty progression in our DDA.

Thirdly, our N-back game module initially required detecting only the N-back matches but later shifted to requiring responses for both matches and non-matches, necessitating a response for every object presented. Introducing this change midway through the task caused significant disruption (Figure S16). The data suggest that such mid-training changes can be counterproductive, as participants' performance dropped sharply, potentially leading to discouragement (see SI section 7). To address this, it would be more effective to gradually introduce changes in response patterns earlier in the game. Additionally, clear instructions and incremental difficulty adjustments could have eased the transition and maintained player engagement.

Finally, in the Spatial-STM game module, we used a simplified DDA with only one dimension of difficulty increase and a rather demanding threshold for progression. Akin to the adaptive staircase procedure often used in the field, players had to succeed in three consecutive trials to advance (see SI section 5). Proficient players showed significant progress in difficulty within the first 15-17 sessions, after which they reached a plateau (Figure S24). Due to the unidimensional nature of the DDA, the variability in gameplay was limited. In contrast, less proficient players struggled to reach and maintain the threshold of three correct trials in a row, preventing them from progressing in difficulty. Notably, since this game lacks "explorable" secondary parameters, there were no rollback trials (Figure S23). These findings highlight that increasing difficulty along only one dimension is suboptimal. Thus, the multidimensional aspect of our proposed DDA appears central for providing an optimal challenge and ensuring effective progression for all types of players.

Conclusions

Our findings underscore the importance of well-designed DDA systems in cognitive development. Effective DDAs should adapt to varied skill levels, dynamically adjust activities, and maintain variability to sustain engagement. While some implementations require refinement, this work offers valuable theoretical insights for designing educational video games as cognitive training tools. Building a strong theoretical framework for video game-based learning is essential for advancing this field and guiding the design of future games that optimize cognitive training and skill acquisition across diverse populations (Stafford & Vaci, 2022). Additionally, our study's data from individuals with clinical depression suggest the potential for DDAs in therapeutic settings. Future research should broaden the analysis to include healthy adults, younger children, and older adults to better understand the generalizability and effectiveness of DDAs across different age groups and health conditions.

References

Anguera, J. A., & Gazzaley, A. (2015). Video games, cognitive exercises, and the enhancement of cognitive abilities. *Current Opinion in Behavioral Sciences*, *4*, 160–165. https://doi.org/10.1016/j.cobeha.2015.06.002

Baddeley, A. D., & Longman, D. (1978). The influence of length and frequency of training session on the rate of learning to type. *Ergonomics*, *21*(8), 627–635.

Baniqued, P. L., Kranz, M. B., Voss, M. W., Lee, H., Cosman, J. D., Severson, J., & Kramer, A. F. (2014). Cognitive training with casual video games: Points to consider. *Frontiers in psychology*, *4*, 68947.

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn?: A taxonomy for far transfer. *Psychological bulletin*, *128*(4), 612.

Bavelier, D., & Cochrane, A. (2024). Understanding How Humans Learn and Adapt to Changing Environments. In *Oxford Research Encyclopedia of Neuroscience*.

Bavelier, D., & Green, C. S. (2019). Enhancing Attentional Control: Lessons from Action Video Games. *Neuron*, *104*(1), Articolo 1. https://doi.org/10.1016/j.neuron.2019.09.031

Bavelier, D., & Green, C. S. (in Press). *Learning and Transfer: A perspective from Action Video Game play.*

Bavelier, D., Green, C. S., Pouget, A., & Schrater, P. (2012). Brain plasticity through the life span: Learning to learn and action video games. *Annual Reviews of Neuroscience*, *35*, 391–416. https://doi.org/10.1146/annurev-neuro-060909

Bavelier, D., Pasqualotto, A., Nahum, M., Menestrina, Z., & Siesser, A. (2024). *Computer system and method for automatically adapting difficulty levels of a video game*.

Bediou, B., Adams, D. M., Mayer, R. E., Tipton, E., Green, C. S., & Bavelier, D. (2018). Meta-Analysis of Action Video Game Impact on Perceptual , Attentional , and Meta-Analysis of Action Video Game Impact on Perceptual , Attentional , and Cognitive Skills. *Psychological Bulletin*, *November*, Articolo November. https://doi.org/10.1037/bul0000130

Bediou, B., Rodgers, M. A., Tipton, E., Mayer, R. E., Green, C. S., & Bavelier, D. (2023). Effects of action video game play on cognitive skills: A meta-analysis. *Technology, Mind, and Behavior*.

Bejjanki, V. R., Zhang, R., Li, R., Pouget, A., Green, C. S., Lu, Z.-L., & Bavelier, D. (2014). Action video game play facilitates the development of better perceptual templates. *Proceedings of the National Academy of Sciences*, *111*(47), 16961–16966. https://doi.org/10.1073/pnas.1417056111

Benso, E. (2012). *La dislessia: Una guida per genitori e insegnanti: Teoria, trattamenti e giochi*. Il Leone Verde Edizioni.

Bjork, E. L., & Bjork, R. A. (2011). *Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning.* https://api.semanticscholar.org/CorpusID:894160

Blumberg, F. C., Flynn, R. M., Homer, B. D., Bailey, J. O., Eng, C. M., Green, C. S., Giannakos, M., Papadakis, S., & Gentile, D. A. (2024). Current state of play: Children’s learning in the context of digital games. *Journal of Children and Media*, *18*(2), 293–299. https://doi.org/10.1080/17482798.2024.2335725

Bogost, I. (2007). Persuasive games: The expressive power of videogames. *Persuasive games: The expressive power of videogames.*, xii, 450–xii, 450.

https://doi.org/10.7551/mitpress/5334.001.0001

Bogost, I. (2016). *Play anything: The pleasure of limits, the uses of boredom, and the secret of games*. Basic Books.

Bowman, N. D., Klecka, H., Li, Z., Yoshimura, K., & Green, C. S. (2024). A continuous-space description of video games: A preliminary investigation. *Psychology of Popular Media*.

Cardoso-Leite, P., Joessel, A., & Bavelier, D. (2020). Games for enhancing cognitive abilities. In J. Plass, R. Mayer, & B. Homer (Eds.). (2020)., *Handbook of Game-based Learning*. MIT Press. https://mitpress.mit.edu/books/handbook-game-based-learning

Chaiklin, S. (2003). The zone of proximal development in Vygotsky's analysis of learning and instruction. *Vygotsky's educational theory in cultural context*, *1*(2), 39–64.

Choi, E., Yoon, E.-H., & Park, M.-H. (2022). Game-based digital therapeutics for children and adolescents: Their therapeutic effects on mental health problems, the sustainability of the therapeutic effects and the transfer of cognitive functions. *Frontiers in Psychiatry*, *13*, 986687.

Chopin, A. (2022). Adaptive methods to quickly estimate psychometric functions: The case of Psi-marg-grid and the effect of non-monotony. *Journal of Vision*, *22*(14), 3302–3302. https://doi.org/10.1167/jov.22.14.3302

Dale, G., Joessel, A., Bavelier, D., & Green, C. S. (2020). A new look at the cognitive neuroscience of video game play. *Annals of the New York Academy of Sciences*, *1464*(1), 192–203.

Dayan, E., & Cohen, L. G. (2011). Neuroplasticity subserving motor skill learning. *Neuron*, *72*(3), 443–454.

de Freitas, S. (2018). Are Games Effective Learning Tools? A Review of Educational Games. *Journal of Educational Technology & Society*, *21*(2), 74–84. JSTOR.

Deveau, J., Jaeggi, S. M., Zordan, V., Phung, C., & Seitz, A. R. (2015). How to build better memory training games. *Frontiers in systems neuroscience*, *8*, 243.
Deza, E., Deza, M. M., Deza, M. M., & Deza, E. (2009). *Encyclopedia of distances*. Springer.
Donders, F. C. (1868). Over de snelheid van psychische processen. *Onderzoekingen gedaan in het Physiologisch Laboratorium der Utrechtsche Hoogeschool (1968–1869)*, *2*, 92–120.
Dziedzic, D., & Włodarczyk, W. (2018). Approaches to Measuring the Difficulty of Games in Dynamic Difficulty Adjustment Systems. *International Journal of Human–Computer Interaction*, *34*(8), 707–715. https://doi.org/10.1080/10447318.2018.1461764
Ericsson, K. A. (2006). The influence of experience and deliberate practice on the development of superior expert performance. *The Cambridge handbook of expertise and expert performance*, *38*(685–705), 2–2.
Ericsson, K. A., & Harwell, K. W. (2019). Deliberate practice and proposed limits on the effects of practice on the acquisition of expert performance: Why the original definition matters and recommendations for future research. *Frontiers in psychology*, *10*, 2396.
Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & psychophysics*, *16*(1), 143–149.
Gee, J. P. (2005). Learning by Design: Good Video Games as Learning Machines. *E-Learning and Digital Media*, *2*(1), Articolo 1. https://doi.org/10.2304/elea.2005.2.1.5
Gehring, W. J., Goss, B., Coles, M. G., Meyer, D. E., & Donchin, E. (1993). A neural system for error detection and compensation. *Psychological science*, *4*(6), 385–390.
Gehring, W. J., Goss, B., Coles, M. G., Meyer, D. E., & Donchin, E. (2018). The

error-related negativity. *Perspectives on Psychological Science*, *13*(2), 200–204.

Gozli, D. G., Bavelier, D., & Pratt, J. (2014). The effect of action video game playing on sensorimotor learning: Evidence from a movement tracking task. *Human Movement Science*, *38*, 152–162. https://doi.org/10.1016/j.humov.2014.09.004

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics* (Vol. 1). Wiley New York.

Guo, Z., Thawonmas, R., & Ren, X. (2024). Rethinking dynamic difficulty adjustment for video game design. *Entertainment Computing*, *50*, 100663. https://doi.org/10.1016/j.entcom.2024.100663

Hagelback, J., & Johansson, S. J. (2009). *Measuring player experience on runtime dynamic difficulty scaling in an RTS game*. 46–52.

Hardy, J. L., Nelson, R. A., Thomason, M. E., Sternberg, D. A., Katovich, K., Farzin, F., & Scanlon, M. (2015). Enhancing cognitive abilities with comprehensive training: A large, online, randomized, active-controlled trial. *PLoS ONE*, *10*(9), Articolo 9. https://doi.org/10.1371/journal.pone.0134467

Hung, S.-C., & Seitz, A. R. (2014). Prolonged training at threshold promotes robust retinotopic specificity in perceptual learning. *Journal of Neuroscience*, *34*(25), 8423–8431.

Hunicke, R. (2005). *The case for dynamic difficulty adjustment in games*. 429–433.

Jaeggi, S. M., Buschkuehl, M., Jonides, J., Shah, P., Morrison, A. B., & Chein, J. M. (2011). Short-and long-term benefits of cognitive training. *Proceedings of the National Academy of Sciences*, *108*(25), 46–60. https://doi.org/10.1073/pnas.1103228108

Jaeggi, S. M., Studer-Luethi, B., Buschkuehl, M., Su, Y.-F., Jonides, J., & Perrig, W. J. (2010). The relationship between n-back performance and matrix reasoning—Implications for training and transfer. *Intelligence*, *38*(6), 625–635.

Joessel, F. (2022). *Development of a video game to investigate the AVG features promoting attentional control*. Université de Genève.

Joormann, J., & Gotlib, I. H. (2010). Emotion regulation in depression: Relation to cognitive inhibition. *Cognition and Emotion*, *24*(2), 281–298. https://doi.org/10.1080/02699930903407948

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. *Journal of experimental psychology*, *55*(4), 352.

Klahr, D., & Chen, Z. (2011). Finding one’s place in transfer space. *Child Development Perspectives*, *5*(3), 196–204.

Lopes, J. C., & Lopes, R. P. (2022). *A review of dynamic difficulty adjustment methods for serious games*. 144–159.

Madigan, J. (2015). *Getting gamers: The psychology of video games and their impact on the people who play them*. Rowman & Littlefield New York.

Martincevic, M., & Vranic, A. (2020). Casual game or cognitive gain: Multitask casual game as a training for young adults. *Journal of cognitive enhancement*, *4*(4), 434–445.

Mayer, R. E. (2020). *Cognitive foundations of game-based learning.*

Menestrina, Z., Pasqualotto, A., Siesser, A., Venuti, P., & De Angeli, A. (2021). Engaging children in story co-creation for effective serious games. *Sustainability*, *13*(18), 10334.

Mishra, J., Anguera, J. A., & Gazzaley, A. (2016). Video Games for Neuro-Cognitive Optimization. *Neuron*, *90*(2), Articolo 2. https://doi.org/10.1016/j.neuron.2016.04.010

Mishra, J., & Gazzaley, A. (2014). Harnessing the neuroplastic potential of the human brain & the future of cognitive rehabilitation. *Frontiers in human neuroscience*, *8*, 218.

Mortazavi, F., Moradi, H., & Vahabie, A.-H. (2024). Dynamic difficulty adjustment approaches in video games: A systematic literature review.

Multimedia Tools and Applications, 1–48.

Oudeyer, P.-Y., Gottlieb, J., & Lopes, M. (2016). Intrinsic motivation, curiosity, and learning: Theory and applications in educational technologies. *Progress in brain research*, *229*, 257–284.

Oudeyer, P.-Y., Kaplan, F., & Hafner, V. V. (2007). Intrinsic motivation systems for autonomous mental development. *IEEE transactions on evolutionary computation*, *11*(2), 265–286.

Owen, A. M., Hampshire, A., Grahn, J. A., Stenton, R., Dajani, S., Burns, A. S., Howard, R. J., & Ballard, C. G. (2010). Putting brain training to the test. *Nature*, *465*(7299), 775–778. https://doi.org/10.1038/nature09042

Paraschos, P. D., & Koulouriotis, D. E. (2023). Game difficulty adaptation and experience personalization: A literature review. *International Journal of Human–Computer Interaction*, *39*(1), 1–22.

Pasqualotto, A., Altarelli, I., De Angeli, A., Menestrina, Z., Bavelier, D., & Venuti, P. (2022). Enhancing reading skills through a video game mixing action mechanics and cognitive training. *Nature human behaviour*, *6*(4), Articolo 4.

Pasqualotto, A., Parong, J., Green, C. S., & Bavelier, D. (2023). Video game design for learning to learn. *International Journal of Human–Computer Interaction*, *39*(11), Articolo 11.

Pato, V. M. Á., & Delgado-Mata, C. (2013). Dynamic difficulty adjusting strategy for a two-player video game. *Procedia Technology*, *7*, 315–321.

Pizzagalli, D. A., & Roberts, A. C. (2022). Prefrontal cortex and depression. *Neuropsychopharmacology*, *47*(1), 225–246. https://doi.org/10.1038/s41386-021-01101-7

Plass, J. L., Homer, B. D., & Kinzer, C. K. (2015). Foundations of game-based learning. *Educational psychologist*, *50*(4), 258–283.

Plass, J. L., Homer, B. D., Pawar, S., Brenner, C., & MacNamara, A. P. (2019). The effect of adaptive difficulty adjustment on the effectiveness of a game to

develop executive function skills for learners of different ages. *Cognitive Development*, *49*, 56–67.
Plass, J. L., & Pawar, S. (2020). Toward a taxonomy of adaptivity for learning. *Journal of Research on Technology in Education*, *52*(3), 275–300. https://doi.org/10.1080/15391523.2020.1719943
Pylyshyn, Z. W., & Storm, R. W. (1998). Tracking multiple independent targets: Evidence for a parallel tracking mechanism*. *Spatial Vision*, *3*(3), Articolo 3. https://doi.org/10.1163/156856888X00122
Rao Fernandes, W., & Levieux, G. (2019). *-logit: Dynamic Difficulty Adjustment Using Few Data Points*. 158–171.
Raviv, L., Lupyan, G., & Green, S. C. (2022). How variability shapes learning and generalization. *Trends in cognitive sciences*, *26*(6), 462–483.
Rieger, D., Wulf, T., Kneer, J., Frischlich, L., & Bente, G. (2014). The winner takes it all: The effect of in-game success and need satisfaction on mood repair and enjoyment. *Computers in Human Behavior*, *39*, 281–286. https://doi.org/10.1016/j.chb.2014.07.037
Rigby, S., & Ryan, R. M. (2011). Glued to games: How video games draw us in and hold us spellbound. In *Glued to games: How video games draw us in and hold us spellbound.* (pp. xiii, 186). Praeger/ABC-CLIO.
Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in human behavior*, *69*, 371–380.
Sala, G., Tatlidil, K. S., & Gobet, F. (2018). Video game training does not enhance cognitive ability: A comprehensive meta-analytic investigation. *Psychological bulletin*, *144*(2), 111.
Sayalı, C., Heling, E., & Cools, R. (2023). Learning progress mediates the link between cognitive effort and task engagement. *Cognition*, *236*, 105418.
Schell, J. (2014). *The Art of Game Design: A book of lenses*. CRC Press.

Schmidt, R. A., & Bjork, R. A. (1992). New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological science*, *3*(4), Articolo 4.

Schwartz, D. L., Chase, C. C., Oppezzo, M. A., & Chin, D. B. (2011). Practicing versus inventing with contrasting cases: The effects of telling first on learning and transfer. *Journal of educational psychology*, *103*(4), 759.

Sekhavat, Y. A. (2017). Behavior trees for computer games. *International Journal on Artificial Intelligence Tools*, *26*(02), 1730001.

Shimony, O., Einav, N., Bonne, O., Jordan, J. T., Van Vleet, T. M., & Nahum, M. (2021). The association between implicit and explicit affective inhibitory control, rumination and depressive symptoms. *Scientific Reports*, *11*(1), 11490.

Silva, M. P., do Nascimento Silva, V., & Chaimowicz, L. (2015). *Dynamic difficulty adjustment through an adaptive AI*. 173–182.

Spronck, P., Ponsen, M., Sprinkhuizen-Kuyper, I., & Postma, E. (2006). Adaptive game AI with dynamic scripting. *Machine Learning*, *63*, 217–248.

Stafford, T., & Dewar, M. (2014). Tracing the trajectory of skill learning with a very large sample of online game players. *Psychological science*, *25*(2), 511–518.

Stafford, T., & Vaci, N. (2022). Maximizing the Potential of Digital Games for Understanding Skill Acquisition. *Current Directions in Psychological Science*, *31*(1), 49–55. https://doi.org/10.1177/09637214211057841

Stojanoski, B., Wild, C. J., Battista, M. E., Nichols, E. S., & Owen, A. M. (2021). Brain training habits are not associated with generalized benefits to cognition: An online study of over 1000 “brain trainers”. *Journal of Experimental Psychology: General*, *150*(4), 729.

Sutoyo, R., Winata, D., Oliviani, K., & Supriyadi, D. M. (2015). Dynamic difficulty adjustment in tower defence. *Procedia Computer Science*, *59*, 435–444.

von Bastian, C. C., Belleville, S., Udale, R. C., Reinhartz, A., Essounni, M., & Strobach, T. (2022). Mechanisms underlying training-induced cognitive change.

Nature Reviews Psychology, *1*(1), 30–41. https://doi.org/10.1038/s44159-021-00001-3

Vygotsky, L. S., & Cole, M. (1978). *Mind in society: Development of higher psychological processes*. Harvard university press.

Xue, S., Wu, M., Kolen, J., Aghdaie, N., & Zaman, K. A. (2017). *Dynamic difficulty adjustment for maximized engagement in digital games*. 465–471.

Yotsumoto, Y., Watanabe, T., & Sasaki, Y. (2008). Different dynamics of performance and brain activation in the time course of perceptual learning. *Neuron*, *57*(6), 827–833.

Zhang, R.-Y., Chopin, A., Shibata, K., Lu, Z.-L., Jaeggi, S. M., Buschkuehl, M., Green, C. S., & Bavelier, D. (2021). Action video game play facilitates “learning to learn”. *Communications biology*, *4*(1), 1154.

Zohaib, M. (2018). Dynamic difficulty adjustment (DDA) in computer games: A review. *Advances in Human-Computer Interaction*, *2018*.

Zook, A., & Riedl, M. (2012). *A temporal data-driven player model for dynamic difficulty adjustment*. *8*(1), 93–98.

SUPPLEMENTARY INFORMATION

1. **Participants information**

Data was analyzed from a subset of participants from two recently-completed studies: The DiSCoVeR trial (N=23; Dechantsreiter et al., 2023) and the Beer Yaakov study (N=11; MOH_2020-06-30_009090).

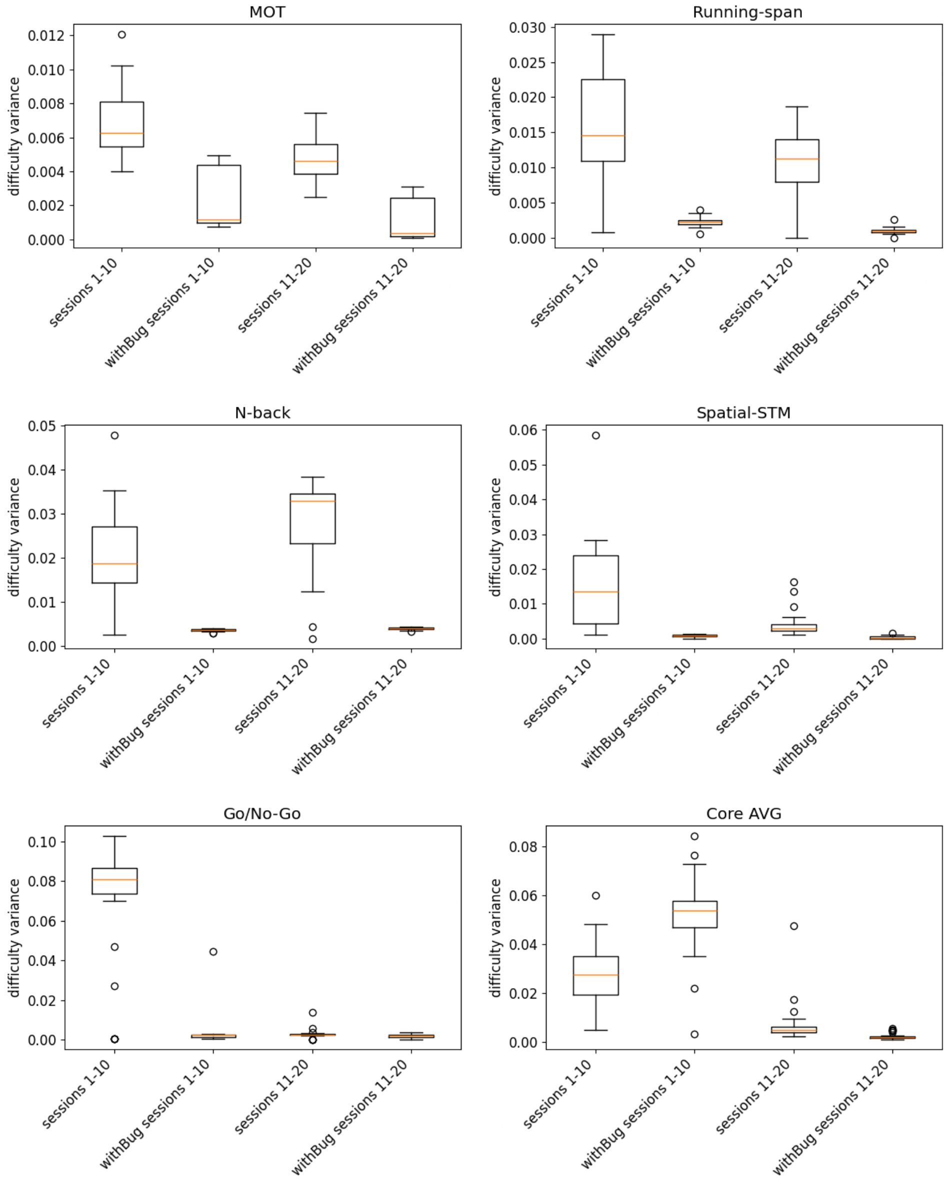
The mean age of the sample was 35.4+10.8 years (range: 20-60 years). Most participants in the sample were female (N=21; 61.7%). Study participants had a primary diagnosis of an unipolar major depressive episode (single or recurrent) according to the DSM-5 criteria. The duration of the current depressive episode ranged between 4 weeks and 5 years. Participants were included if they had at least mild depression severity, which was determined based on a cutoff score of ≥ 13 on the Hamilton Depression Rating Scale (HDRS-17). In the current sample, 29.4% of participants (N=10) had mild depression (HDRS-17 scores of 16 or less), 35.3% (N=12) had moderate depression (HDRS-17 scores of 17-23) and 35.3% (N=12) had severe depression (HDRS-17 scores of over 24). Of note, participants taking antidepressant medication were on a stable (i.e., for at least 4 weeks) dose of medications.

Participants affected by a software bug. In the early stages of the DiSCoVeR study there was a software bug which prevented participants from advancing to higher difficulty levels in some active condition LoH game modules (see Figure S1). The bug was present for the Running memory span, MOT, Go/No-Go, N-back, and Security System game modules. 27 participants out of the 61 who completed at least 20 sessions were found to have been affected by the software bug, leaving 34 participants in the active condition (44.3%) who were not affected. These 27 participants have been excluded from the main results of this manuscript.

There were obvious differences in the player experience between participants who experienced the software bug and those who did not. Specifically, the variability of the gameplay, which is primarily driven by the multidimensional DDA system, was severely compromised for the participants who experienced the software bug. In the figure below, the variance of the difficulty is computed for each game module in the first 10 sessions and for sessions 11 through 20 separately for the participants who experienced the software bug and those who didn't. The game modules affected by the software bug show a significantly lower variance for the affected participants for both the first 10 sessions and sessions 11-20. For comparison, the Gate module, which was not part of the affected games, shows no significant differences between the two groups of participants. Interestingly, the Flight module (Core AVG) shows higher variance for the group of affected participants. This should be further investigated to determine the root cause of this discrepancy.

Figure S1

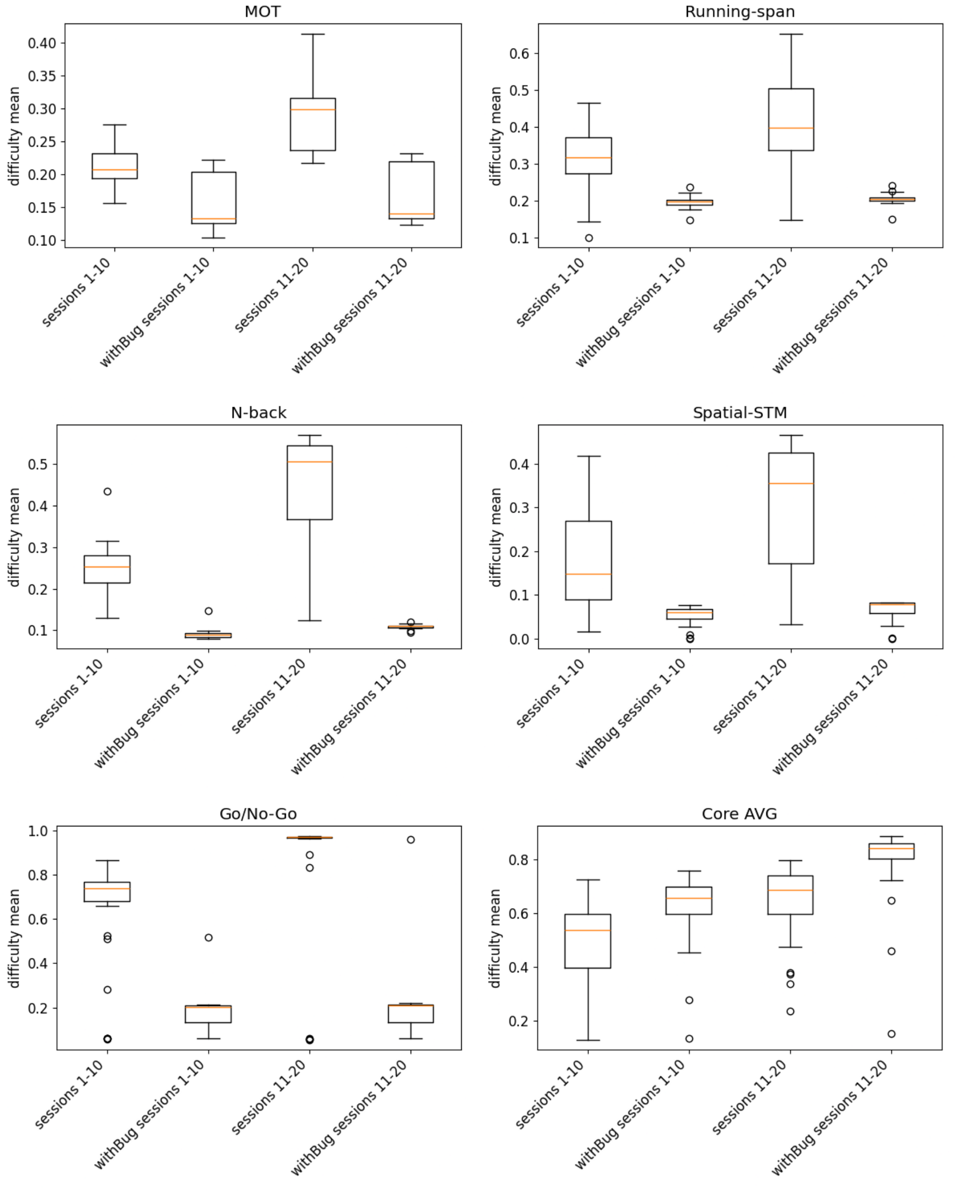
Variance in the difficulty of each affected game module for sessions 1 through 10 and sessions 11 through 20. Results are presented separately for players who experienced the software bug (N=27) and for those who did not (N=34).



In Figure S2, the mean difficulty is computed for the first 10 sessions and for sessions 11-20 for each game module separately for the two groups of participants. As expected, participants who were not affected by the software bug could advance to higher difficulty levels compared to those affected participants, who were limited. The Flight module (Core AVG) indicates that the participants affected by the software bug were able to advance to higher difficulty levels, explaining the previous results in the variance. Still, it is unclear why participants who were consistently underchallenged in the rest of the game modules, perform better in the Flight module. Several avenues can be explored, including the role of mental fatigue to explain the poorer performance of participants not affected by the bug, and the role of positive reinforcement from the high success rate in the other game modules which could have resulted in increased performance in the Flight game.

Figure S2

Mean difficulty of each affected game module for sessions 1 through 10 and sessions 11 through 20. Results are presented separately for players who experienced the software bug (N=27) and those who did not (N=34)


MOT
Running-span
N-back
Spatial-STM
Go/No-Go
Core AVG
difficulty mean
sessions 1-10
withBug sessions 1-10
sessions 11-20
withBug sessions 11-20

2. Adaptive Game Training Path used in the DiSCoVeR project

The overall duration for each game session is predetermined, typically to 30 minutes. The final task in a session is determined by a balancing algorithm that takes into account the frequency of previous task selections. If a player has engaged more with either the Energy Panel or Security System, the less frequent task is selected; in the event of a tie, the choice is made randomly. The duration for this task is set between 180 and 240 seconds.

The penultimate task is invariably the MOT task. Its duration is randomized within a defined time frame that is contingent upon its frequency in recent sessions: 150 to 210 seconds if it appeared in the last session, 190 to 210 seconds if it was absent, and 210 to 240 seconds if it was not played in the last two or more sessions. This systematic randomness ensures varied cognitive engagement.

For the remaining non-transitional tasks, four are selected through a probability-based algorithm, which adjusts for previous performance and session history. A task's likelihood of selection increases if it has been absent in past sessions or if the player’s performance was lower, fostering improvement in weaker areas. Notably, if Running memory span module is chosen, it is divided into two segments, with each allotted half the duration.

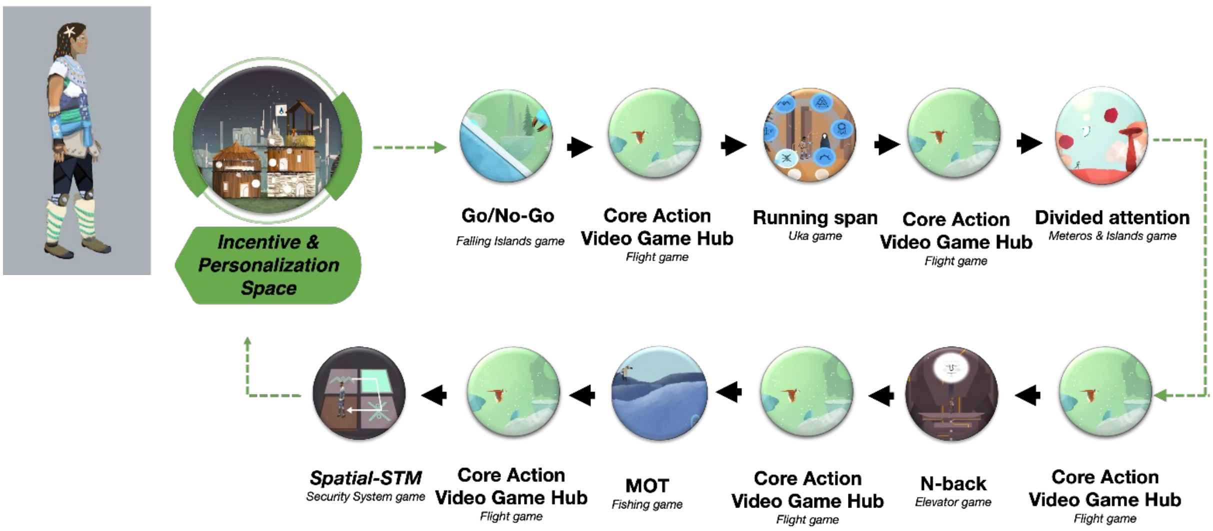
The four instances of the Core Action Game Hub (Flight) are interspersed between the selected tasks, with their duration equally divided by the remaining time. If insufficient time is available, the system will adjust the durations, aiming for a minimum of 120 seconds each.

Finally, durations are meticulously recalculated to ensure the total adds up to the 30-minute target. The session is structured with a sequence of task-flight pairings, followed by MOT and the final task (either Deductive Reasoning or the Spatial-STM). A delta is calculated to reconcile any discrepancies with the target duration, which is then evenly distributed across all tasks, typically resulting in a reduction to fit the session's temporal confines. See Figure S3.

We note that to ensure the integrity of participant blinding within these clinical trials and to control for non-specific factors of gameplay and time spent on the computer, a control game, LoH_control, has also been developed. By mirroring the aesthetic and interactive elements of the LoH environment, LoH_control serves as an effective placebo as it is devoid of the specific intervention components under investigation. More information about LoH_control's structure and functionality can be found in Supplementary Information (SI) section 3.

Figure S3

LoH – DiSCoVeR project structure and training path.



3. LOH - Control game

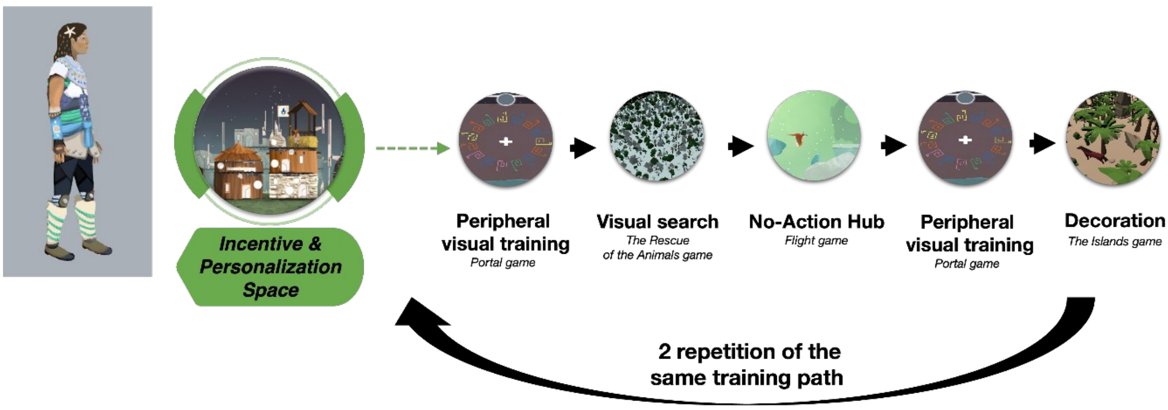
The control game, titled LoH_control, has been meticulously designed as part of the DiS-CoVeR project to offer a gameplay experience that parallels the LoH video game. The essence of this design lies in its ability to maintain the blindness of study participants to the particular intervention arm they are assigned to. Comprising four uniquely crafted mini-games, LoH_control diverges from its counterpart by excluding action mechanics as well as emotional and cognitive control challenges. Instead, it introduces slower-paced activities like puzzles or tasks that emphasize the slow and deliberate movement of focused attention or visual search with low target prevalence. Such activities are grounded in past research that has engaged with depressed or dysphoric patients (Calkins et al., 2011; Segrave et al., 2013; Siegle, Ghinassi, & Thase, 2007).

The first game module (i.e., No-Action Hub) is a flight simulation where players use a cursor to guide Raku, a bird character, across the skies. This game module retains the aesthetic appeal of the action-packed version found in the experimental game, LoH. Nevertheless, the player's interaction is limited to collecting resources without the challenge of confronting or dodging adversaries. The second game module involves an adaptive peripheral vision task (PVT; Siegle, Ghinassi, & Thase, 2007), where players must focus their attention (but not their gaze) on a circular array of disks, responding to auditory cues to identify the color or symbol presented. The third game module (Visual Search) sharpens the player's visual search capabilities, requiring them to spot four concealed targets within a densely cluttered map. In the final game (Decoration), players take on the role of island caretakers, where they are presented with an interactive environment allowing them to plant flora, befriend and care for fauna, and gather resources.

Both LoH and LoH_control transport players into an adventure-rich world, filled with tasks and a quest to discover the Village – a hub designed to keep players engaged by offering various aesthetic upgrades for their character. However, unlike LoH, the control version does not feature an adaptive training pathway. Instead, all players in LoH_control are presented with a fixed sequence of the four mini-games, each played twice within the same training session (Figure S4).

Figure S4

LOH_control game structure and training path.



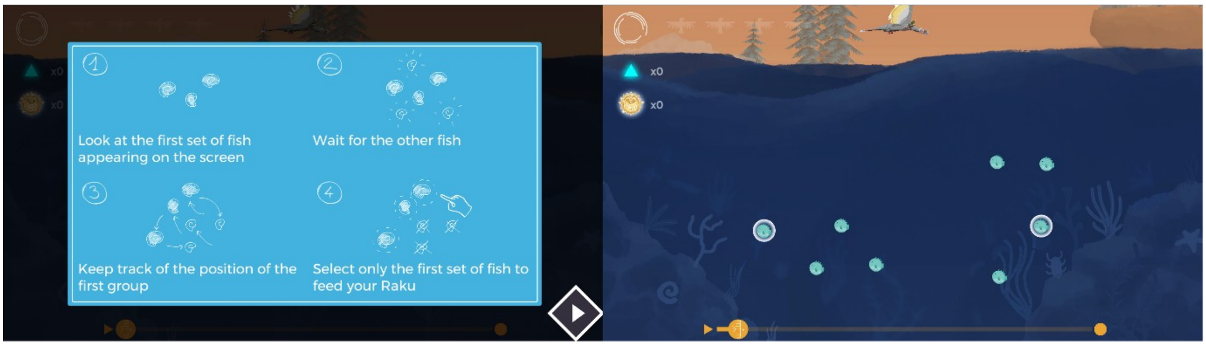
4. MOT Game Module and Core Action Video Game Hub Visuals

The accompanying figures (Figure S5 and Figure S6) illustrate the visual representations of the MOT task and core AVG hub discussed in the main manuscript. Figure S6 displays the MOT task (Fishing Satellite Module), where participants engage in tracking moving objects amidst distractors, with the difficulty progression detailed by the number of objects tracked and the varying conditions of distractors, duration, and motion speed. Figure S7 showcases the core AVG hub, where the player navigates the Raku through a dynamic environment filled with waves of obstacles, highlighting the stratified DDA mechanism that adjusts difficulty based on player performance. These visuals serve to provide a clear understanding of the task structures and their respective adaptive difficulty adjustments.

Primary multi-dimensional DDA algorithm

Figure S5

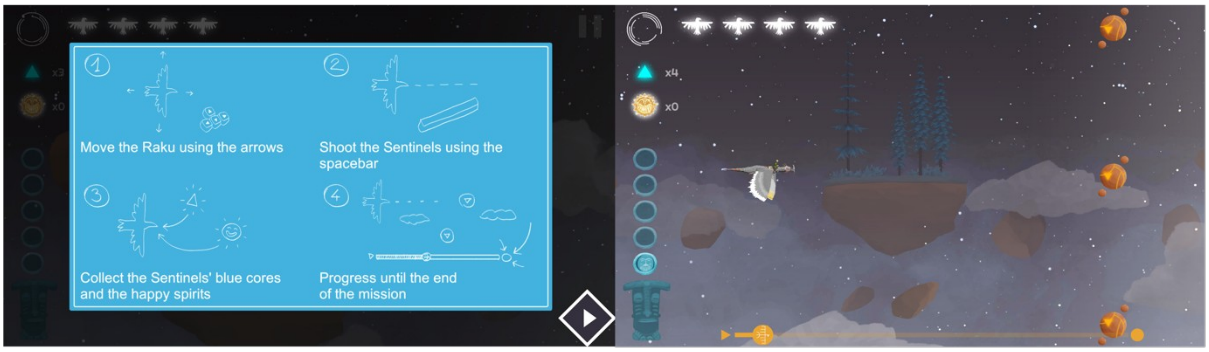
Instructions (left) and screenshot of the MOT task (Fishing Satellite Module)



Stratified DDA algorithm

Figure S6

Instructions and screenshot of the Core Action Video Game Hub (Flight)



5. Additional Satellite module DDA

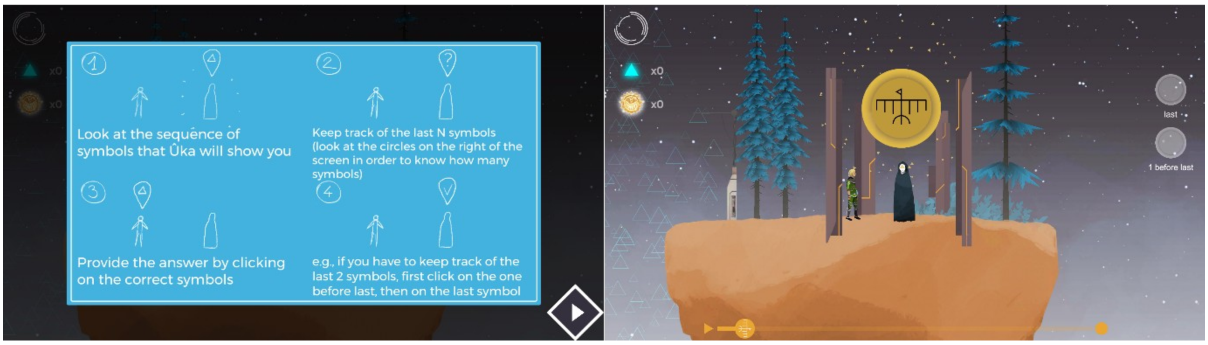
Primary multi-dimensional DDA algorithm: MOT-like DDA

Running memory span task (Uka Satellite Module). The Running memory span game (Figure S7) is a working memory game modeled after the Running memory span task (Broadway & Engle, 2010). In this task, participants are exposed to a series of stimuli varying in length from 2 to 9 symbols. During the presentation of these symbols, participants are not required to respond. However, once the sequence ends, they must recall the last one, two, or three symbols—referred to as target symbols—within a specified time limit. A trial is successful if all target symbols are recalled in the correct order. This task is designed to train visual working memory by requiring ordered recall of targets from a list that extends beyond the targets number in length. The ability to update working memory, assessed through the Running memory span task, has been recognized as a crucial executive function. Interestingly, this capability shows a strong correlation with fluid intelligence (Friedman et al., 2006).

The level is defined by the number of last symbols that must be memorized (target symbols). Sub-levels include (i) the length of the symbol sequence, (ii) the variety of symbols used, (iii) the presentation duration of each symbol, (iii) the response duration or time during which the player is allowed to answer. As in the MOT, the update period is 4 trials, and the path in levels/sub-levels is under the same probabilistic constraints as enunciated above.

Figure S7

Instructions and screenshot of the Running memory span task (Uka Satellite Module)



N-back task (Elevator Satellite Module). The Elevator game (Figure S8) is a working memory game inspired by the N-back task (Kirchner, 1958). In this game, players are presented with a series of faces each displaying one of several emotions: positive (happy), neutral, or negative (sad and angry). Each emotion category includes four variants, enriching the range of expressions players must recognize. The task requires players to identify whether each face matches the one shown N steps previously in the sequence. Each presentation of a face constitutes a trial, with successful trials occurring when the player correctly confirms a matching face or accurately withholds response to a distractor face.

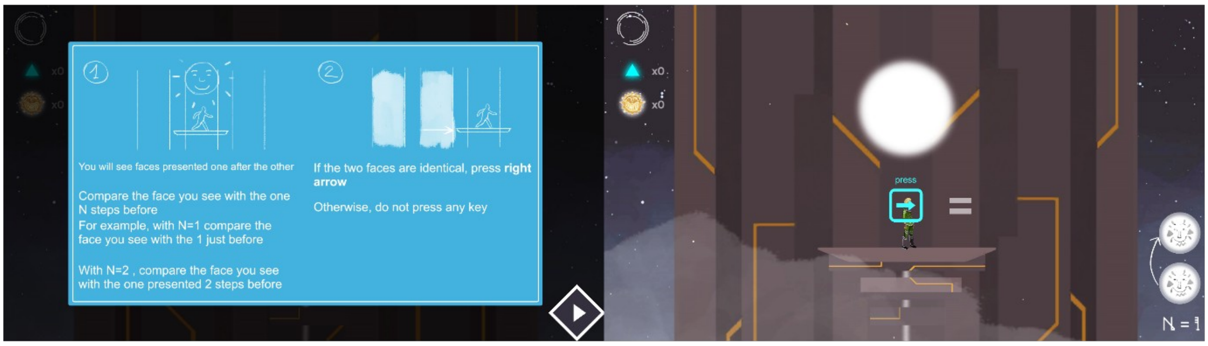
Successful performance in N-back is supported by a complex set of cognitive processes (Chatham et al., 2011; Chen et al., 2008, Jansma et al., 2000; Owen et al., 2005). These processes include: encoding the new item to WM; binding the item to its position within the set of items held in

WM; comparing the new item to the one that appeared N trials before; inhibiting irrelevant distraction to the comparison process which stems from other items inside or outside WM (Szmalec et al., 2011); updating the item-position associations of all items in WM items (e.g., the item in position $N-1$ should be associated with position $N-2$ when a new item enters WM); and removing outdated information from positions that are no-longer relevant (i.e., items that appeared more than n trials ago). Of note, the task structure was designed to change after the third week of training, progressing from a single-response task (see Figure 9) to a dual-response task requiring participants to answer not only positively to the N-back matching symbol but also negatively through a different key to all other non-matching symbols.

The difficulty level of the N-back task is defined by the N-back factor, which determines how many steps back in the sequence the player must remember. Additional sub-levels influencing task complexity include: (i) the variety of faces used, (ii) the presentation duration of each face, (iii) the time interval between faces, (iv) the allowed response duration, and (v) lure discriminability, which refers to the likelihood of encountering a face similar to the N-back target at non-N-back positions. The update period is 4 trials.

Figure S8

Instructions and screenshot of the N-back task (Elevator Satellite Module)

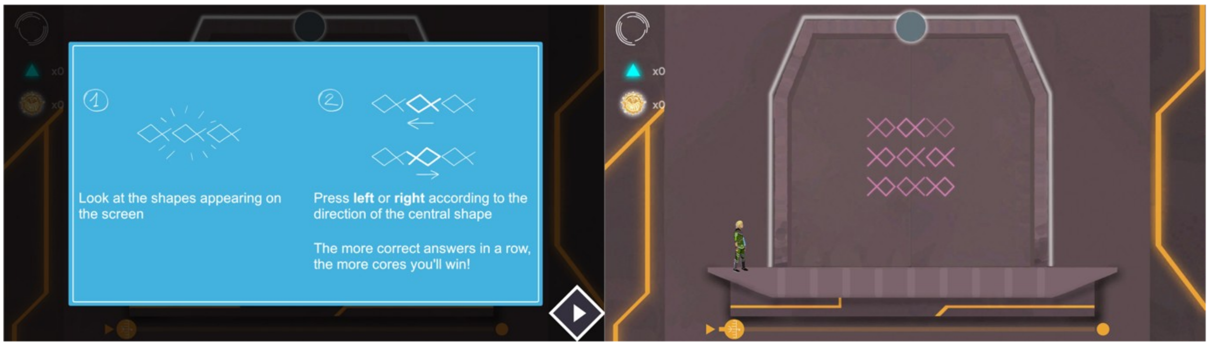


Flanker task (Gate Satellite game module). For the Gate module (Figure S9), we employed a modified version of the Flanker Task, originally developed by Eriksen & Eriksen (1974). Unlike the traditional task which utilizes arrows, our adaptation incorporates a set of six distinct symbols. These symbols were specifically designed to align with the game's thematic elements while adhering to the directional requirements essential for a Flanker task. Each symbol is presented briefly, aligned centrally on the screen, and oriented either to the left or right. Participants are required to rapidly identify the direction in which the central symbol is pointing. The task is less challenging when the central symbol is flanked by symbols pointing in the same direction, and more demanding when flanked by symbols pointing in opposite directions. A trial is deemed successful when participants accurately determine the direction of the central symbol. This task is designed to train skills in selective attention and response inhibition processes, with each presentation of the symbols constituting a single trial.

The level in this game module is defined by the display presentation time, which directly affects the player's speed and accuracy. Additionally, the various sub-level parameters adjusted to modulate difficulty levels include: (i) the number of distractors, (ii) the size of the symbols, (iii) the spacing between them, and (iv) the contrast between the symbols and the background. The update period is 4 trials.

Figure S9

Instructions and screenshot of the Flanker task (Gate Satellite game module)



Go/No-Go (Falling Islands Satellite game module). Falling Islands (Figure S10) is a Go/No-Go task (Donders, 1868/1969). In this game, players are sequentially presented with faces that vary by color and emotional expression. The emotions include four variants of happy faces, two neutral, one sleepy, and one sad. Players must respond ("go") when a green face or a happy white face appears. Conversely, they are to withhold their response ("no-go") when blue faces or white faces that are neutral, sad, or sleepy appear. Each presentation of a face constitutes a trial. A trial is deemed successful if the player correctly executes the appropriate action for either the 'go' or 'no-go' condition. This task is specifically designed to enhance response inhibition, requiring a substantial WM load to effectively guide this process (Simmonds et al., 2008).

The level in this game module is defined by the presentation time with sub-level parameters being: (i) the probability of a go stimulus (ranges from 70% to 90%), (ii) the probability of the white, more control-demanding stimuli, (iii) the time interval between stimuli, (iv) the time duration in which the player must provide an answer. The update period is 4 trials.

Figure S10

Instructions and screenshot of the Go/No-Go (Falling Islands Satellite game module)

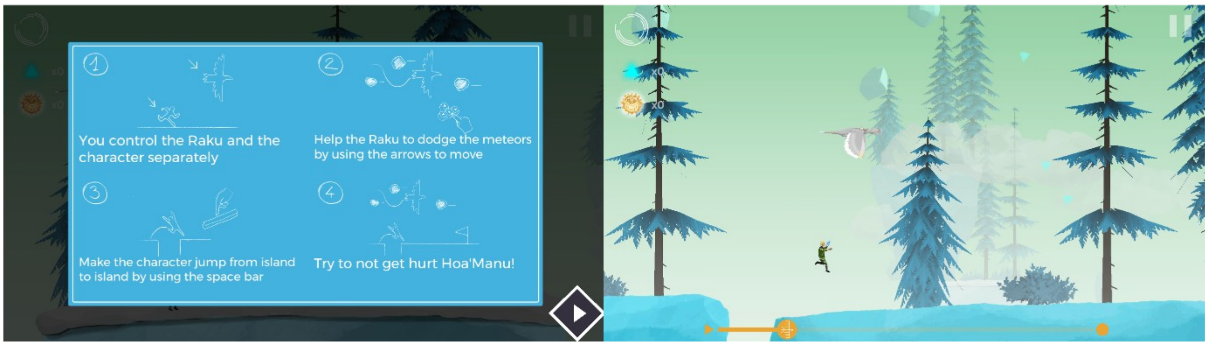
Fast-paced DDA

Divided Attention Task (Meteors and islands Satellite game module). The Divided attention game is designed as a dual task, loosely adapted from the Useful Field of View (see Figure 11). Leveraging the platformer style game, the player character is separated from its Raku avatar, as a result the player must control both simultaneously. The player character must jump over gaps between platforms (player must control when the character jumps) while Raku must avoid getting hit by meteors (the player controls the position of Raku in 2 dimensions). This task trains divided attention and task switching. A trial in this module is defined as one continuous play session; these last approximately 150 to 240 seconds.

The level controls the speed of the player character. Sub-level parameters include: (i) the meteors' speed, (ii) the meteors' size, (iii) the variability of the meteors spawn position, (iv) the size of the gap between the platforms, (v) the probability of collapse of the platform the player is currently on. In this game, if the player character or Raku does not receive any damage within a period of 7.5 seconds, then the difficulty moves up in a probabilistic manner using the same difficulty update mechanic as the MOT module. Each time the player character falls from a platform or the Raku gets hit by a meteor, a decrease in difficulty is triggered. This results in multiple difficulty updates within each trial, resulting in a *fast-paced* adaptation of the difficulty.

Figure S11

Instructions and screenshot of the Divided Attention Task (Meteors and islands Satellite game module)



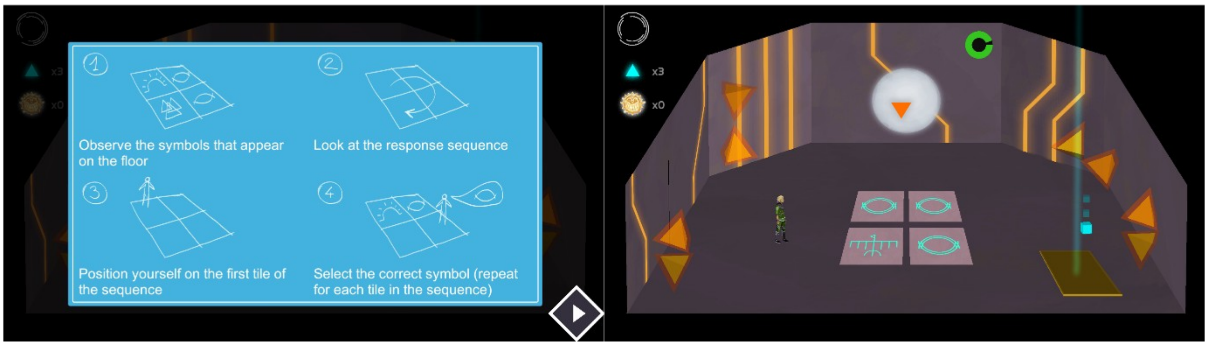
Simplified DDA algorithm: DDA for games without explorable sub-level parameters

Corsi-like WM (Security System Satellite game module). The Security System game (Figure S12) is designed to enhance visuo-spatial WM, featuring a square grid interface (Benso, 2012). Initially, players are shown a blank grid. This is followed by the simultaneous appearance of various symbols across the grid. After the symbols are displayed, the grid reverts to a blank state, and the sequence or path through which the symbols should be organized is then highlighted. Players are then tasked with accurately placing each symbol on the blank grid, replicating both the spatial arrangement and the temporal order of the symbols as they were originally presented. A trial is successful if all symbols are recalled at their correct location following the correct temporal order of presentation. A trial was defined as each time a set of symbols and the path are presented.

In this game module, the level controls both the size of the grid (2x2 or 3x3) and the complexity of the path. Each level has fixed sub-parameters that include: (i) the number of different symbols, (ii) the duration of symbol presentation, and (iii) the response time allotted for player answers. Unlike other modules, each level is defined by a unique fixed set of these parameters. That is, each level array is zero-dimensional, i.e. composed of only a single position. Consequently, the DDA mechanism differs from that described so far for the other modules: the difficulty is increased by a level after every three successful trials and decreased by one level following any failed trial.

Figure S12

Instructions and screenshot of the Corsi-like WM (Security System Satellite game module)



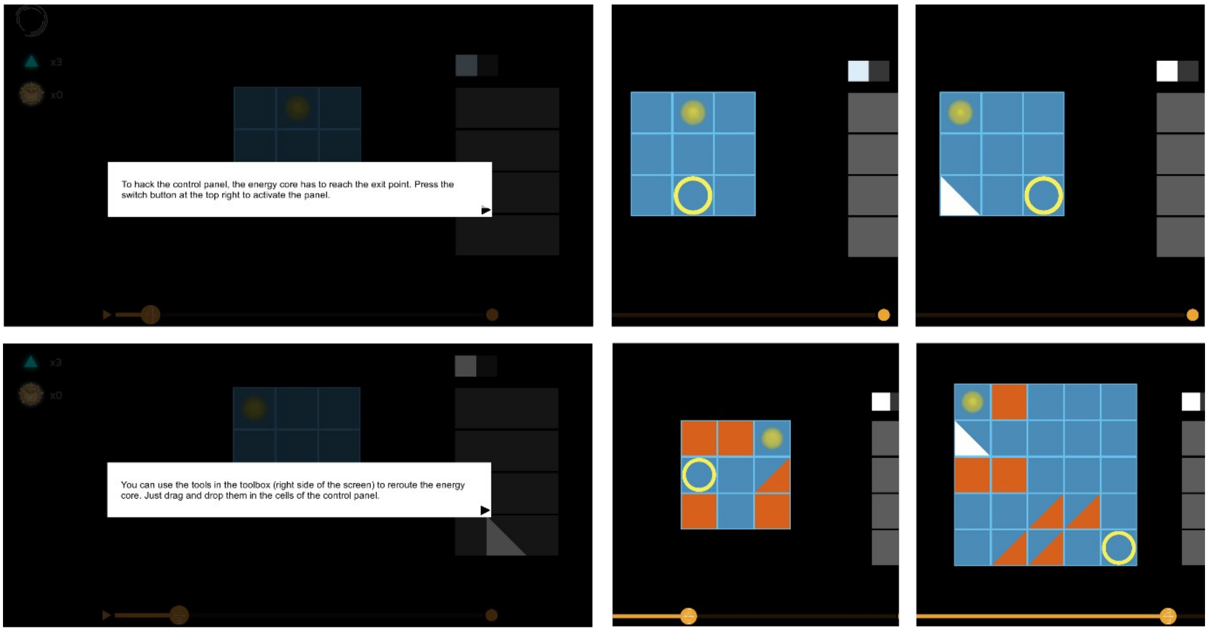
No DDA

Deductive Reasoning task (Energy panel). This task draws design inspiration from Rube Goldberg Machines, mirroring the complex, interactive gameplay found in "The Incredible Machine," a seminal video game within this genre. In this puzzle-based task, participants are required to direct a ball towards a designated target area (Figure S13). To facilitate this, they are provided with an assortment of blocks differing in shape, which must be strategically positioned on a grid. The objective is to maneuver the ball around various obstacles to ensure it reaches the target. This exercise necessitates advanced spatial imagery abilities, as players must predict and plan the ball’s trajectories, thereby engaging and developing spatial deductive reasoning skills.

In this game, a level is defined by the difficulty of the puzzle. There is one puzzle per level and each time the player solves a puzzle they advance to the next puzzle of higher difficulty; thus, our adaptive DDA does not apply here. A trial is defined as each time a new puzzle is presented and the update period is 1 trial (puzzle).

Figure S13

Instructions and screenshot of the Reasoning task (Energy panel)


To hack the control panel, the energy core has to reach the exit point. Press the switch button at the top right to activate the panel.
You can use the tools in the toolbox (right side of the screen) to reroute the energy core. Just drag and drop them in the cells of the control panel.

6. Satellite module DDA performance analysis: Difficulty-weighted performance and progression index

To fully characterize participants' game progression, it is necessary to consider performance in the context of the game difficulty experienced. We thus develop a difficulty-weighted performance, computed by multiplying the performance of a trial (a value between 0 and 1) by the normalized difficulty ranking of that trial (value between 0 and 1). The resulting value was squared root to linearize the effect (also between 0 and 1; Figure S14)

Since the performance across consecutive trials (short-term) can be noisy, the difficulty-weighted performance was smoothed by a time weighted function that dies off within 4 trials such that we can reveal more long-term patterns in the players' progression within each game module. Game progression is thus computed by applying a time-weighted smoothing window filter over the difficulty-weighted performance.

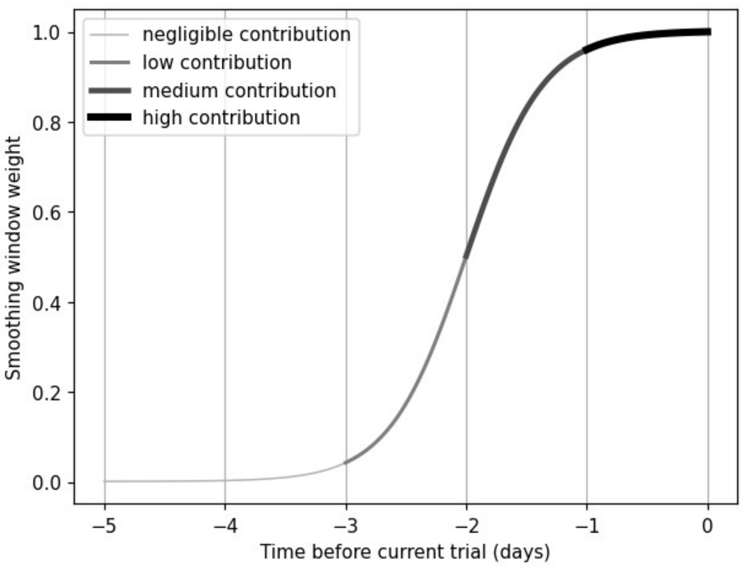
Finally, rollback trials were excluded from this computation as they are not representative of players' performance at the current difficulty level. The rollback trials are, however, used as an auxiliary lower bound on a player's game progression.

The time-weighted smoothing window function is defined by the following equation:

In the first term of the equation, is the number of days before the current trial, determines the location of the inflection midpoint, and is the point where the rate of growth is significantly decreased. These two parameters were set to 2 and 1 respectively. The second term of the equation ensures that at the filter value is exactly 1.

Figure S14

This plot illustrates the smoothing (time averaging) function for computing the progression index from the difficulty-weighted performance



7. Additional Satellite module DDA performance analysis

Primary multi-dimensional DDA algorithm: MOT-like DDA

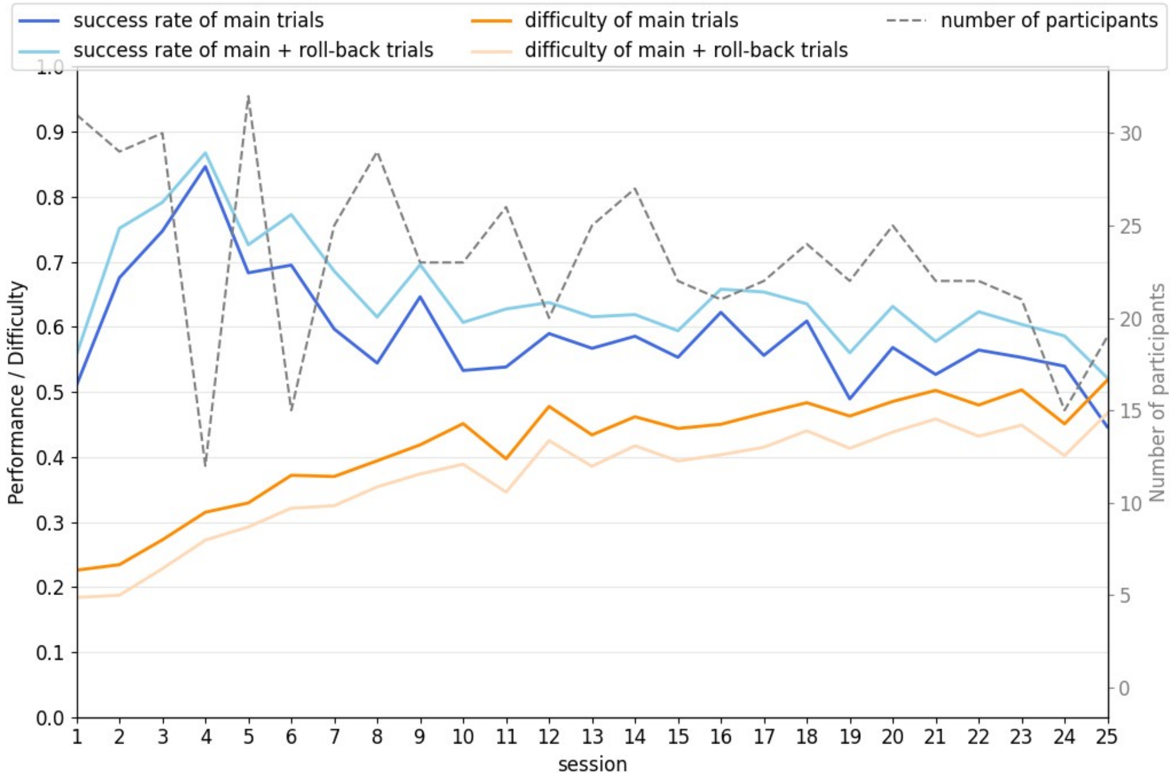
Running memory span task (Uka)

Variability in the player's experience for the Running memory span task (Uka) module is maintained using the same DDA algorithm applied in the MOT (Fishing) module (Figure S15).

Across all participants, the difficulty system maintains a success rate between 0.5 and 0.6 from session 15 onwards. Introducing rollback trials raises the success rate to around 0.6. While the increase is modest, it may still contribute to sustaining player motivation. During the initial 15-session period, the success rate is maintained between 0.5 and 0.85. In the first few sessions it can be see nthat the success rate starts rather low (around 0.5) and rapidly increases to 0.7. This may be due to procedural learning taking place in the first few sessions. As with the MOT game module, the players progress in difficulty throughout the intervention on average. The highest level reached by any player was level 5 (5 elements in the sequence to remember).

Figure S15

Difficulty level and success rate as a function of session number for the Running memory span (Uka) game aggregated across participants. Fluctuations in the number of participants in each session are due to this *module occasionally not being selected by the adaptive training path mechanism for some participants*



N-back task (Elevator)

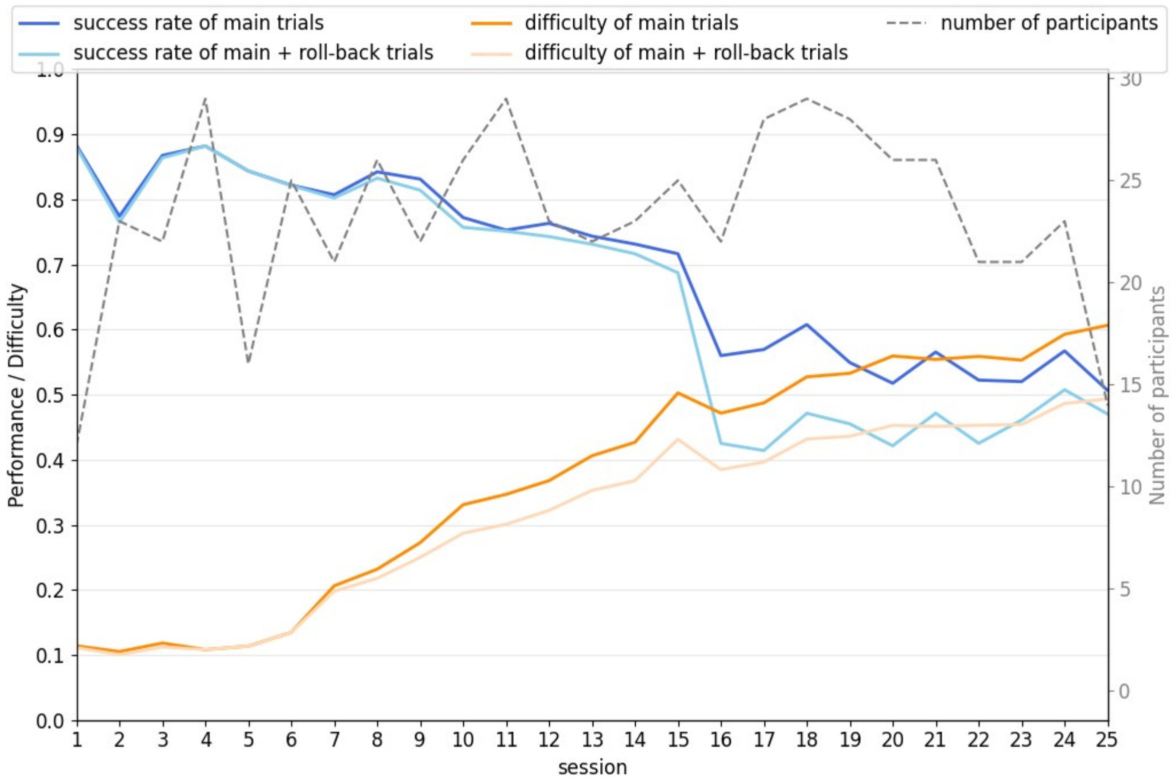
Players advance to a challenging level within the first 15 sessions on average during which their success rate is between 0.7 and 0.95 (see Figure S16). In contrast to the other game modules, the transition to the challenging difficulty level is not smooth, but is rather abrupt with a very noticeable drop in the success rate.

Unlike the other game modules, the rollback trials seem to have the opposite of the intended effect, and they decrease the overall performance of players. Although this effect is small at first, as the difficulty increases past the point where the task switches from a single-response to dual-response task, this gap increases significantly. As the intervention continues, players keep progressing in difficulty. The highest level reached by any player was level 3 (3-back).

Unlike the MOT game, which was presented at least once per session, the adaptive path mechanism resulted in the N-back game module not being presented in every session, leading to greater variation in the number of participants per session over time. Note that this is the case for all modules that were part of the adaptive training path mechanism (Running memory span, N-back, Flanker, Go/No-Go, and Divided attention).

Figure S16

Difficulty and success rate as a function of session number for the N-back (Elevator) game aggregated across participants



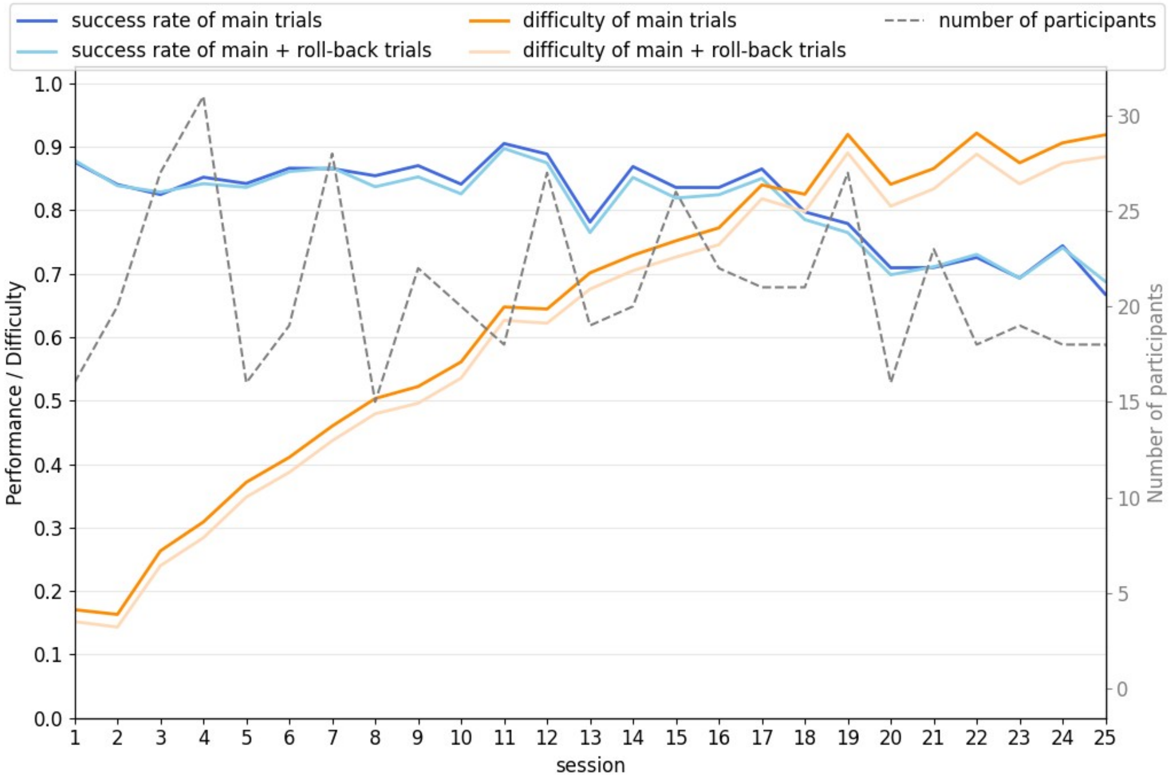
A significant drop in the average success rate is seen in session 16, likely due to a change in the structure of the task (see Figure S13). During the first 3 weeks of training (i.e., first 15 sessions), participants were presented with a simplified version of the task, wherein they were required to tap on the right side of the screen if the symbol currently displayed matched the one presented n positions earlier. After completing this initial phase, participants transitioned to a more complex version of the task. In the advanced stage, they had to identify and respond to matching symbols by tapping on the right side and distinguish and respond to non-matching symbols by tapping on the left side.

Flanker task (Gate)

The Flanker game module was the easiest game for players to master (see Figure S17). The difficulty system reaches its upper limit while the players' success rate remains high with the system having no further options to adapt. Players maintain a success rate above 0.65 on average throughout the intervention and reach the highest difficulty levels by session 18. A noticeable dip in success rate is seen from session 17, although it remains above 0.65. For this game module, the difficulty range may need to be modified to provide more challenge for players.

Figure S17

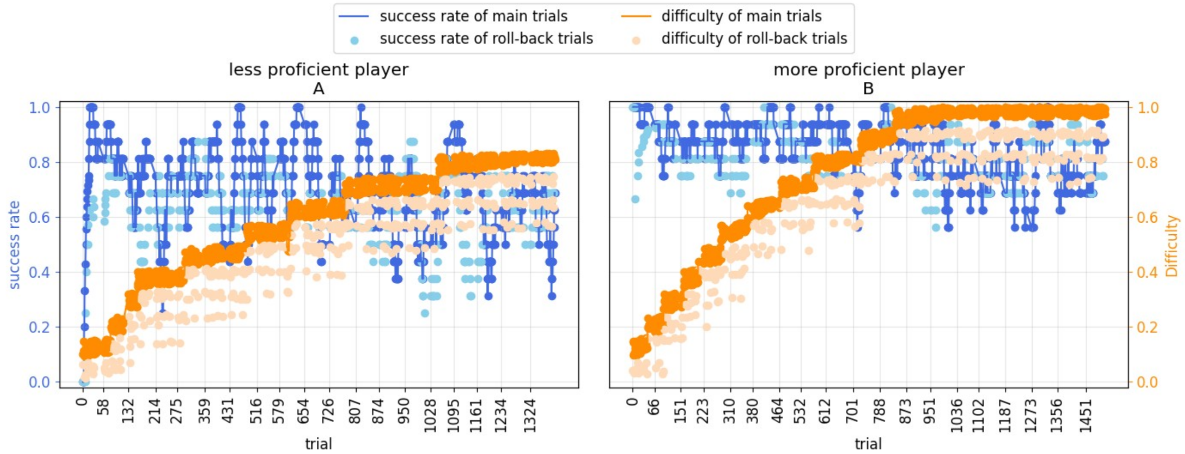
Difficulty and success rate as a function of session number for the Flanker (Gate) game aggregated across participants



Below we see an example of a single player for the Flanker module (Figure S18). We observe that indeed the player reaches the maximum difficulty of this game module well before the end of the intervention, signaling that the game difficulty should be increased overall.

Figure S18

Trial by trial progression of a player in the Flanker (gate) game module

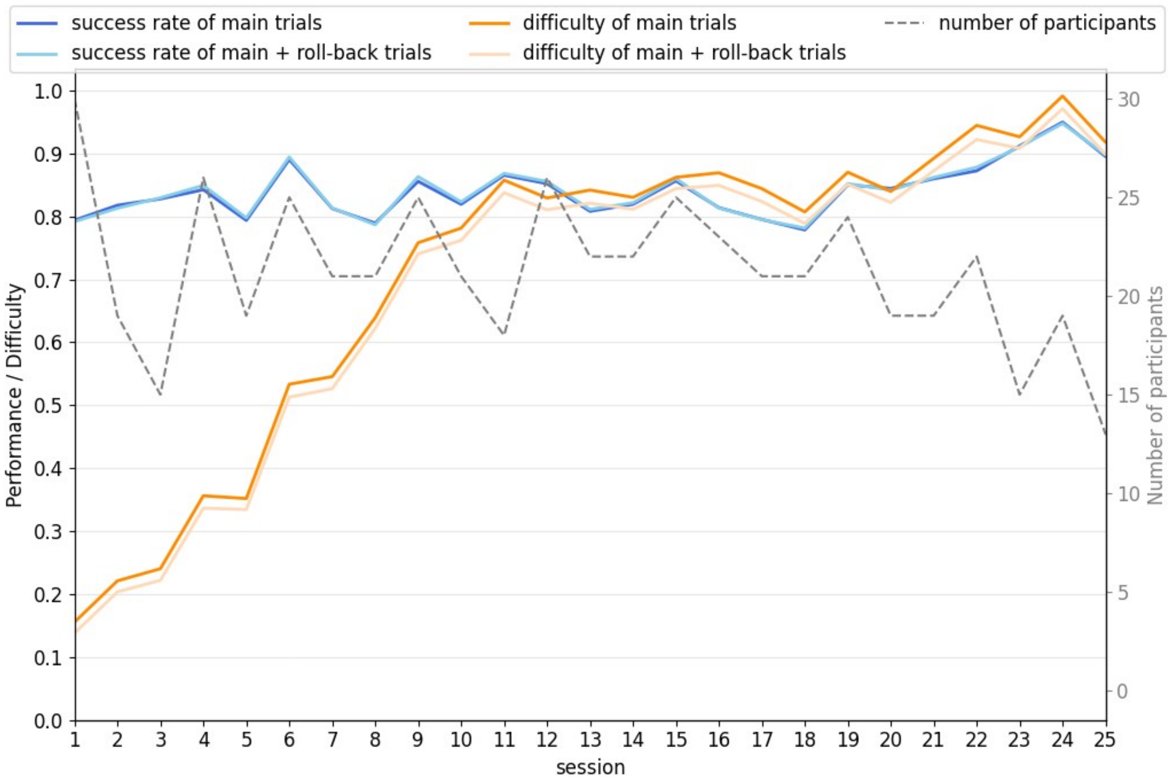


Go/No-Go task (Falling islands)

The players advanced in difficulty rather quickly in this game module during the first 10 sessions after which progression is observably slower (see Figure S19). Yet, most players still reach the maximum difficulty before the end of the intervention. Success rate is maintained above 0.75 throughout the intervention, which is expected since the success rate computation (same used for the DDA algorithm) includes both the go and no-go trials together. Recall that the go trials are presented with a probability varying between 70% to 90% allowing for an easy hit rate of at least 70%.

Figure S19

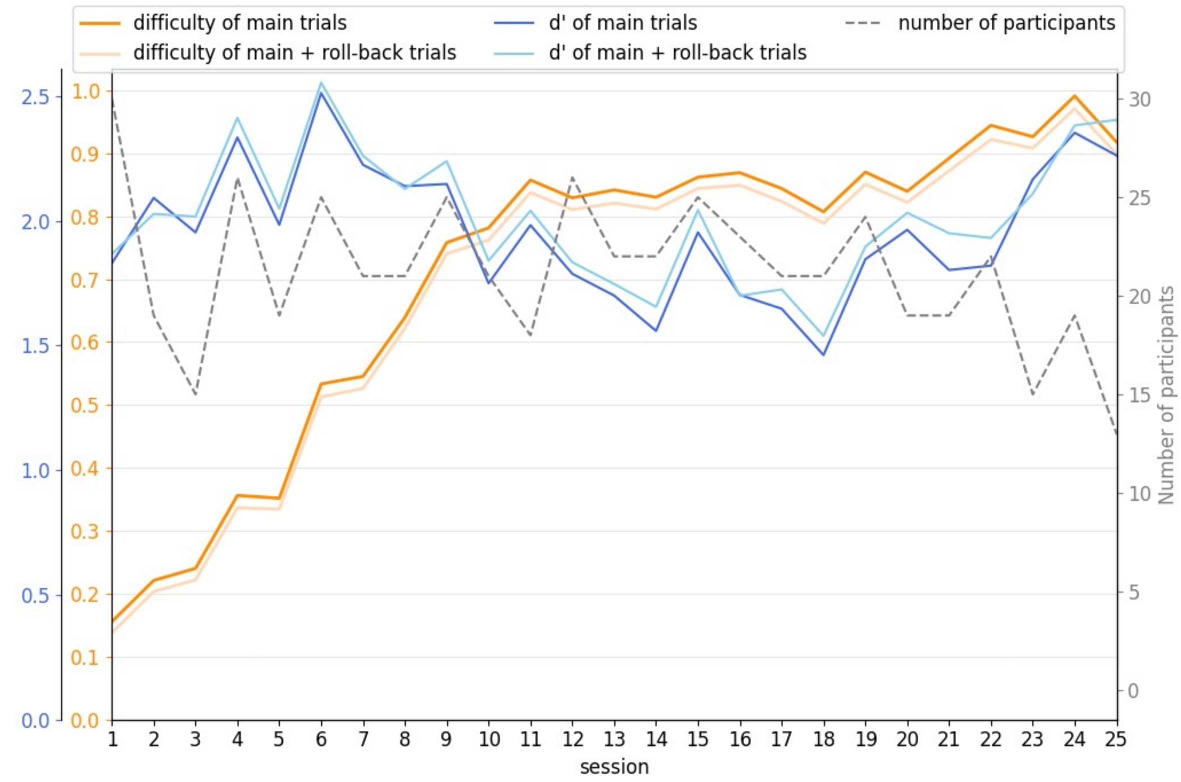
Difficulty and success rate as a function of session number for the Go/No-Go (Falling islands) game aggregated across participants



A look at a proficient and a less proficient player shows that the proficient player reaches the highest difficulty within the first 6 sessions, with success rate remaining above 0.9 for much of the intervention (Figure S20). The less proficient player's success rate is slightly worse than the proficient one, but still rarely goes below 0.7. As a result, the difficulty system continuously increases the difficulty for the less proficient players in a similar manner as to the proficient player. Success rate (hit to Go and correct reject to No-go) appears inadequate to calibrate task difficulty.

Figure S20

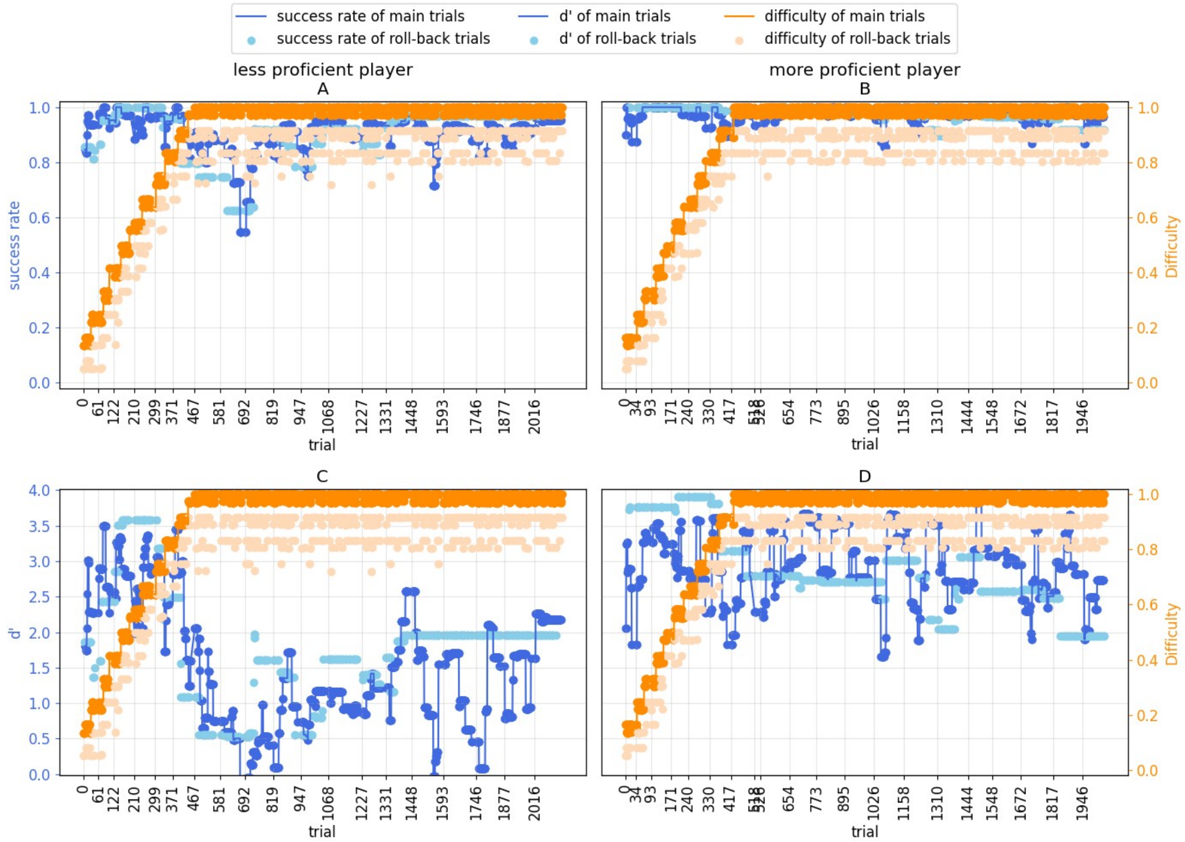
Difficulty and d' as a function of session number for the Go/No-Go (Falling islands) game aggregated across participants



In the context of at least 7 out of 10 trials being Go trials and thus potential hit in our performance measure, a metric that correctly takes into consideration the rate of failed No-Go trials (false positive rate), like the sensitivity measure d-prime (Green & Swets, 1966) would seem to align better with the intended objective of the game module. Specifically, the d-prime (d') measure in signal detection theory quantifies an individual's sensitivity in distinguishing between signal and noise, with higher values indicating better discriminability. A re-analysis of game performance replacing the success rate with d' is shown in Figure S20, as well as Panels C and D in Figure S21 for our poor and good performers. To ensure that there were sufficient samples of both go and no-go trials, the d’ was computed over a varying window such that there were always 4 no-go trials within the window. Depending on the frequency of the no-go trials, this resulted in windows that could have a length anywhere between 10 and 40 trials. Encouragingly, it results in a slightly stronger effect of the rollback trials on the performance and a much more distinct performance between the proficient and less proficient player. Here, the proficient player’s d’ is mostly above 2 for the entire intervention while the less proficient player’s d’ is above 2 only in the first 6 sessions until the difficulty reaches the maximum value at which point the player’s d’ remains below 2, at an average of approximately 1, for the rest of the intervention. The present analyses highlight the importance of using the proper success rate measurements to drive the DDA and suggest adaptation to a d’ for our next game implementation.

Figure S21

Trial by trial progression of a less and more proficient player in the Go/No-Go (Falling islands) game module. On the top row (panels A and B), the success rate is used as the performance measure, on the bottom row (panels C and D), d’ is used as the performance measure



Fast-paced DDA

DivAttent task (Meteors and Islands)

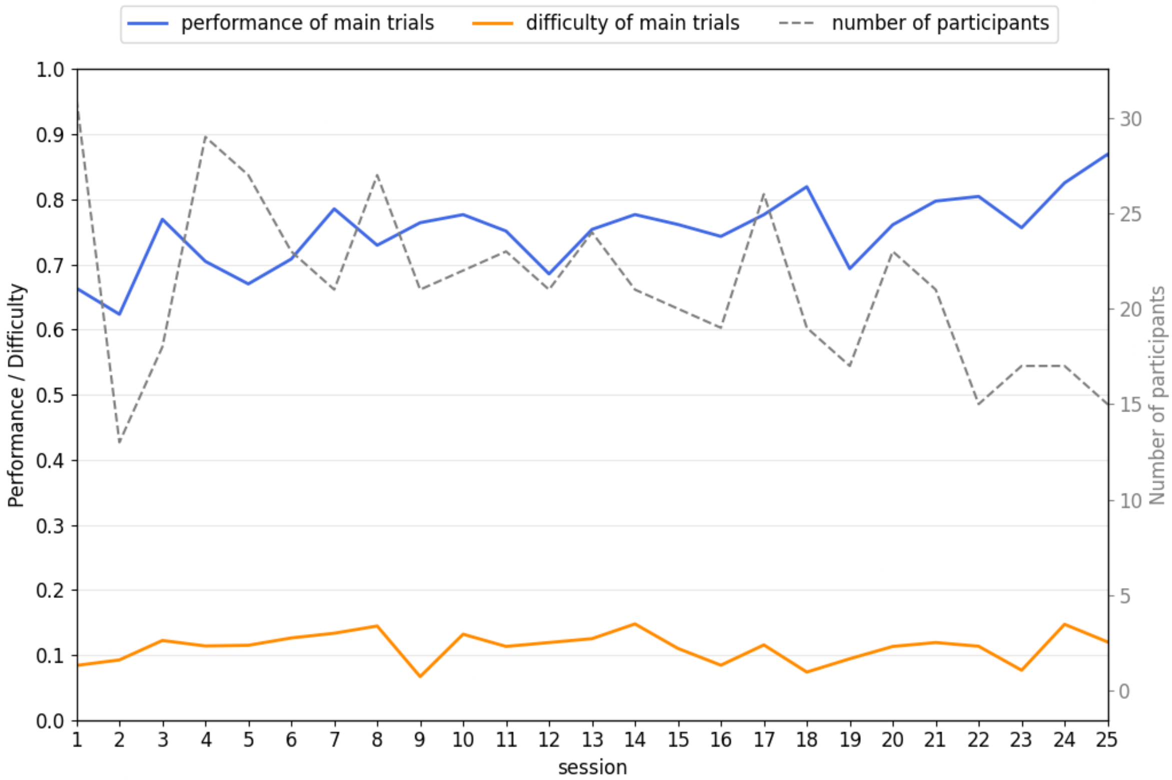
For the DivAttent game module, there was no fail condition, so we computed a performance value as a function of the various game elements. The overall DivAttent performance at each trial was a combination of measures which depended on the amount of damage taken (from both meteors and falls), the number of platforms that the player fell from compared to the total platforms, and the number of cores picked. These measures were weighted such that the damage taken contributed 3 /4 of the performance value, since it was the main driver for the difficulty updates, while the remaining measures contributed only

1 /4 of the performance value. The reader can refer to the Core AVG Hub performance section for additional details on the equations used, as the performance computation mirrors that used in the AVG Hub. These equations are applied with a modification to m and d which were set to 13 and 10 respectively for this task based on the specific heuristics of that game such that the midpoint coincides with the amount of damage which results in the overall difficulty remaining the same.

Figure S22 shows that players remained at relatively low difficulty levels. Due to the fast pace of difficulty adaptation in this game module, players likely reached a challenging level already from the first few trials and then maintained this level throughout the remainder of the intervention. Unfortunately, the difficulty data for this game included only the starting and final *overall* difficulty level of each trial and thus we could not confirm this assumption nor reliably analyze each player's individual trial performance.

Figure S22

Difficulty and performance as a function of session number for the Divided Attention (Meteors and Islands) game aggregated across participants



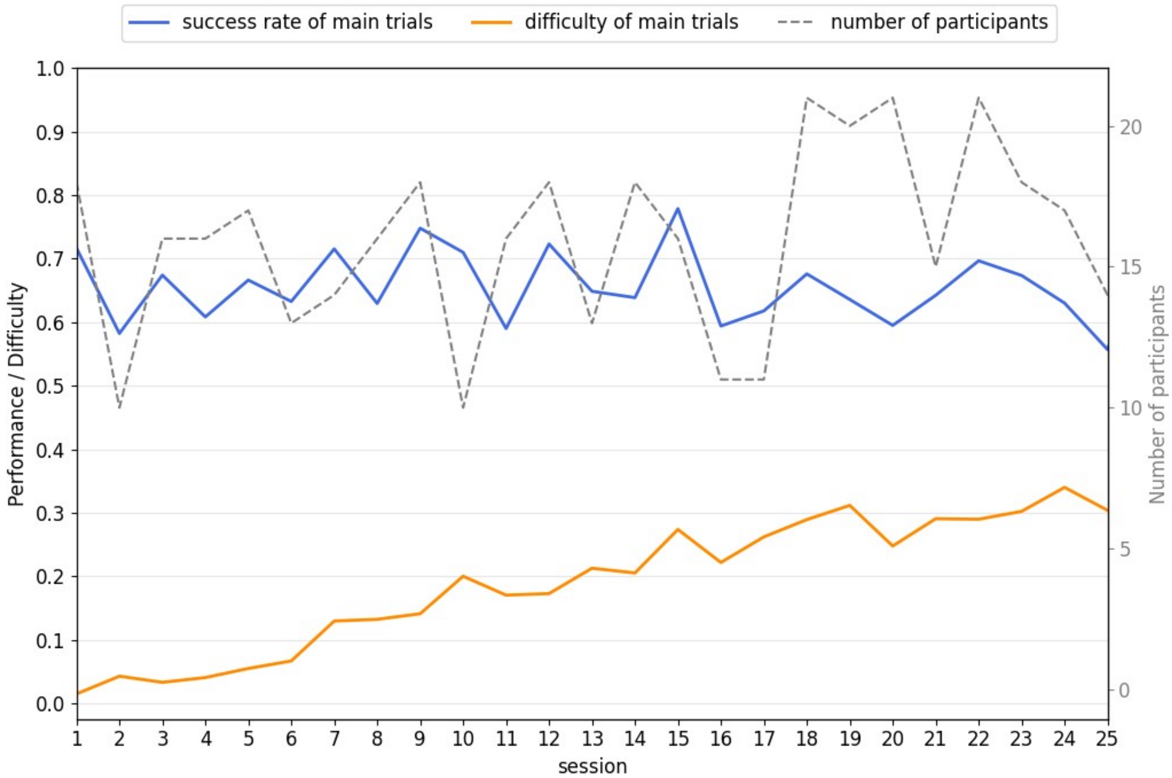
Simplified DDA algorithm: DDA for games without explorable sub-level parameters

Spatial-STM (Security system)

On average, players in this game started with a lower success rate but quickly (after 5-7 sessions) reached a success rate of approximately 0.75 (Figure S23). In the first 15-17 sessions players see the biggest progress in difficulty after which it seems to reach a relative plateau. Since this game does not have "explorable" secondary parameters, there were no rollback trials. Fluctuations in the number of participants in each session are the result of the random selection of this module and the reasoning module as the last module in each session. This also results in approximately half of the participants encountering this module in each session, the other half encountering the reasoning module.

Figure S23

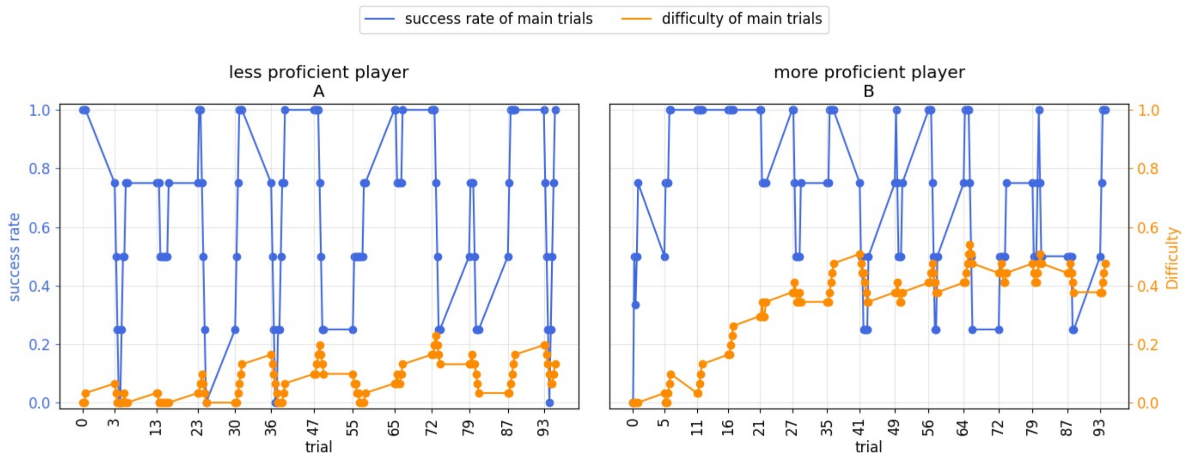
Difficulty and success rate as a function of session number for spatial-STM (security system) game aggregated across participants



Below we see examples of a proficient and a less proficient player for this spatial STM task (Security system game) module (Figure S24). The proficient player has similar properties as the average performance that we looked at above. The less proficient player has a success rate which remains mostly below 0.75, preventing them from progressing in difficulty. Recall that for this game module the player must succeed 3 trials in a row to advance in difficulty, and based on this modified DDA, we expect that the success rate is maintained around 0.75 while the player is optimally challenged (compared to 0.5 for the games we have presented in this section thus far).

Figure S24

Trial by trial progression of a less and more proficient player in the spatial-STM (security system) game module



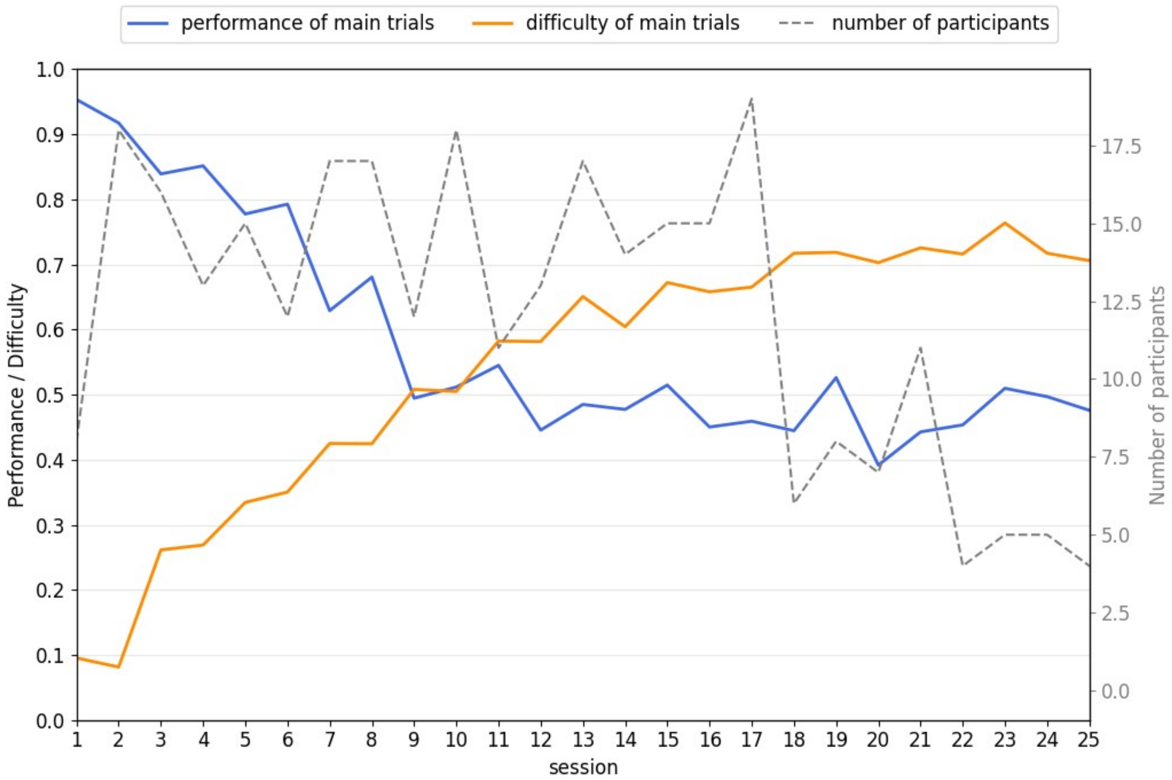
No DDA

Deductive reasoning task (Energy panel)

There was no fail condition for this module as the player could take as much time as needed to solve the puzzle. The performance of this module was computed as a combination of a performance value derived from the time spent solving the puzzle based on game heuristics, the number of attempts at solving the puzzle, and the number of hints used out of the available hints (Figure S25). More weight was given to the performance based on the time spent on each puzzle since it was the main factor limiting the difficulty progression. Fluctuations in the number of participants in each session are the result of the random selection of this module and the reasoning module as the last module in each session. This also results in approximately half of the participants encountering this module in each session, the other half encountering the spatial-STM module. Note that this module did not make use of an adaptive difficulty system and puzzles were presented in sequential difficulty each time one was solved.

Figure S25

Difficulty and success rate as a function of session number for the Deductive reasoning (energy panel) game aggregated across participants



Below we see an example of a proficient and a less proficient player for the Reasoning module. This module is allotted a specific duration in each session and multiple trials (puzzles) can be completed during that time. A proficient player who can solve puzzles quickly will be presented with more puzzles in a session compared to a less proficient player who is slower. This is precisely what we observe in the figure below (Figure S26). Performance in this game is mainly driven by the time spent solving each puzzle (more time leads to lower performance). Hence, we observe that sessions with a low performance have fewer trials. Consequently, the proficient player manages to complete 83 trials within 6 sessions while the less proficient player does so in 10 sessions.

Figure S26

Trial by trial progression of a less and more proficient player in the Deductive reasoning (energy panel) game module