Computers in Human Behavior 177 (2026) 108878

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Game on or gone too far? Executive functioning and implicit sequence learning in problematic vs. recreational gamers

Krisztina Berta [a,b,c,2], Zsuzsanna Viktória Pesthy [a,b,c,2], Teodóra Vékony [d], Bence Csaba Farkas [e,f,g], Orsolya Király [b,i], Zsolt Demetrovics [h,b,i], Dezső Németh [d,j,k,1,3], Bernadette Kun [b,*,1,3]

[a] *Doctoral School of Psychology, ELTE Eötvös Loránd University, Budapest, Hungary*
[b] *Institute of Psychology, ELTE Eötvös Loránd University, Budapest, Hungary*
[c] *Institute of Cognitive Neuroscience and Psychology, HUN-REN Research Centre for Natural Sciences, Budapest, Hungary*
[d] *Gran Canaria Cognitive Research Center, Department of Education and Psychology, Atlántico Medio University, Las Palmas de Gran Canaria, Spain*
[e] *Université Paris-Saclay, UVSQ, INSERM, CESP, Villejuif, France*
[f] *Pôle Pilotage activités et Projets, Direction Générale Adjointe Enfance Famille Santé (DGAEFS), Guyancourt, France*
[g] *Centre de Recherche en Épidémiologie et en Santé des Populations, INSERM U1018, Université Paris-Saclay, Université Versailles Saint-Quentin, Paris, France*
[h] *Flinders University Institute for Mental Health and Wellbeing, College of Education, Psychology and Social Work, Flinders University, Bedford Park, SA, Australia*
[i] *Centre of Excellence in Responsible Gaming, University of Gibraltar, Gibraltar, Gibraltar*
[j] *Centre de Recherche en Neurosciences de Lyon, INSERM, CNRS, Université Claude Bernard Lyon 1, CRNL U1028 UMR5292, Bron, France*
[k] *BML-NAP Research Group, Institute of Psychology, Eötvös Loránd University & Institute of Cognitive Neuroscience and Psychology, Research Centre for Natural Sciences, Budapest, Hungary*

ARTICLE INFO

Keywords:
Gaming disorder
Recreational gaming
Executive functions
Statistical learning
Behavioral addiction
Cognitive profiles
Competition theory
Video games
Addictive behavior
Impulsive behavior

ABSTRACT

Video gaming often sparks controversy, though negative effects are mainly linked to gaming disorder, not gaming itself. Research shows that gaming disorder correlates with reduced executive functioning and greater reliance on habitual processes, while recreational gaming may relate to enhanced cognitive functions. However, comprehensive comparisons of cognitive profiles across gaming behaviors remain scarce. We aimed to compare the cognitive functioning of non-gamers (NG), recreational gamers (RG), and gaming disorder risk individuals (GDR). Based on the Ten-Item Internet Gaming Disorder Test scores, 114 participants were classified into these three groups. Executive functions were assessed with the Go/No-Go, Counting Span, Digit Span, Card Sorting, 1-back, and 2-back tasks; implicit sequence learning with the Alternating Serial Reaction Time task. Group effects were adjusted for weekly gaming time. The GDR group showed reduced working memory, performing worse on the Digit Span task than the NG group, and worse on the Counting Span task than both NG and RG groups. Conversely, the RG group displayed enhanced attention-related performance compared to the NG group. No group differences emerged in implicit sequence learning. Interaction analyses revealed a negative relationship between implicit sequence learning and inhibitory control/updating across groups, while a positive link between working memory and implicit sequence learning in NG and GDR groups suggests possible compensatory mechanisms. This study underscores that cognitive impairments are linked to gaming disorder rather than gaming time itself, while recreational gaming may offer cognitive benefits. These findings provide insights into the distinct cognitive profiles of recreational gaming and gaming disorder.

1. Introduction

While gaming is usually an everyday recreational activity that can enhance daily life and provide social benefits, these positive effects can be overshadowed when gaming turns into addiction, severely impacting quality of life (Brand et al., 2025). In 2019, the World Health

* Corresponding author.
E-mail address: kun.bernadette@ppk.elte.hu (B. Kun).
[1] senior authors.
[2] These authors contributed equally: Krisztina Berta and Zsuzsanna Viktória Pesthy.
[3] These authors jointly supervised this work: Dezső Németh and Bernadette Kun.

https://doi.org/10.1016/j.chb.2025.108878
Received 27 June 2025; Received in revised form 20 November 2025; Accepted 27 November 2025
Available online 3 December 2025

Organization (WHO) officially recognized Gaming Disorder as a medical condition in the 11th revision of the International Classification of Diseases (ICD-11), defining it as a persistent inability to control gaming, where it takes precedence over daily activities despite negative consequences. The diagnosis requires significant impairment in personal, family, social, educational, or occupational functioning for at least 12 months (Király et al., 2023; World Health Organization, 2018). Similarly, the DSM-5 acknowledges internet gaming disorder as a condition warranting further research, although it has not yet been officially classified as a clinical disorder (American Psychiatric Association, 2013). Given the growing concern over the potential negative impact of gaming disorder, research has increasingly focused on understanding its underlying cognitive mechanisms. Understanding whether these cognitive processes differ from those involved in recreational gaming is crucial, as such differences may help distinguish maladaptive patterns from healthy engagement. To address this, we investigated executive functions and implicit sequence learning across three groups: individuals at risk for gaming disorder, recreational gamers, and non-gamers.

Within the dual-system framework, addictive disorders are conceptualized as resulting from an imbalance between the goal-directed and the habitual systems. Addiction has been linked to reduced goal-directed control, leading behavior increasingly dominated by habitual processes that rely on automatic stimulus–response associations rather than on current goals or expected outcomes (Everitt & Robbins, 2016; Furlong & Corbit, 2018; McKim & Boettiger, 2015). Goal-directed processes are supported by executive functions, which allow individuals to regulate behavior according to internal goals and changing circumstances (Diamond, 2013; Miyake et al., 2000), whereas habitual processes operate automatically and often persist even when they conflict with objectives (Furlong & Corbit, 2018; Ostlund & Balleine, 2008). Implicit sequence learning represents a fundamental aspect of habitual processing, capturing the acquisition of environmental regularities without conscious awareness or explicit feedback (Armstrong et al., 2017; Horváth et al., 2022). Although these processes act at different levels of cognitive processing and cannot be directly mapped onto the goal-directed and habitual systems, nor should they be viewed as symmetric counterparts, executive functions and implicit sequence learning still interact dynamically. According to the competition theory (Pedraza et al., 2024; Poldrack & Packard, 2003), this interaction may manifest such that when prefrontal regulatory functions, including executive functions, are attenuated, procedural processes like implicit sequence learning may gain greater influence. Studying both processes is particularly relevant in the context of addictive behaviors, as they may contribute to loss of control and help clarify the mechanisms distinguishing recreational gaming from gaming disorder.

Among the three core executive functions, inhibitory control plays a central role in models of internet-related addictive behaviors, as deficits in this function are thought to contribute to loss of behavioral control (Brand et al., 2016; Dong & Potenza, 2014). It is also the most frequently examined component in gaming disorder, where findings consistently indicate moderate impairment (Argyriou et al., 2017). Working memory and cognitive flexibility have been less thoroughly investigated, and findings are inconsistent: some studies report deficits (Jeong et al., 2016; Jiang et al., 2020; Ngetich et al., 2023; Zhou et al., 2016), whereas others find no significant differences (Cudo et al., 2025; Ding et al., 2014; Mukherjee & Banerjee, 2022). While individuals with gaming disorder may exhibit executive function impairments, recreational gaming is associated with comparable or even superior performance relative to non-gamers (Colzato et al., 2013; Cudo et al., 2025; Waris et al., 2019). Comparative research between gaming disorder and recreational gaming has largely focused on inhibitory control, yielding mixed results: some studies report weaker inhibitory control and altered neural activation in gaming disorder (Dong et al., 2017), others find differences only in response to gaming-related stimuli (Maleki et al., 2024), while some report no significant differences at all (Jeromin et al., 2016). These mixed findings and the limited scope of existing research highlight the need for a comprehensive examination of executive functions in different gaming behaviors. To address this gap, we planned to assess the three core executive functions using neuropsychological tasks: inhibitory control and cognitive flexibility were measured with dedicated tasks, and working memory with simple and complex paradigms to separately capture storage and updating components, given their weak intercorrelations (Redick & Lindsey, 2013). This approach allows for a more precise understanding of the foundational processes underlying higher-order cognitive functions and their role in recreational versus problematic gaming.

In the context of habitual processes, it is important to distinguish between two broad forms of learning: supervised learning, in which behavior is shaped by explicit feedback such as rewards or errors, and unsupervised learning, in which individuals implicitly extract statistical regularities without external feedback (Conway & Pisoni, 2008). Implicit sequence learning belongs to the latter category, capturing automatized learning that operates largely outside conscious control (Zhong et al., 2025). Research directly targeting habitual mechanisms in gaming behavior is limited; insights typically come from paradigms that directly examine the interaction between goal-directed and habitual systems (Kwon et al., 2024; Lei et al., 2025; W. Zhou et al., 2021). These paradigms often involve supervised learning tasks, where feedback guides adjustments in behavior. For instance, studies using the two-step task and instrumental learning task have reported disrupted thalamocortical communication in individuals with gaming disorder (Zhou et al., 2021), altered goal-directed signaling without a clear behavioral imbalance between the two systems (Kwon et al., 2024), and reduced goal-directed (model-based) learning alongside heightened habitual signals (Lei et al., 2025). Research examining unsupervised learning processes in the gaming context is limited, with one study reporting that recreational gamers may exhibit enhanced implicit statistical learning, suggesting strengthened habitual processes (Romano Bergstrom et al., 2012). Sequence learning tasks are a promising way to capture automatized learning that reflects the habitual patterns of addictive behaviors, yet studies investigating implicit sequence learning across different gaming patterns remain scarce (Doñamayor et al., 2022). To address this gap, we employed an implicit sequence learning task to directly examine potential differences in the learning performance between individuals at risk for gaming disorder, recreational gamers, and non-gamers.

Building on these considerations, the present study examined executive functions, implicit sequence learning, and their interaction in individuals at risk for gaming disorder, recreational gamers, and non-gamers. We hypothesized that (1) individuals at risk for gaming disorder would show impairments in executive functions compared to both recreational gamers and non-gamers; (2) recreational gamers would outperform non-gamers on tasks requiring executive functions; and (3) individuals at risk for gaming disorder would show enhanced implicit sequence learning relative to the other two groups, reflecting a stronger reliance on habitual mechanisms. (4) Finally, we expected that the interaction between executive functions and implicit sequence learning would differ across the three groups, reflecting distinct cognitive profiles associated with varying levels of gaming involvement.

2. Methods

2.1. Participants and procedure

Participants were recruited in two phases as part of a larger study on behavioral addictions (Kun et al., 2020). Non-gaming controls were invited from a previous study, while active gamers were recruited online through a Hungarian gaming media outlet. Prospective participants completed a brief screening that included weekly gaming time and the Ten-Item Internet Gaming Disorder Test (IGDT-10; Király et al., 2017). Exclusion criteria included substance use on the day of testing. The final sample consisted of 114 participants ($M_{age} = 35.39$ years; SD = 10.11;

64.04 % male). Participants with extreme task scores or technical issues were excluded from the corresponding analyses. Additional information about exclusions, recruitment procedures, and the sociodemographic characteristics of the sample is provided in Supplementary Materials S1. Based on IGDT-10 scores and weekly playtime, individuals were assigned to non-gaming, recreational gaming, or gaming disorder risk groups.

- a non-gaming (NG) group ($n = 41$, $M_{age} = 42.15$ years; $SD = 10.31$, 24 females, 17 males; $M_{gaming\ time/week} = 0$ h), who did not play video games at all;
- a recreational gaming (RG) group ($n = 42$, $M_{age} = 33.83$ years; $SD = 7.54$, 9 females, 33 males, $M_{gaming\ time/week} = 29.32$ h), who played video games of any kind for at least 14 h per week but did not meet the IGDT-10 criteria;
- and gaming disorder risk (GDR) group ($n = 31$, $M_{age} = 28.55$ years; $SD = 7.19$, 8 females, 23 males, $M_{gaming\ time/week} = 45.42$ h), who played any kind of video games of any kind for at least 14 h per week and scored at or above the literature-defined threshold of 5 on the IGDT-10 questionnaire (Király et al., 2017).

Participants attended a 1.5- to 2-h face-to-face session, which began with a briefing followed by the signing of an informed consent form. The session comprised neuropsychological tasks (detailed in the Measures section), sociodemographic questions, and a self-report questionnaire, which participants completed via the Qualtrics platform. To assess video game usage, participants reported their average gaming time on weekdays and weekends, specifying the number of hours played on each. Total weekly playtime was then calculated as: (5 × weekday hours) + (2 × weekend hours). As compensation, participants received gift vouchers worth €35.

The data were processed anonymously, and the tasks were neither physically nor mentally demanding for participants. The study complied with established ethical research guidelines and was approved by the Institutional Research Ethics Committee (registration number 2020/401). All procedures followed the ethical principles set forth in the Declaration of Helsinki.

2.2. Measures

The computational tasks in this study were developed using the JavaScript library jsPsych (de Leeuw, 2015; Vékony, 2021/2021, 2021, 2022, 2021/2022). Participants performed these tasks on a laptop using a QWERTZ keyboard, where non-essential keys were removed to prevent accidental key presses.

2.2.1. Go/No-Go

We measured inhibitory control using a Go/No-Go task where participants viewed a 2 × 2 square grid, each cell containing a blue star (Bezdjian et al., 2009). A letter, either P or R, would randomly replace one of the stars. Participants were instructed to press the spacebar when the letter P appeared (Go trials) and to withhold their response when the letter R appeared (No-Go trials). The task begins with a 20-trial practice session where participants receive feedback on their responses. Following this, the main task starts without feedback, consisting of 160 trials—128 Go-trials and 32 No-Go trials—maintaining an 80:20 ratio. Each trial is displayed for 500 ms (or until a response is made), with a 1500 ms interval between trials. Midway through the task, the instructions were reversed: press the spacebar for R and refrain from pressing for P. The instructions are followed by a 20-trial practice session with feedback. The second part then begins, consisting of another 160 trials with an 80:20 ratio of Go to No-Go trials. Performance was measured by three metrics: correct responses to Go trials (hits), incorrect responses to No-Go trials (false alarms), and d-prime score, which calculates the standardized value of the difference between hits and false alarms (higher values indicating better inhibitory control), as follows:

$$\text{d} - \text{prime} = \text{Z}(\text{hit rate}) - \text{Z}(\text{false alarm rate})$$

2.2.2. Digit span task

To assess phonological working memory capacity, we employed the Digit Span Task (DSPAN) (Jacobs, 1887; Racsmány et al., 2006). In this task, the examiner verbally presents a sequence of digits, and the participant is required to memorize and then accurately recall the sequence in the same order it was presented. The task starts with recalling a sequence of three digits, with four different sets of these sequences. If the participant correctly recalls at least three of these, they advance to four-digit sequences, and so on. The digit span score is determined by the longest sequence length the participant successfully completes.

2.2.3. Counting Span task

The Counting Span Task (CSPAN) (Case et al., 1982) is used to evaluate complex working memory. In this task, participants see various geometric shapes—yellow and blue squares and circles—on the screen. They are required to count the blue circles aloud and remember the total count. This process is repeated across several images. After all images are shown, a question mark appears, prompting the participant to recall and report the sequence of numbers corresponding to the counts they previously repeated, in the correct order. The exercise begins with three practice sets, each containing two trials of geometric shapes. The task then starts with a sequence of two trials, and after a correct response, it progresses to longer sequences, adding one trial at a time, up to a maximum of six trials. This sequence is repeated three times in total. In each round, we recorded the length (i.e., the number of digits that had to be memorized) of the longest sequence that the participant reproduced correctly. The counting-span score was calculated as the average of these three longest-sequence lengths.

2.2.4. N-back tasks

The N-back tasks (Kirchner, 1958) are designed to assess complex working memory, with a particular focus on the updating function of executive processes. In this task, participants view a sequence of letters presented one at a time at the center of the screen. They must determine if the current letter matches the one shown one position earlier (1-back) or two positions earlier (2-back). For matching letters, they press the "J" key; for non-matching letters, they press the "F" key. We set the target ratio at 20 %, with 20 targets and 80 non-targets per level. The 1-back and 2-back tasks were administered consecutively, each beginning with a 10-trial practice session that included feedback. Afterward, 100 letters were presented, each displayed for 500 ms or until a response was made, with a 1500 ms interval between them. For analysis, we assessed hit, false alarm, their reaction times, and the d-prime score to evaluate performance.

2.2.5. Card Sorting task

Cognitive flexibility was assessed using the Card Sorting task (CST) (Berg, 1948; Fox et al., 2013). In this task, participants are shown four cards in the center of the screen, each displaying geometric shapes that vary by number, color, and shape. A card appears below these, and the participant must match it to one of the top cards based on a specific rule (color, number, or shape). The rule is not given in advance and changes periodically; participants must deduce the rule from feedback indicating whether their match was correct. Participants categorize a total of 64 cards, with the rule changing every 10 cards. Perseverative errors, where participants continue using an outdated rule, indicate challenges in cognitive flexibility. The fewer such errors, the better their cognitive flexibility is considered.

2.2.6. Alternating Serial Reaction Time task

To measure implicit sequence learning, we used the Alternating Serial Reaction Time task (ASRT) Howard & Howard, 1997; Song et al., 2007), which implicitly assesses the learning of sequential patterns, essential for habit formation (Horváth et al., 2022). Participants interacted with a screen displaying four circles, each linked to a specific key ('S', 'F', 'J', 'L'). Images of dog heads would appear as target stimuli in the circles, and participants were instructed to press the corresponding key as quickly and accurately as possible.

The stimuli followed a hidden alternating pattern: every first stimulus was randomly selected, while every second stimulus followed a set sequence. Each sequence consisted of eight elements, such as r 2 r 4 r 1 r 3, where numbers represent pattern-based stimuli, and r denotes random stimuli that could appear in any of the four positions. From this structured sequence, high- and low-probability triplets can be identified. A high-probability triplet (e.g., 2 r 4 or 4 r 1) occurs more frequently because it can be formed both when the triplet begins with a pattern-based stimulus and when it begins with a random one, together accounting for 62.5 % of all triplet occurrences. In contrast, a low-probability triplet (e.g., 4 r 2 or 1 r 4) can only be formed when both the first and last elements are random, resulting in a lower frequency of 37.5 %. As a result of this distribution, participants are typically faster and more accurate in responding to high-probability triplets, which serves as a behavioral measure of implicit sequence learning (see further details in Supplementary Materials S2; Fig. 1).

The task starts with one practice block containing 80 random trials. Following the practice, participants completed 20 blocks of the ASRT task, with a short 15-min break after the 15th block, during which they completed questionnaires. Each block consists of 10 repetitions of a randomly selected 8-element sequence, resulting in 1600 stimuli per participant in total. For analysis, the blocks were grouped into four epochs, each containing five blocks.

A summary of the tasks used in the study, including their cognitive domains and the key variables extracted from each, is presented in Table 1.

Table 1
Summary of neurocognitive tasks and key variables.

Task name	Cognitive domain	Key variables
Go/No-Go	Inhibitory control	number of hits, number of false alarms, d-prime
Digit Span (DSPAN)	simple working memory capacity	Digit Span value
Counting Span (CSPAN)	complex working memory capacity	Counting Span Value
1-back	simple working memory updating	number of hits, number of false alarms, d-prime
2-back	complex working memory updating	number of hits, number of false alarms, d-prime
Card Sorting Task (CST)	cognitive flexibility	number of perseverative errors
Alternating Serial Reaction time Task (ASRT)	implicit sequence learning	accuracy and reaction time

2.2.7. *Ten-Item Internet Gaming Disorder Test*

Gaming Disorder risk (GDR) was assessed using a self-report measure, the Hungarian version of the Ten-Item Internet Gaming Test (IGDT-10) (Király et al., 2017). This questionnaire is one of the most widely accepted and commonly used tools for assessing GDR, as it is based on the DSM-5 criteria and demonstrates good psychometric properties (Király et al., 2019; Yoon et al., 2021).

The IGDT-10 consists of ten items, each corresponding to one of the DSM-5 diagnostic criteria for IGD. The only exception is criterion 9, which refers to "jeopardizing or losing a significant relationship, job, or educational or career opportunity due to participation in internet games." This criterion was assessed using two separate items (items 9 and 10). However, to ensure consistency, responses to these two items were combined so that only a single point was assigned if the participant responded "often" to either or both items. Participants rated each item on a 3-point Likert scale (0 = never, 1 = sometimes, 2 = frequently). However, to align with the dichotomous scoring approach used in the DSM-5, responses of "never" and "sometimes" were coded as not meeting the criterion (0 points), while "frequently" was coded as meeting the criterion (1 point). Consequently, participants could achieve a maximum score of 9 points. Based on the DSM-5 classification system, individuals who met at least five criteria were categorized into the GDR group. It is important to emphasize that the IGDT-10 is not a diagnostic tool but rather a screening instrument intended to assess GD risk at a preliminary level. In the current sample, the questionnaire demonstrated adequate reliability with Cronbach's alpha of .84.

2.3. *Statistical analysis*

Statistical analyses were conducted using JASP (Version .19.3.0; JASP Team, 2024) and IBM SPSS Statistics (Version 28; IBM Corp., 2021) for descriptive statistics and data cleaning. Group comparisons were performed in RStudio (Version 2024.12.0.467), while interaction analyses were conducted using RStudio (Version 2023.6.2.561). For

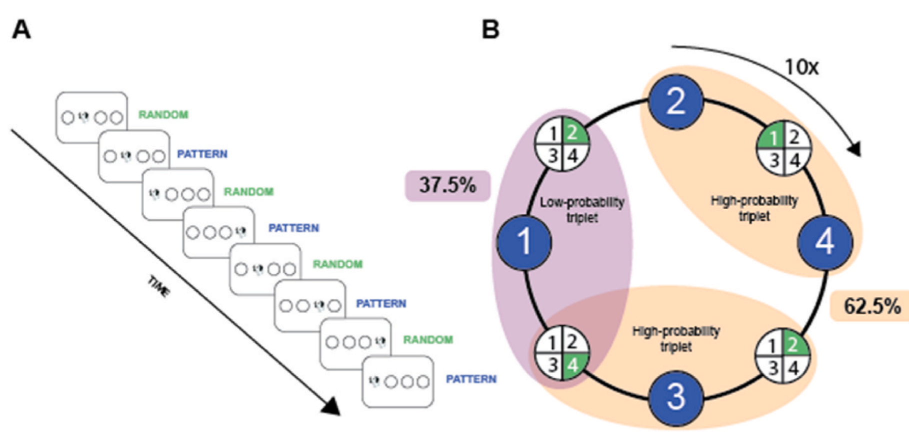

Fig. 1. Structure of the ASRT. A) The eight-element sequence consisted of alternating random and pattern stimuli. The first and every other element was randomly selected from four possible locations, and the remaining elements followed a fixed pattern (e.g., r 2 r 4 r 3 r 1, see Fig. 1A). The alternating sequence was repeated 10 times within a block. B) High-probability triplets occurred more frequently, as they could be formed both when a triplet started with a pattern-based stimulus and when it started with a random stimulus—together accounting for 62.5 % of all triplet occurrences. In contrast, low-probability triplets could only occur when the triplet began with a random stimulus, resulting in a lower frequency (37.5 %). Because high-probability triplets appear more frequently, participants are more likely to implicitly learn them over time. Therefore, the performance difference between high- and low-probability triplets serves as an index of habit learning.

data visualization, we used Python (Version 3.10.12) with the *pandas, io*, and *matplotlib* packages (Hunter, 2007; McKinney, 2010). We first examined group differences in sociodemographic variables (gender, age, education, place of residence, current and childhood socioeconomic status), and planned to include any significantly differing variables as covariates to control for potential confounding effects. Additionally, for theoretical reasons, we controlled for weekly gaming time in all models to ensure that any between-group differences reflect addiction symptoms rather than the amount of time spent gaming (Katz et al., 2024).

We tested group differences in executive function scores using ANCOVA models, including covariates that were associated with the dependent variables, as required by ANCOVA assumptions, as well as weekly gaming time in all cases. When statistical assumptions (e.g., normality, homogeneity of variances) were violated, appropriate alternatives—such as rank-based or permutation-based ANCOVA—were applied. Effect sizes were reported as partial eta squared (ηp^2). To assess habitual learning, we analyzed accuracy and reaction time (RT) scores from the ASRT task using mixed-design ANOVAs. Weekly gaming time and relevant sociodemographic covariates were included based on preliminary regressions. The three-level group variable (GDR, RG, NG) was entered as a between-subject factor, while triplet type (high vs. low probability) and epoch (four levels) served as within-subject factors. When the assumption of sphericity was violated, Greenhouse–Geisser correction was applied. Post hoc comparisons for significant group effects were conducted using Bonferroni correction, and Cohen's d was calculated as the effect size for pairwise comparisons. A detailed description of the assumption checks and statistical procedures is provided in the Supplementary Materials S3.

To capture a more unified indicator of executive functioning and examine its relationship with implicit sequence learning, we conducted an exploratory factor analysis (EFA) on the executive function (EF) measures. This approach allowed us to integrate the EF tasks into a composite factor score representing overall executive functioning, enabling a direct examination of how executive functions, implicit sequence learning, and their interaction differentiate recreational gamers from individuals at risk for gaming disorder. Details of the EFA are provided in Supplementary Materials S6. Resulting factor scores were used in group comparisons, following the same statistical procedures described earlier. To examine the interaction between goal-directed and habitual processes, we used generalized linear mixed models (GLMMs) on ASRT task data, with triplet type, epoch, group, and EF factor scores as fixed effects, and relevant covariates included. Reaction times were analyzed with linear models (on log-transformed data), and accuracy with logistic models. Full model specifications and results are available in Supplementary Materials S7.

3. Results

3.1. Sociodemographic variables

When comparing the groups, we found significant differences in age, gender, and level of education. Regarding age, both the RG and GDR groups were significantly younger than the NG group, and the GDR group was also younger than the RG group. In terms of gender, the proportion of female participants was highest in the NG group (58.54 %) and lower in the RG (21.42 %) and GDR (25.81 %) groups. Regarding the level of education, a larger proportion of participants held a college or university degree in the NG group (82.93 %) compared to the RG (59.52 %) and GDR (40 %) groups, while the proportion of participants with only a high school diploma was highest in the GDR group (50 %), followed by the RG group (30.95 %) and the NG group (9.76 %). However, no significant group differences were observed in terms of place of residence or current and childhood socioeconomic status (see Supplementary Material S4 for details).

Consequently, age, gender, and education were considered as control variables in the analyses. To assess whether they should be included as covariates in the subsequent ANCOVA models, we examined their associations with the dependent variables through linear regression analyses. Details on which of the three control variables were included for each score can be found in Supplementary Material S5.

3.2. Working memory

To assess working memory capacity, we compared the performance of the GDR, RG, and NG groups on the DSPAN, CSPAN, and n-back tasks. Significant group differences were observed on the DSPAN task ($F(2,108) = 3.73$, $p = .027$, $\eta_p^2 = .046$), with the GDR group ($M = 6.19$, $SD = 1.08$) performing significantly worse than the NG group ($M = 6.98$, $SD = 1.27$; $p_{bonferroni} = .028$, $d = .67$). No significant differences were found between the RG ($M = 6.38$, $SD = 1.41$) and NG ($p_{bonferroni} = 1$, d = .44) groups or between the GDR and RG ($p_{bonferroni} = .144$, $d = .15$) groups on the DSPAN task. Similarly, significant group differences were observed on the CSPAN task ($F(2,107) = 5.35$, $p = .006$, $\eta_p^2 = .058$), which measured complex working memory capacity. The GDR group ($M = 3.21$, $SD = .72$) again performed significantly worse than the NG group ($M = 3.72$, $SD = .85$; $p_{\text{bonferroni}} = .016$, $d = .65$) and also showed significantly lower performance compared to the RG group ($M = 3.71$, $SD = .84$; $p_{\text{bonferroni}} = .014$, $d = .64$). In contrast, no significant differences were observed between the RG and NG groups ($p_{\text{bonferroni}} = 1$, $d = .01$). For the summary of the results, see Table 2 and Fig. 2.

In the 1-back task, there was a significant difference in the number of false alarms ($F(2,89) = 6.44$, $p = .002$, $\eta_p^2 = .125$), with the GDR group ($M = 2.16$, $SD = 1.65$) exhibiting more false alarms compared to the RG group ($M = .86$, $SD = 1.13$; $p_{\text{bonferroni}} = .003$, $d = .92$) and the NG group ($M = 1.28$, $SD = 1.65$; $p_{\text{bonferroni}} = .041$, $d = .53$). However, there was no significant difference in false alarms between the RG and NG groups ($p_{\text{bonferroni}} = 1$, $d = .30$). Additionally, there was a trend level difference in the d-prime score between the three groups ($F(2,92) = 2.43$, $p = .094$, $\eta_p^2 = .054$). The analysis revealed no significant group differences in d-prime scores, number of hits, false alarms, or reaction times in the 2-back task (see Table 2, Fig. 3).

3.3. Inhibitory control

The Go/No-Go task, designed to assess inhibitory control, revealed significant group differences in the number of hits across the three groups ($F(2,100) = 4.50$, $p = .013$, $\eta_p^2 = .047$). The RG group ($M = 241.88$, $SD = 10.27$) outperformed the NG group ($M = 233.87$, $SD = 15.43$), responding correctly to more target stimuli ($p_{\text{bonferroni}} = .021$, $d = .61$). No significant differences were observed between the NG and GDR groups ($M = 237.87$, $SD = 10.42$; $p_{\text{bonferroni}} = 1$, $d = .30$) or between the GDR and RG groups ($p_{\text{bonferroni}} = .274$, $d = .39$). Additionally, no significant differences were found among the three groups in the discriminability or false alarm scores (see Table 2, Fig. 4A).

3.4. Cognitive flexibility

To assess cognitive flexibility, we used the CST task, which revealed trend-level differences among the three groups, although it did not reach significance ($F(2,96) = 2.64$, $p = .077$, $\eta_p^2 = .078$; for further details see Table 2, Fig. 4B). The RG group exhibited the fewest perseverative errors ($M = 5.88$, $SD = 1.63$), followed by the NG group ($M = 6.78$, $SD = 2.17$), while the GDR group ($M = 6.80$, $SD = 2.62$) showed the highest number of perseverative errors.

3.5. Summary of the result of executive functions

In sum, in working memory, the GDR group performed worse than the NG group on simple and complex working memory tasks (DSPAN), and worse than both other groups on the complex CSPAN task. No group differences were found in updating. Only the number of false alarms in the 1-back task was higher in the GDR group compared to the other two

Table 2
Group comparisons of executive function scores with ANCOVA, adjusted for weekly gaming time and significant covariates.

N	Task (NG, RG, GDR)	Non-gamer	Recreational gamer	GD risk group		Statistics		
		M (SD)	M (SD)	M (SD)	df	F	p	η_p^2
Go/No-Go								
number of hits	111 (39, 42, 30)	233.87 (15.43)	241.88 (10.27)	237.87 (10.42)	**2,100**	**4.50**	**.013**	**.047**[b]
number of false alarms	111 (39, 42, 30)	25.36 (12.43)	26.91 (11.92)	28.23 (11.49)	2,106	.41	.665	.004[b]
d-prime	111 (39, 42, 30)	1.77 (.74)	1.94 (.63)	1.69 (.65)	2,106	1.21	.303	.022[a]
CST	113 (41, 42, 30)	6.78 (2.17)	5.88 (1.63)	6.80 (2.62)	2,96	2.64	.077	.078
1-back	96 (36, 36, 24)							
number of hit		16.89 (1.91)	17.61 (2.17)	16.84 (2.64)	2,92	2.06	.134	.047[b]
number of false alarm		1.28 (1.65)	.86 (1.13)	2.16 (1.65)	**2,89**	**6.44**	**.002**	**.125**[b]
d-prime		3.03 (.56)	3.31 (.66)	2.99 (.73)	2,92	2.43	.094	.054[a]
2-back	107 (39, 41, 27)							
number of hit		13.0 (3.33)	13.51 (3.36)	12.52 (3.09)	2,103	.75	.477	.017[a]
number of false alarm		6.67 (4.04)	6.07 (3.70)	9.21 (9.71)	2,94	.40	.670	.023[b]
d-prime		1.86 (.62)	2.02 (.70)	1.84 (.75)	2,94	.74	.479	.029[a]
DSPAN	113 (40, 42, 31)	6.98 (1.27)	6.38 (1.41)	6.19 (1.08)	**2,108**	**3.73**	**.027**	**.046**[a]
CSPAN	112 (40, 42, 30)	3.72 (.85)	3.71 (.84)	3.21 (.72)	**2,107**	**5.35**	**.006**	**.058**[b]
EF1	91 (32,36,23)	.34 (.89)	.15 (.98)	−.42 (.78)	**2,83**	**6.08**	**.003**	**.035**[b]
EF2	91 (32,36,23)	−.02 (.74)	.24 (.77)	−.11 (.80)	**2,86**	**1.92**	**.153**	**.042**[b]

Note. NG, Non-gamer; RG, Recreational Gamer; GDR, Gaming disorder Risk groups; CST, Card Sorting Test; DSPAN, Digit Span task; CSPAN, Counting Span task; EF1, 1st executive function factor; EF2, 2nd executive function factor. Reported statistics refer to the Group main effects. Superscripts denote the analysis used: a = parametric ANCOVA; b = rank-transformed ANCOVA (RANCOVA; applied when residual normality was violated); c = permutation-based ANCOVA (applied when variance homogeneity was violated; the reported statistic refers to the omnibus permutation model. Statistically significant results (p < .05) are shown in bold.

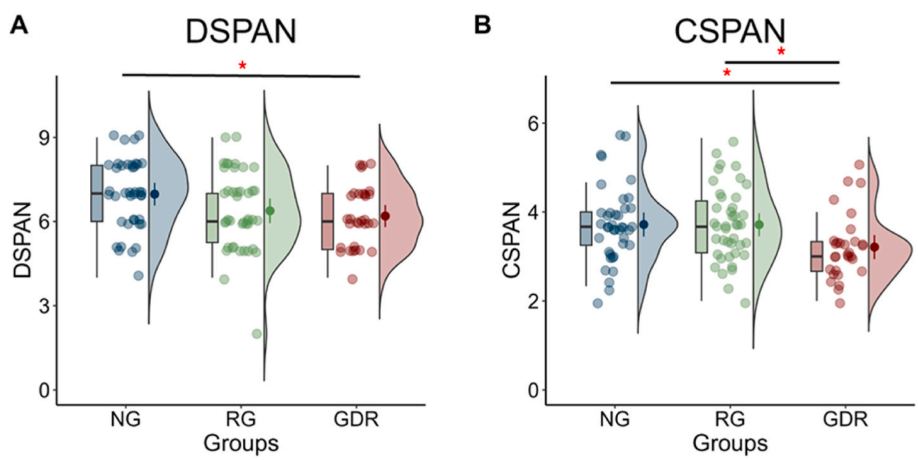

Fig. 2. Digit Span and Counting Span (CSPAN; B) scores of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. *Note.* This figure includes (A) the Digit Span (DSPAN) and (B) Counting Span (CSPAN) scores (*p < .05).

groups.

There was no difference in general inhibitory control, as no significant effect was found in the d-prime score. However, a significant group difference emerged in the number of hits, with the RG group performing better than the NG group, indicating enhanced response readiness and attentional control in recreational gamers. No significant group differences were observed in cognitive flexibility.

3.6. Implicit sequence learning

We performed a mixed-design ANOVA to examine group differences in implicit sequence learning based on reaction times and accuracy. Please note that the main effects and interactions involving the Triplet Type factor indicate differences in implicit sequence learning, while those excluding this factor reflect overall reaction time differences.

Age and gender significantly predicted accuracy, and age, gender and the level of education predicted reaction time (RT) in preliminary linear regression analyses; therefore, these variables were included as covariates in the final models, in addition to weekly gaming time. The mixed-design ANOVA on RT revealed a significant main effect of Group (F(1,85) = 3.49, p = .035, η_p^2 = .076), suggesting overall differences in RT between the groups. However, Bonferroni-adjusted post hoc comparisons did not yield statistically significant pairwise differences, suggesting a general group-level effect, but no robust differences between specific group pairs. Despite this, the effect size suggests a meaningful difference, with the RG group (M = 352.59, SD = 38.43, p = .137, d = 1.03) and the GDR group (M = 358.28, SD = 37.00, p = .262, d = .92) responding faster than the NG group (M = 401.67, SD = 55.70). Moreover, the analysis revealed a significant Group × Epoch interaction (F(5.05, 214.59) = 3.38, p = .006, η_p^2 = .074), indicating that the rate of performance improvement varied across groups over time. Among the covariates, age showed a robust main effect, with older participants generally exhibiting slower reaction times (F(2,85) = 30.49, p < .001, η_p^2 = .264). A significant Age × Epoch interaction (F(2.52, 214.59) = 2.82, p = .049, η_p^2 = .032), further indicated that age influenced how performance changed over time. In contrast, no other covariate-related interactions reached significance. Finally, although the main effect of Triplet Type was significant (F(1,85) = 9.79, p = .002, η_p^2 = .103), —indicating faster responses to high-probability triplets—there was no significant Group × Triplet Type interaction (F(2,85) = .64, p = .530, η_p^2 = .015). This suggests that, after controlling for covariates, the three groups did not differ in their sensitivity to the underlying triplet

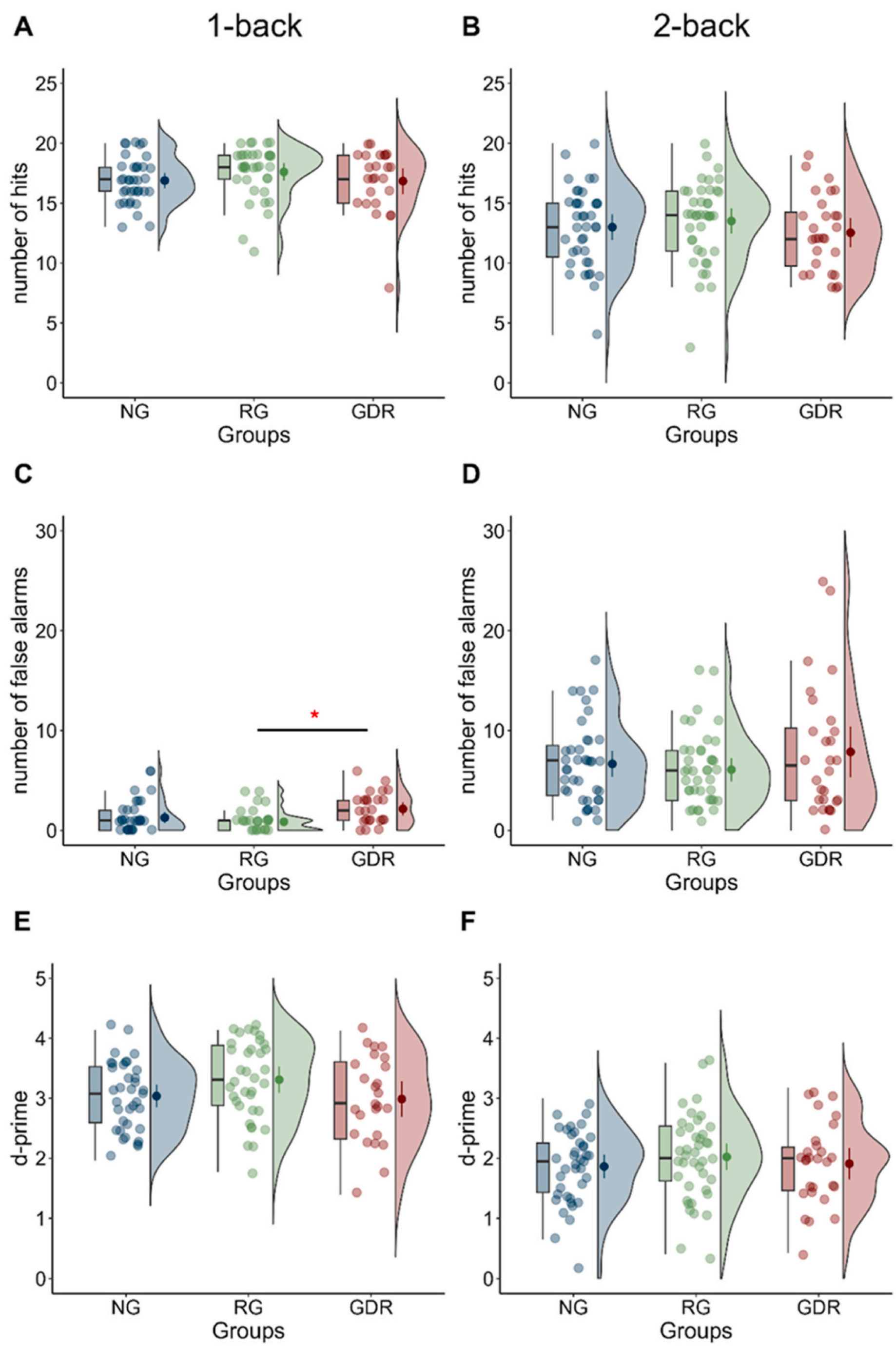

Fig. 3. N-back scores of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. N*ote*. In the first column, the figures display the results of the 1-back test: (A) the number of hits, (C) the number of false alarms, and (E) the d-prime scores. The second column shows the scores for the 2-back test: (B) the number of hits, (D) the number of false alarms, and (F) the d-prime scores (**$p < .01$).

structure, reflecting comparable levels of habitual learning (for further details, see Table 3, Fig. 5).

In the analysis of accuracy, age, gender, and education were included as covariates, as they significantly predicted accuracy in preliminary regression analyses. The ANOVA revealed a significant main effect of Epoch ($F(2.40,216.34) = 3.34$, $p = .029$, $\eta_p^2 = .036$), indicating that participants' accuracy changed over time. In addition, there was a significant main effect of Triplet Type ($F(1,90) = 8.97, p = .004, \eta_p^2 = .091$), demonstrating that participants, overall, showed evidence of implicit sequence learning, with higher accuracy on high-probability triplets compared to low-probability ones. Among the covariates, age emerged as a significant predictor ($F(1,90) = 10.99$, $p = .001$, $\eta_p^2 = .109$), suggesting that performance was influenced by participants' age. No other main effects or interactions have reached significance, including those involving the Group variable. Therefore, we conclude that the three groups did not differ significantly in their implicit sequence learning performance after controlling for covariates (see Table 4, Fig. 6).

Finally, Fig. 7 illustrates the distinct cognitive profiles of the NG, RG, and GDR groups across multiple tasks.

In sum, regarding group differences, the mixed-design ANOVAs did not reveal any significant differences between the NG, RG, and GDR groups in the ASRT task. Although the RG and GDR groups showed descriptively faster reaction times than the NG group, these differences

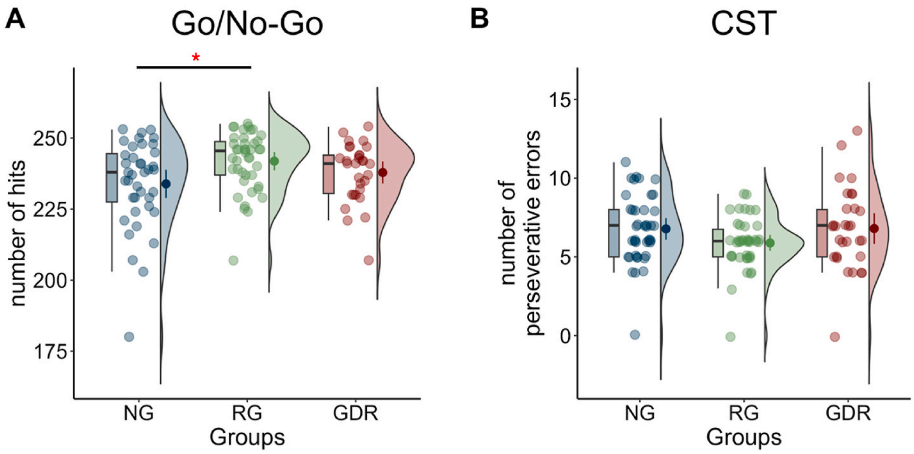

Fig. 4. Cognitive flexibility and inhibitory control scores of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. *Note.* This figure includes (A) the number of hits in the Go/No-Go task and (B) the number of perseverative errors in the Card Sorting Task (CST) (* $p < .05$).

Table 3
Results of the mixed-design ANOVA on the reaction time of the Alternating Serial Reaction Time task.

Effect	*F*	*df*	*p*	η^2p
Group	**3.49**	**1,85**	**.035**	**.076**
Age	**30.49**	**2,85**	**< .001**	**.264**
Gender	2.14	1,85	.147	.025
Education	1.60	4,85	.181	.070
Weekly gaming time	.001	1,85	.937	<.001
Triplet Type	**9.79**	**1,85**	**.002**	**.103**
Group × Triplet Type	.64	2,85	.530	.015
Age × Triplet Type	.28	1,85	.598	.003
Gender × Triplet Type	2.91	1,85	.092	.033
Education × Triplet Type	.95	4,85	.441	.043
Epoch	2.38	2.52, 214.59	.082	.027
Group × Epoch	**3.38**	**5.05, 214.59**	**.006**	**.074**
Age × Epoch	**2.82**	**2.52, 214.59**	**.049**	**.032**
Gender × Epoch	2.44	2.52, 214.59	.076	.028
Education × Epoch	1.38	10.10, 214.59	.191	.061
Triplet Type × Epoch	.62	3,255	.601	.007
Group × Triplet Type × Epoch	1.07	6,255	.384	.024
Age × Triplet Type × Epoch	1.19	3,255	.312	.014
Gender × Triplet Type × Epoch	.21	3,255	.887	.003
Education × Triplet Type × Epoch	.91	12,255	.540	.041
Weekly gaming time × Triplet Type × Epoch	.32	3,255	.810	.004

Note. Values with statistical significance at $p < .05$ are highlighted in bold.

were not statistically significant after correction. Moreover, the groups did not differ in their sensitivity to the probabilistic structure, as indicated by the absence of a Group × Triplet Type interaction in both reaction time and accuracy. Overall, the three groups demonstrated comparable levels of implicit sequence learning.

Table 4
Results of the mixed-design ANOVA on accuracy of the Alternating Serial Reaction Time task.

Effect	*F*	*df*	*p*	η^2p
Group	.83	2,90	.440	.018
Age	**10.99**	**1,90**	**.001**	**.109**
Gender	.89	1,90	.348	.010
Weekly gaming time	.29	1,90	.592	.003
Triplet Type	**8.97**	**1,90**	**.004**	**.091**
Group × Triplet Type	.55	2,90	.578	.012
Age × Triplet Type	2.38	1,90	.126	.026
Gender × Triplet Type	.39	1,90	.534	.004
Weekly gaming time × Triplet Type	.08	1,90	.780	<.001
Epoch	**3.34**	**2.40,216.34**	**.029**	**.036**
Group × Epoch	.81	4.81,216.34	.537	.018
Age × Epoch	.85	2.40,216.34	.152	.020
Gender × Epoch	1.08	2.40,216.34	.352	.012
Weekly gaming time × Epoch	.54	2.40,216.34	.619	.006
Triplet Type × Epoch	1.93	3,270	.125	.021
Group × Triplet Type × Epoch	.96	6,270	.455	.021
Age × Triplet Type × Epoch	1.74	3,270	.160	.019
Gender × Triplet Type × Epoch	.21	3,270	.887	.002
Weekly gaming time × Triplet Type × Epoch	.57	3,270	.636	.006

Note. Values with statistical significance at $p < .05$ are highlighted in bold.

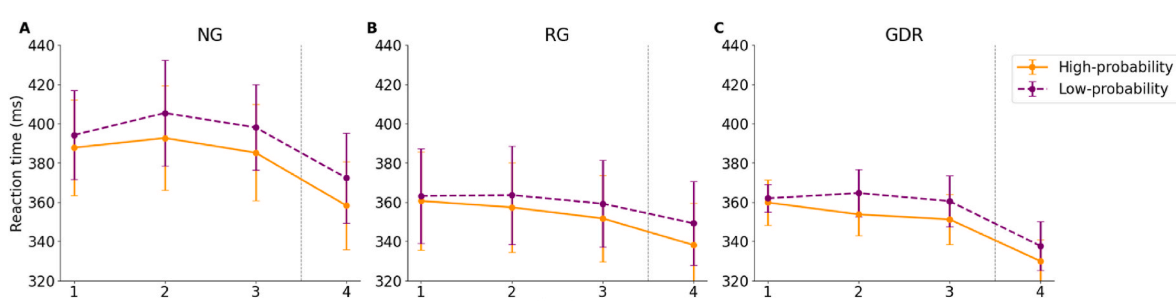

Fig. 5. Reaction time in the Alternating Serial Reaction Time (ASRT) task of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. *Note.* The figure illustrates reaction time (RT) data on the ASRT task. The orange and purple lines correspond to RTs for high-probability and low-probability triplets, respectively. A greater separation between these lines indicates stronger statistical learning. The gray dashed line marks a 20-min break in the procedure. Error bars represent 95 % confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

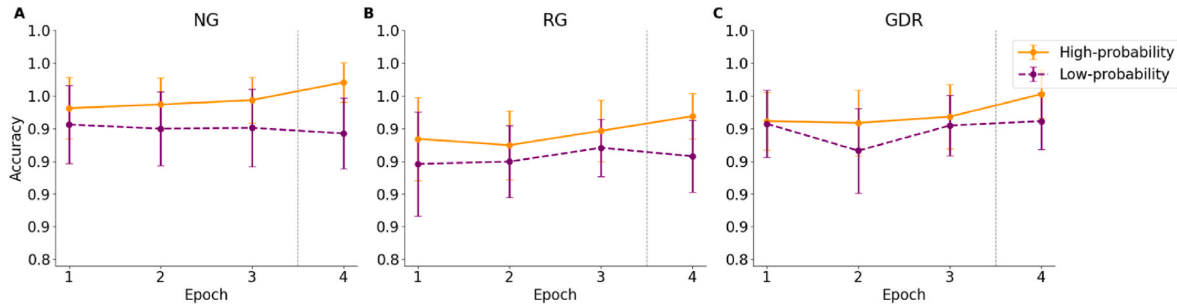

Fig. 6. Accuracy in the Alternating Serial Reaction Time (ASRT) task of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. *Note*. The figure illustrates accuracy (ACC) on the ASRT task. The orange and purple lines correspond to RTs for high-probability and low-probability triplets, respectively. A greater separation between these lines indicates stronger statistical learning. The gray dashed line marks a 20-min break in the procedure. Error bars represent 95 % confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

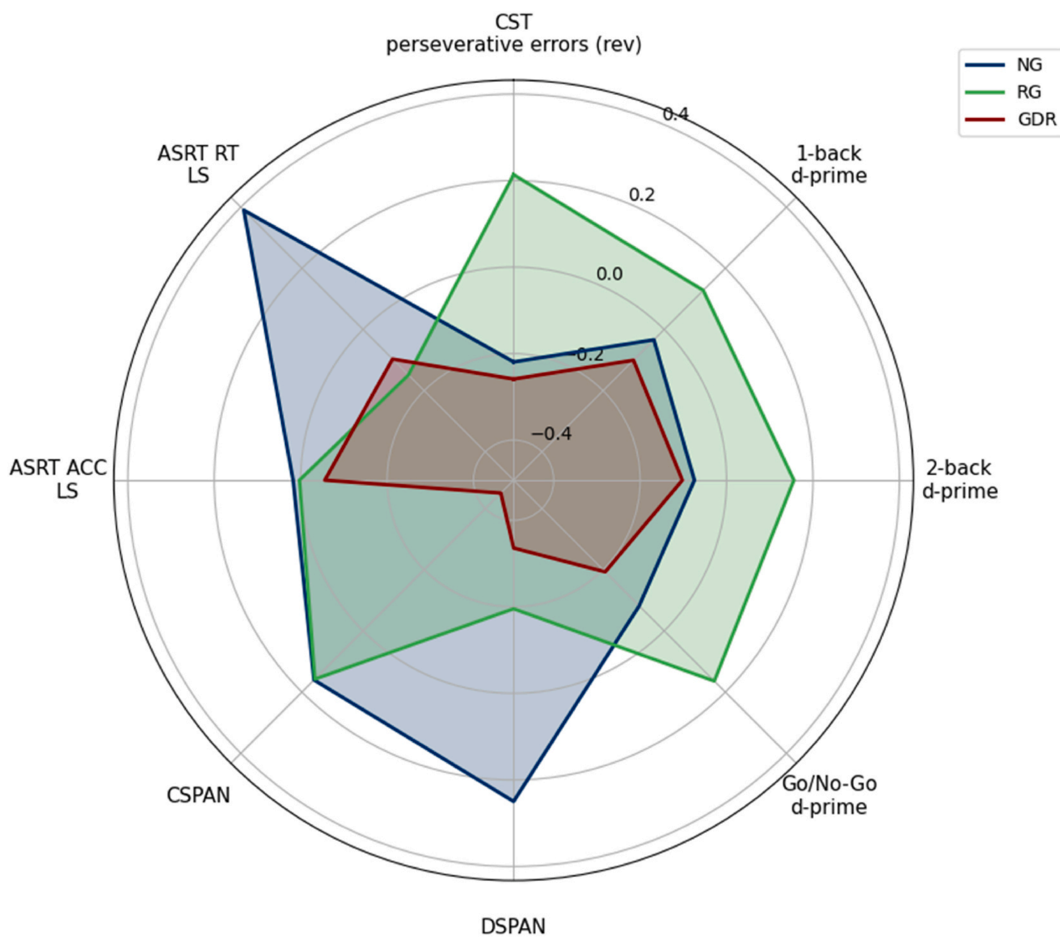

Fig. 7. Cognitive profiles of the non-gamer (NG), recreational gamer (RG), and gaming disorder risk (GDR) groups. *Note.* This radar plot displays standardized residual scores from various cognitive tasks, including the Card Sorting Test (CST), 1-back (d-prime), 2-back (d-prime), Go/No-Go (d-prime), Digit Span (DSPAN), Complex Span (CSPAN), and learning scores from the Alternating Serial Reaction Time task (ASRT): Accuracy Learning Score (ACC LS) and Reaction Time Learning Score (RT LS). The plot compares cognitive profiles of non-gamers (NG), recreational gamers (RG), and individuals at risk for Gaming Disorder (GDR). For the CST, the number of perseverative errors was used as the performance indicator. As lower error counts indicate better performance, these values were reverse-coded so that higher values consistently reflect better cognitive functioning across all axes.

3.7. Factor analysis of executive function tasks

A detailed factor analysis of executive function (EF) tasks is presented in Supplementary Materials S6. Briefly, parallel analysis supported a two-factor solution, explaining 35 % of the total variance. The first factor reflected simple working memory capacity (CSPAN, DSPAN), while the second factor was primarily associated with complex working memory and inhibition tasks (1-back, 2-back, Go/No-Go). CST did not load strongly on either factor. Factor scores derived from this solution were used in the subsequent analyses (see details in Table 5 and Supplementary Materials S6).

3.8. Comparison of executive function factors between the groups

For EF1, which was primarily loaded on CSPAN, and DSPAN tasks, a significant group difference was observed (F(2,83) = 6.08, $p = .003$, η_p^2

Table 5
Factor loadings and communalities of each EF measure in the two factor varimax rotated solution.

	Factor 1	Factor 2	Communality
CST	.27	.02	.06
1-back	.04	**.46**	.20
2-back	.28	**.52**	.37
Go/No-Go	.01	**.70**	.47
CSPAN	**.98**	.19	.87
DSPAN	**.32**	.04	.14

Note. Loadings above .30 are highlighted in bold to aid interpretation.

= .035). Specifically, the GDR group performed significantly worse on this factor compared to both the NG and RG groups, while no significant difference was found between the NG and RG groups. In contrast, no significant group differences emerged for EF2 ($F(2,86) = 1.92$, $p = .153$, $\eta_p^2 = .042$), which was primarily associated with the Go/No-Go, 1-back, and 2-back tasks (see details in Table 2).

3.9. *Implicit sequence learning and executive functions in the three groups*

The detailed results of the GLMMs examining the interaction between implicit sequence learning and executive functions across the three groups are presented in Supplementary Materials S7. In summary, in the models using RT-based implicit sequence learning scores, the results suggest that overall visuomotor performance was comparable between the groups, and that competition between EF2 and implicit sequence learning was stronger in the RG group than in either the NG or GDR groups.

In the models using accuracy-based implicit sequence learning scores, EF1 scores were unrelated to overall accuracy. Instead, they were positively associated with implicit sequence learning ability in the NG and GDR groups, with no such association in the RG group. EF2 scores were associated with better overall accuracy only in the GDR group and showed a generally negative relationship with implicit sequence learning across all groups.

4. Discussion

Although many individuals can regulate their gaming habits, some experience such a profound loss of control that it becomes a central issue in their lives, manifesting as behavioral addiction. To better understand the cognitive mechanisms underlying these differing gaming habits, we examined executive functions, implicit sequence learning, and how these processes interact. Our findings revealed selective executive function impairments in individuals at risk for gaming disorder, particularly reduced working memory capacity and more impulsive response tendencies, reflected in higher false alarm rates. In contrast, recreational gamers showed enhanced attention control, suggesting potential cognitive benefits of non-problematic gaming. No significant group differences emerged in working memory updating, inhibitory control, or cognitive flexibility, and implicit sequence learning appeared comparable across groups. However, the relationship between executive control and implicit sequence learning varied across groups. To the best of our knowledge, this is the first study to compare comprehensive cognitive profiles—including both executive functioning and implicit sequence learning, as well as their interaction—across non-gamers, recreational gamers, and individuals at risk for gaming disorder.

4.1. *Executive functions*

In line with our hypotheses, the gaming disorder risk group performed significantly worse than the non-gamer group on the short-term memory task, and worse on the complex working memory task than the other two groups. Importantly, these tasks primarily assess the storage function of working memory (Case et al., 1982; Racsmány et al., 2006). In tasks measuring the updating component, such as the 1-back and the 2-back tasks, no group differences were found (Ragland et al., 2002). These findings indicate that gaming disorder is associated with decreased working memory capacity, specifically related to storage processes. However, the lack of differences between recreational gamers and non-gamers suggests that gaming, in the absence of addiction, possibly is not related to impaired working memory performance. This result aligns with previous research summarized in the review by Ngetich et al. (2023), which highlights working memory impairments in gaming disorder, similar to those reported in other behavioral addictions such as gambling disorder, compulsive buying disorder, and work addiction (Berta et al., 2023; Derbyshire et al., 2014; Ngetich et al., 2023). While models of behavioral addictions (Brand et al., 2016, 2019; Dong & Potenza, 2014) primarily emphasize inhibitory control, recent interpretations of the I-PACE model by Brand et al. (2016, 2019, 2025) suggest that other executive function domains may also play a role in addictive behaviors. Although working memory is not explicitly listed in these models, our results suggest that its specific processes may be affected in gaming disorder.

Although no significant group differences were found in overall performance on the n-back tasks, the analysis of error types revealed a more nuanced picture. Specifically, performance on the 1-back task showed a higher number of false alarms in the gaming disorder risk group compared to the recreational gamer group. Although this is a relatively simple working memory task, a high false alarm rate without a correspondingly high hit rate may reflect increased behavioral impulsivity (Bezdjian et al., 2009). This finding is especially relevant in light of the potential dual nature of gaming effects: while gaming may enhance stimulus detection and response accuracy, gaming disorder may be accompanied by more impulsive response styles that counteract these benefits. This pattern may also be important considering that such impulsive behavior and lack of self-control could contribute to the difficulty in resisting the urge to play (Warburton et al., 2022).

Contrary to our initial hypothesis, no significant differences were observed between the groups in inhibitory control, as assessed by the d-prime score in the Go/No-Go task (Hinton, 2015). This finding contradicts previous research, which has consistently shown a link between gaming disorder and impaired inhibitory control (Argyriou et al., 2017). Theoretical frameworks (Brand et al., 2016, 2019; Dong & Potenza, 2014) emphasize the central role of inhibitory control in gaming disorder. Importantly, the I-PACE model (Brand et al., 2016, 2019, 2025) highlights not only general inhibitory control but also the influence of reward-related processes, especially in later stages of addiction. That inhibitory control impairments are most likely to emerge in the presence of addiction-related cues is supported by findings showing that results with neutral stimuli are often inconsistent (Lorenz et al., 2013; Maleki et al., 2024; Yao et al., 2015). These considerations underscore the importance of incorporating both neutral and addiction-specific stimuli (e.g., images from video games) within the same paradigm in future studies to more accurately capture context-dependent impairments in inhibitory control. It is also important to note that, since most cognitive tasks are performed on computers, the testing environment itself may serve as a game-related cue—particularly for individuals at risk for gaming disorder. Therefore, identifying alternative methods, such as virtual reality (VR), could help mitigate attentional biases triggered by addiction-related cues and also provide a more ecologically valid environment for assessing executive functions.

Although no significant differences were observed in the Go/No-Go's d-prime score, a notable difference was found in the hit rate, with the recreational gaming group demonstrating a significantly higher rate compared to the non-gamer group. This result, while not conclusive for superior inhibitory functioning, may suggest enhanced response readiness and attentional control in the recreational gaming group (Eimer, 1993). This finding aligns with prior research suggesting that video game play can improve attentional processing and visuospatial abilities (Stanmore et al., 2017). An alternative explanation is that video games may not enhance cognitive abilities per se, but rather individuals with higher baseline cognitive skills are more likely to engage in gaming (Waris et al., 2019). Their superior performance may lead to more frequent positive reinforcement during gaming, which in turn increases their motivation to continue playing. However, it is interesting that this result did not appear in the gaming disorder risk group, who also have gaming experience, suggesting that gaming experience alone may not account for the differences observed. Instead, these findings point to the possibility that the cognitive benefits of video gaming—such as enhanced attentional control—may be present only in the context of non-problematic use and may diminish or disappear when gaming becomes problematic. It is also possible that in cases where gaming becomes problematic, other factors—such as sleep deprivation, or stress resulting from conflicts related to gaming—may negatively impact inhibitory functions (Choong et al., 2025; Roos et al., 2017). While these explanations remain speculative, clarifying the direction and causality of these relationships would require longitudinal studies to better understand how cognitive functioning evolves in relation to gaming behavior over time.

Contrary to our initial hypothesis, the results of the Card Sorting Test showed no significant differences in cognitive flexibility between the groups, suggesting that this executive function may not be linked to either recreational gaming or gaming disorder. While the recreational gaming group exhibited the fewest perseverative errors, this trend did not reach statistical significance, indicating a subtle pattern that may merit further investigation. These findings are particularly interesting in light of previous studies that reported reduced cognitive flexibility in individuals with gaming disorder (Jeong et al., 2016; Jiang et al., 2020) relied on clinically diagnosed samples. In contrast, one study using self-reported questionnaires (Ryu et al., 2021) found no behavioral-level differences in cognitive flexibility—only neural-level alterations. While it is possible that cognitive flexibility is a relatively preserved function in individuals with gaming disorder, these inconsistencies also point to the potential moderating role of clinical severity and diagnostic approach. Therefore, future studies should further explore whether impairments in cognitive flexibility are more pronounced in clinically diagnosed populations or under more demanding task conditions.

To complement the task-level analyses, we conducted a factor analysis, which revealed two factors: one reflecting storage functions (DSPAN, CSPAN) and another reflecting updating and inhibition (1-back, 2-back, Go/No-Go). The Card Sorting test did not load on either factor. Consistent with the task-level results, only the storage-related factor showed group differences, with the high-risk gaming disorder group performing worse than both recreational gamers and non-gamers, who did not differ from each other, which suggest that impairments in gaming disorder are most pronounced in working memory capacity, particularly in storage functions. These findings highlight that basic functions such as executive functions may be selectively affected, which in itself could be sufficient to contribute to the underperformance of higher-level goal-directed processes, consistent with dual-system models that emphasize such impairments (Everitt & Robbins, 2016; Furlong & Corbit, 2018; McKim & Boettiger, 2015).

4.2. Implicit sequence learning

Contrary to our hypotheses, neither gaming disorder nor recreational gaming was found to be associated with enhanced implicit sequence learning. Though Romano Bergstrom et al. (2012) found improved sequence learning on the ASRT task among video game players, their sample was limited to university students, which may indicate that gaming's benefits on implicit sequence learning are more pronounced in younger populations. Notably, their educational context and associated life circumstances might have facilitated the emergence of the effects they observed. In our sample, despite the absence of enhanced implicit sequence learning in the gamer groups, there was a significant group difference in general reaction times. However, this effect was not robust enough to remain significant in the post hoc comparisons. Still, the effect sizes indicated notable differences between the non-gamer and both recreational gamer and gaming disorder risk groups, with the gamer groups showing faster reaction times. These faster responses were independent of sequence learning and were not accompanied by a decline in accuracy, suggesting potential benefits of gaming for visuomotor processing, even in cases of problematic gaming (Stanmore et al., 2017). This finding is consistent with our results from the Go/No-Go task, where recreational gaming was linked to improved attentional control, supporting the idea that recreational gamers may experience advantages in attentional abilities and processing speed.

Interestingly, we did not observe enhanced implicit sequence learning in the gaming disorder risk group, despite previous research suggesting an over-reliance on habitual processes in individuals with gaming disorder (W. Zhou et al., 2021). Notably, these earlier findings were based on instrumental learning tasks, which capture different aspects of habit formation. In contrast, the ASRT task used in the present study measures implicit sequence learning—a specific facet of habitual functioning—which, according to our results, may remain intact in individuals with gaming disorder (Horváth et al., 2022). This is consistent with findings from work addiction, where no enhancement in implicit sequence learning was observed despite the presumed role of habit-oriented processes (Pesthy et al., 2025) and may suggest that this pattern extends to other behavioral addictions as well. Our results challenge dual-system models that propose a simple, monolithic "habitual system" that is uniformly enhanced in addiction, and instead point toward the involvement of more supervised, reward-driven processes. Brand et al. (2025) also emphasize that the role of habitual processes in addiction is debated, and that these processes alone are not necessarily dominant. They further note that addictive behaviors may appear habitual while still operating under goal-directed control, as habitual tendencies are likely linked to specific goals that can be automatically triggered by external cues or internal states such as stress or low mood. This could explain why we did not find differences between the groups, as habitual processes alone—such as those reflected in implicit sequence learning—may not be dominant in gaming disorder.

4.3. Interaction between executive function factors and implicit sequence learning

To investigate the relationship between executive functions and implicit sequence learning, we examined how the two executive function-related factors—EF1 and EF2—were associated with implicit sequence learning scores across the three groups. While no significant group differences emerged in overall implicit sequence learning performance, the analysis of the two cognitive systems revealed several noteworthy patterns, underscoring complex, group-specific interactions.

Supporting the competition theory (Pedraza et al., 2024; Poldrack & Packard, 2003), we found a negative relationship between implicit sequence learning and EF2—the factor primarily loading on inhibitory control and the updating component of working memory—across all three groups, regardless of gaming habits or risk for behavioral addiction. A similar pattern was reported by Virag et al. (2015), who also found a negative association between executive functions and implicit sequence learning in both healthy controls and individuals with alcohol dependence. Their findings also support the notion of a competitive interaction: when prefrontal cortex–related regulatory processes are weaker, habit-based mechanisms such as implicit sequence learning tend to become more dominant. It is worth noting that these competitive patterns appeared only in models that used the implicit sequence learning score based on reaction time. In the case of accuracy, a negative relationship with implicit sequence learning was only found among recreational gamers, and only at certain points during the task. This suggests that accuracy- and reaction time-based measures in the ASRT task may reflect different cognitive processes (Janacsek et al., 2012; Kiss et al., 2022; Mulder & Van Maanen, 2013).

Interestingly, for the other factor which comprises tasks measuring working memory storage, a positive association between implicit sequence learning and EF1 emerged specifically in the non-gaming and gaming disorder risk groups, but not in the recreational gaming group. This raises the question of why both non-gamers and individuals at risk of gaming disorder showed a similar positive association between working memory storage and implicit sequence learning, even though group comparisons revealed significantly lower EF1 performance among those at gaming disorder risk. This discrepancy suggests that, although the relationship between cognitive processes appears similar, their underlying functioning may differ—possibly due to the engagement of different compensatory mechanisms.

One potential explanation is that working memory capacity, particularly its role in attentional resource allocation and the detection of recurring patterns, may facilitate implicit sequence learning under certain conditions. Although working memory is typically thought to aid performance in tasks with explicit learning components (Janacsek & Nemeth, 2013), previous research has shown that it may also contribute to learning in predominantly implicit contexts (Bo et al., 2012)—a possibility consistent with our findings. From this perspective, individuals with higher working memory capacity in both the non-gamer and gaming disorder risk groups may have been better able to allocate cognitive resources, thereby supporting improved task performance. These findings align with the suggestion by Pedraza et al. (2024) that it is not working memory capacity per se, but rather the updating and long-term retrieval components that interfere with implicit sequence learning. We speculate about the meaning of this dissociation. Specifically, we suggest that executive control (EF2) competes with the speed of habitual responding, whereas working memory capacity (EF1) supports the accuracy of implicit learning. However, more targeted studies are warranted to empirically validate this theoretical perspective.

Taken together, these findings suggest that while the competitive relationship between specific executive functions (EF2) and habit-based processes appears to be a generalizable feature of cognitive functioning—independent of gaming habits or behavioral addiction risk—there are also group-specific interactions involving working memory storage (EF1). In particular, the positive relationship between EF1 and implicit sequence learning in the non-gaming and gaming disorder risk groups may reflect compensatory mechanisms that support implicit sequence learning when working memory resources are available. A more in-depth analysis—especially at the neural level—could provide valuable insights into the mechanisms of implicit sequence learning and executive functions, offering a more complete understanding of how these interactions play out across different groups and individual profiles. However, it is important to note that executive functions and implicit sequence learning operate at different levels of cognitive processing, which means that they should be viewed as interacting but non-symmetric mechanisms.

4.4. Limitations

When interpreting our findings, it is important to consider the limitations of this study. Although the IGDT-10 questionnaire, which we used for group classification, is a widely used and reliable assessment tool based on DSM-5 criteria (Király et al., 2019; Yoon et al., 2021), it does not have standalone diagnostic value. Therefore, we cannot definitively determine whether participants met the clinical criteria for gaming disorder; we can only infer that they exhibited a high risk of it. Moreover, as the IGDT-10 is a self-report questionnaire, the lack of self-awareness and the influence of social desirability may distort participants' responses. In addition, we did not assess the duration of the reported symptoms, which limits our ability to evaluate their clinical significance. Future studies should also consider evaluating the types of video games participants engage with, as different genres have been linked to improvements in distinct cognitive domains (Deleuze et al., 2017; Hong et al., 2022).

An important open question remains whether gaming induces changes in cognitive functioning, whether individuals with pre-existing cognitive strengths are more likely to engage in gaming, or whether cognitive deficits are exacerbated in the case of gaming disorder (Waris et al., 2019). Since our study employed a cross-sectional design, longitudinal research is needed to clarify these directional relationships by tracking cognitive changes over time. Given the particular relevance of decision-making and emotional regulation in gaming disorder (Estupiñá et al., 2024; Schiebener & Brand, 2017), future studies should examine these higher-order functions in individuals with gaming disorder, comparing them with recreational gamers to clarify which differences are characteristic of recreational gaming and which tend to co-occur with addictive patterns. Finally, we acknowledge that the relatively small sample size and the use of convenience sampling limit the statistical power and generalizability of the present findings. Although increasing the sample size was not feasible in the current study, future research should aim to replicate and extend these results using larger and more diverse samples, ideally recruited through more representative sampling methods, to confirm the robustness and external validity of the observed associations.

4.5. Conclusions

This was the first study to comprehensively examine the cognitive profiles of individuals at risk of gaming disorder, recreational gamers, and non-gamers, offering new insights into how gaming habits relate to cognitive functioning. Importantly, our analyses controlled for weekly gaming time, ensuring that the observed differences reflect addiction-related patterns rather than the amount of time spent gaming. Our findings indicate that playing video games regularly in itself is not linked to cognitive difficulties. Instead, it is the presence of problematic, addictive gaming patterns that is associated with cognitive underperformance—particularly in working memory and impulse control—differentiating those at risk of gaming disorder from recreational gamers. In contrast, recreational gamers showed enhanced attentional control, indicating potential cognitive benefits of non-problematic gaming. Notably, we moved beyond examining executive functions in isolation by highlighting their potentially competitive relationship with implicit sequence learning. This interaction varied across groups, reflecting how individual gaming habits shape cognitive functioning. These results highlight the importance of not demonizing regular gaming itself but rather focusing on identifying and addressing maladaptive patterns that distinguish recreational gaming from gaming disorder. By mapping these distinct cognitive characteristics, our study advances a more nuanced, functional understanding of gaming behavior and lays a foundation for targeted interventions.

CRediT authorship contribution statement

Krisztina Berta: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Visualization, Writing – original draft. **Zsuzsanna Viktória Pesthy:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Visualization, Writing – original draft. **Teodóra Vékony:** Formal analysis, Software, Supervision, Methodology, Writing – review & editing. **Bence Csaba Farkas:** Formal analysis, Methodology, Writing – review & editing. **Orsolya Király:** Conceptualization, Writing – review & editing. **Zsolt Demetrovics:** Conceptualization, Writing – review & editing. **Dezső Németh:** Conceptualization, Funding acquisition, Formal analysis, Methodology, Resources, Supervision, Writing – review & editing. **Bernadette Kun:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of generative AI use

In the preparation of this manuscript, ChatGPT was used for language and grammar editing to improve clarity and readability. All intellectual content, data analysis, and conclusions are the sole responsibility of the authors.

Funding

This research was supported by the ANR grants awarded (Grant numbers: ANR-22-CPJ1–0042; ANR-24-CE37-5807); the National Brain Research Program by Hungarian Academy of Sciences (project NAP2022-I-1/2022); and the Hungarian National Research, Development and Innovation Office (Grant numbers: K128016, FK134807, and STARTING 150089) and by the ÚNKP-23–2 New National Excellence Program and the EKÖP-24University Excellence Scholarship Program of the Ministry for Culture and Innovation from the source of the National Research, Development and Innovation Fund. Bernadette Kun and Orsolya Király were supported by the the János Bolyai Research Scholarship of the Hungarian Academy of Sciences; nos Bolyai Research Scholarship of the Hungarian Academy of Sciences.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108878.

Data availability

All data are available at the following link: https://osf.io/2658w/?view_only=52521253360f423998eb7c0a3b00d978.

References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders: DSM-5* (5th ed.). American Psychiatric Association.

Argyriou, E., Davison, C. B., & Lee, T. T. C. (2017). Response inhibition and internet gaming disorder: A meta-analysis. *Addictive Behaviors, 71*, 54–60. https://doi.org/10.1016/j.addbeh.2017.02.026

Armstrong, B. C., Frost, R., & Christiansen, M. H. (2017). The long road of statistical learning research: Past, present and future. *Philosophical Transactions of the Royal Society B: Biological Sciences, 372*(1711). https://doi.org/10.1098/rstb.2016.0047. Article 1711.

Berg, E. A. (1948). A simple objective technique for measuring flexibility in thinking. *The Journal of General Psychology, 39*(1). https://doi.org/10.1080/00221309.1948.9918159. Article 1.

Berta, K., Pesthy, Z. V., Vékony, T., Farkas, B. C., Németh, D., & Kun, B. (2023). The neuropsychological profile of work addiction. *Scientific Reports, 13*(1). https://doi.org/10.1038/s41598-023-47515-9. Article 1.

Bezdjian, S., Baker, L. A., Lozano, D. I., & Raine, A. (2009). Assessing inattention and impulsivity in children during the Go/NoGo task. *British Journal of Developmental Psychology, 27*(2). https://doi.org/10.1348/026151008X314919. Article 2.

Bo, J., Jennett, S., & Seidler, R. D. (2012). Differential working memory correlates for implicit sequence performance in young and older adults. *Experimental Brain Research, 221*(4), 467–477. https://doi.org/10.1007/s00221-012-3189-2

Brand, M., Müller, A., Wegmann, E., Antons, S., Brandtner, A., Müller, S. M., Stark, R., Steins-Loeber, S., & Potenza, M. N. (2025). Current interpretations of the I-PACE model of behavioral addictions. *Journal of Behavioral Addictions, 14*(1), 1–17. https://doi.org/10.1556/2006.2025.00020

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The interaction of person-affect-cognition-execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews, 104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific internet-use disorders: An interaction of person-affect-cognition-execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews, 71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033

Case, R., Kurland, D. M., & Goldberg, J. (1982). Operational efficiency and the growth of short-term memory span. *Journal of Experimental Child Psychology, 33*(3). https://doi.org/10.1016/0022-0965(82)90054-6. Article 3.

Choong, S. Y., Byrne, J. E. M., Drummond, S. P. A., Rispoli-Yovanovic, M., Jones, A., Lum, J. A. G., & Staiger, P. K. (2025). A meta-analytic investigation of the effect of sleep deprivation on inhibitory control. *Sleep Medicine Reviews, 80*, Article 102042. https://doi.org/10.1016/j.smrv.2024.102042

Colzato, L. S., Van Den Wildenberg, W. P. M., Zmigrod, S., & Hommel, B. (2013). Action video gaming and cognitive control: Playing first person shooter games is associated with improvement in working memory but not action inhibition. *Psychological Research, 77*(2). https://doi.org/10.1007/s00426-012-0415-2. Article 2.

Conway, C. M., & Pisoni, D. B. (2008). Neurocognitive basis of implicit learning of sequential structure and its relation to language processing. *Annals of the New York Academy of Sciences, 1145*(1), 113–131. https://doi.org/10.1196/annals.1416.009

Cudo, A., Kopiś-Posiej, N., Zabielska-Mendyk, E., & Griffiths, M. D. (2025). Association between gaming disorder, action videogames, working memory capacity and cognitive control. *International Journal of Mental Health and Addiction*. https://doi.org/10.1007/s11469-024-01429-3

de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a web browser. *Behavior Research Methods, 47*(1). https://doi.org/10.3758/s13428-014-0458-y. Article 1.

Deleuze, J., Christiaens, M., Nuyens, F., & Billieux, J. (2017). Shoot at first sight! first person shooter players display reduced reaction time and compromised inhibitory control in comparison to other video game players. *Computers in Human Behavior, 72*, 570–576. https://doi.org/10.1016/j.chb.2017.02.027

Derbyshire, K. L., Chamberlain, S. R., Odlaug, B. L., Schreiber, L. R., & Grant, J. E. (2014). *Neurocognitive functioning in compulsive buying disorder, 26*(1). No. 1.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135–168.

Ding, W., Sun, J., Sun, Y.-W., Chen, X., Zhou, Y., Zhuang, Z., Li, L., Zhang, Y., Xu, J., & Du, Y. (2014). Trait impulsivity and impaired prefrontal impulse inhibition function in adolescents with internet gaming addiction revealed by a Go/No-Go fMRI study. *Behavioral and Brain Functions: BBF, 10*, 20. https://doi.org/10.1186/1744-9081-10-20

Doñamayor, N., Ebrahimi, C., Arndt, V. A., Weiss, F., Schlagenhauf, F., & Endrass, T. (2022). Goal-directed and habitual control in human substance use: State of the art and future directions. *Neuropsychobiology, 81*(5). https://doi.org/10.1159/000527663. Article 5.

Dong, G., Li, H., Wang, L., & Potenza, M. N. (2017). Cognitive control and reward/loss processing in internet gaming disorder: Results from a comparison with recreational internet game-users. *European Psychiatry, 44*, 30–38. https://doi.org/10.1016/j.eurpsy.2017.03.004

Dong, G., & Potenza, M. N. (2014). A cognitive-behavioral model of internet gaming disorder: Theoretical underpinnings and clinical implications. *Journal of Psychiatric Research, 58*, 7–11. https://doi.org/10.1016/j.jpsychires.2014.07.005

Eimer, M. (1993). Effects of attention and stimulus probability on ERPs in a Go/Nogo task. *Biological Psychology, 35*(2). https://doi.org/10.1016/0301-0511(93)90009-W. Article 2.

Estupiñá, F. J., Bernaldo-de-Quirós, M., Vallejo-Achón, M., Fernández-Arias, I., & Labrador, F. (2024). Emotional regulation in gaming disorder: A systematic review. *American Journal on Addictions, 33*(6), 605–620. https://doi.org/10.1111/ajad.13621

Everitt, B. J., & Robbins, T. W. (2016). Drug addiction: Updating actions to habits to compulsions ten years on. *Annual Review of Psychology, 67*(1). https://doi.org/10.1146/annurev-psych-122414-033457. Article 1.

Fox, C. J., Mueller, S. T., Gray, H. M., Raber, J., & Piper, B. J. (2013). Evaluation of a short-form of the berg card sorting test. *PLoS One, 8*(5). https://doi.org/10.1371/journal.pone.0063885. Article 5.

Furlong, T. M., & Corbit, L. H. (2018). Drug addiction. In *Goal-directed decision making* (pp. 367–386). Elsevier. https://doi.org/10.1016/B978-0-12-812098-9.00016-4.

Hinton, K. E. (2015). *Go/No-Go performance is related to white matter microstructure in a broad range of regions* [Thesis]. https://ir.vanderbilt.edu/handle/1803/13090.

Hong, D. H., Lee, J., Oh, D., Park, S., Yoo, S. Y., & Choi, J. (2022). Differential resting-state neurophysiological activity associated with game usage patterns and genres in internet gaming disorder. *Addiction Biology, 27*(5). https://doi.org/10.1111/adb.13213. Article 5.

Horváth, K., Nemeth, D., & Janacsek, K. (2022). Inhibitory control hinders habit change. *Scientific Reports, 12*(1). https://doi.org/10.1038/s41598-022-11971-6. Article 1.

Howard, J. H., & Howard, D. V. (1997). Age differences in implicit learning of higher order dependencies in serial patterns. *Psychology and Aging, 12*(4). Article 4.

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering, 9*(3). https://doi.org/10.1109/MCSE.2007.55. Article 3.

IBM Corp. (2021). *IBM SPSS statistics for windows, version 28.0. armonk, NY*. IBM Corp [Computer software].

Jacobs, J. (1887). Experiments ON "prehension.". *Mind, os, 12*(45). https://doi.org/10.1093/mind/os-12.45.75. Article 45.

Janacsek, K., Fiser, J., & Nemeth, D. (2012). The best time to acquire new skills: Age-related differences in implicit sequence learning across the human lifespan. *Developmental Science, 15*(4). https://doi.org/10.1111/j.1467-7687.2012.01150.x. Article 4.

Janacsek, K., & Nemeth, D. (2013). Implicit sequence learning and working memory: Correlated or complicated? *Cortex, 49*(8), 2001–2006. https://doi.org/10.1016/j.cortex.2013.02.012

JASP Team. (2024). Jasp *[Computer software]* Version 0.18.3. https://jasp-stats.org/.

Jeong, B. S., Han, D. H., Kim, S. M., Lee, S. W., & Renshaw, P. F. (2016). White matter connectivity and internet gaming disorder. *Addiction Biology, 21*(3). https://doi.org/10.1111/adb.12246. Article 3.

Jeromin, F., Rief, W., & Barke, A. (2016). Using two web-based addiction Stroops to measure the attentional bias in adults with internet gaming disorder. *Journal of Behavioral Addictions, 5*(4), 666–673. https://doi.org/10.1556/2006.5.2016.075

Jiang, C., Li, C., Zhou, H., & Zhou, Z. (2020). Individuals with internet gaming disorder have similar neurocognitive impairments and social cognitive dysfunctions as methamphetamine-dependent patients. *Adicciones, 1342*.

Katz, D., Horváth, Z., Pontes, H. M., Koncz, P., Demetrovics, Z., & Király, O. (2024). How much gaming is too much? An analysis based on psychological distress. *Journal of Behavioral Addictions, 13*(3), 716–728. https://doi.org/10.1556/2006.2024.00036

Király, O., Bőthe, B., Ramos-Diaz, J., Rahimi-Movaghar, A., Lukavska, K., Hrabec, O., Miovsky, M., Billieux, J., Deleuze, J., Nuyens, F., Karila, L., Griffiths, M. D., Nagygyörgy, K., Urbán, R., Potenza, M. N., King, D. L., Rumpf, H.-J., Carragher, N., & Demetrovics, Z. (2019). Ten-Item Internet Gaming Disorder Test (IGDT-10): Measurement invariance and cross-cultural validation across seven language-based samples. *Psychology of Addictive Behaviors, 33*(1). https://doi.org/10.1037/adb0000433. Article 1.

Király, O., Koncz, P., Griffiths, M. D., & Demetrovics, Z. (2023). Gaming disorder: A summary of its characteristics and aetiology. *Comprehensive Psychiatry, 122*, Article 152376. https://doi.org/10.1016/j.comppsych.2023.152376

Király, O., Sleczka, P., Pontes, H. M., Urbán, R., Griffiths, M. D., & Demetrovics, Z. (2017). Validation of the ten-item internet gaming disorder test (IGDT-10) and evaluation of the nine DSM-5 internet gaming disorder criteria. *Addictive Behaviors, 64*, 253–260. https://doi.org/10.1016/j.addbeh.2015.11.005

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. *Journal of Experimental Psychology, 55*(4). https://doi.org/10.1037/h0043688. Article 4.

Kiss, M., Nemeth, D., & Janacsek, K. (2022). Do temporal factors affect whether our performance accurately reflects our underlying knowledge? The effects of stimulus presentation rates on the performance versus competence dissociation. *Cortex, 157*, 65–80. https://doi.org/10.1016/j.cortex.2022.09.003

Kun, B., Urbán, R., Bőthe, B., Griffiths, M. D., Demetrovics, Z., & Kökönyei, G. (2020). Maladaptive Rumination Mediates the Relationship between Self-Esteem, Perfectionism, and Work Addiction: A Largescale Survey Study. *International journal of environmental research and public health, 17*(19), 7332. https://doi.org/10.3390/ijerph17197332

Kwon, M., Choi, H., Park, H., Ahn, W.-Y., & Jung, Y.-C. (2024). Neural correlates of model-based behavior in internet gaming disorder and alcohol use disorder. *Journal of Behavioral Addictions, 13*(1), 236–249. https://doi.org/10.1556/2006.2024.00006

Lei, W., Huang, Y., Peng, Y., Chen, G., Gong, K., Liu, K., Wu, D., Qin, C., Cheng, X., Tian, M., Zhang, L., Zhou, Y., Yu, R., & Chen, J. (2025). Imbalanced goal-directed and habitual control in individuals with internet gaming disorder. *Journal of Behavioral Addictions*. https://doi.org/10.1556/2006.2025.00037

Lorenz, R. C., Krüger, J., Neumann, B., Schott, B. H., Kaufmann, C., Heinz, A., & Wüstenberg, T. (2013). Cue reactivity and its inhibition in pathological computer game players. *Addiction Biology, 18*(1). https://doi.org/10.1111/j.1369-1600.2012.00491.x. Article 1.

Maleki, F., Shakiba, S., Dolatshahi, B., Yoosefi, A., & Jamialahmadi, S. (2024). Cognitive profiling of internet gaming disorder: Distinguishing factors between problematic, recreational, and non-gaming individuals. *Current Psychology, 43*(48), 37154–37166. https://doi.org/10.1007/s12144-024-07140-9

McKim, T. H., & Boettiger, C. A. (2015). Addiction as maladaptive learning, with a focus on habit learning. In S. J. Wilson (Ed.), *The wiley handbook on the cognitive neuroscience of addiction* (1st ed., pp. 1–28). Wiley. https://doi.org/10.1002/9781118472415.ch1.

McKinney, W. (2010). Data structures for statistical computing in python. *Proceedings of the 9th Python in Science Conference, 445*(1), 51–56.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The Unity and diversity of executive functions and their contributions to complex "Frontal Lobe" tasks: A latent variable analysis. *Cognitive Psychology, 41*(1). https://doi.org/10.1006/cogp.1999.0734. Article 1.

Mukherjee, C., & Banerjee, U. (2022). A comparative study of executive functioning and personality of young adults with alcohol use disorder and internet gaming disorder. *Mind & Society, 11*(2). https://doi.org/10.56011/mind-mri-112-202210. Article 02.

Mulder, M. J., & Van Maanen, L. (2013). Are accuracy and reaction time affected via different processes? *PLoS One, 8*(11), Article e80222. https://doi.org/10.1371/journal.pone.0080222

Ngetich, R., Burleigh, T. L., Czakó, A., Vékony, T., Németh, D., & Demetrovics, Z. (2023). Working memory performance in disordered gambling and gaming: A systematic review. *Comprehensive Psychiatry, 126*, Article 152408. https://doi.org/10.1016/j.comppsych.2023.152408

Ostlund, S. B., & Balleine, B. W. (2008). On habits and addiction: An associative analysis of compulsive drug seeking. *Drug Discovery Today: Disease Models, 5*(4). https://doi.org/10.1016/j.ddmod.2009.07.004. Article 4.

Pedraza, F., Farkas, B. C., Vékony, T., Haesebaert, F., Phelipon, R., Mihalecz, I., Janacsek, K., Anders, R., Tillmann, B., Plancher, G., & Németh, D. (2024). Evidence for a competitive relationship between executive functions and statistical learning. *Npj Science of Learning, 9*(1). https://doi.org/10.1038/s41539-024-00243-9. Article 1.

Pesthy, Z. V., Berta, K., Vékony, T., Németh, D., & Kun, B. (2025). Intact habit learning in work addiction: Evidence from a probabilistic sequence learning task. *Addictive Behaviors Reports, 21*, Article 100589. https://doi.org/10.1016/j.abrep.2025.100589

Poldrack, R. A., & Packard, M. G. (2003). Competition among multiple memory systems: Converging evidence from animal and human brain studies. *Neuropsychologia, 41*(3), 245–251. https://doi.org/10.1016/S0028-3932(02)00157-4

Racsmány, M., Lukács, Á., Németh, D., & Pléh, C. (2006). A verbális munkamemória magyar nyelvű vizsgálóeljárásai. *Magyar Pszichológiai Szemle, 60*(4). https://doi.org/10.1556/mpszle.60.2005.4.3. Article 4.

Ragland, J. D., Turetsky, B. I., Gur, R. C., Gunning-Dixon, F., Turner, T., Schroeder, L., Chan, R., & Gur, R. E. (2002). Working memory for complex figures: An fMRI comparison of letter and fractal n-back tasks. *Neuropsychology, 16*(3). https://doi.org/10.1037/0894-4105.16.3.370. Article 3.

Redick, T. S., & Lindsey, D. R. B. (2013). Complex span and n-back measures of working memory: A meta-analysis. *Psychonomic Bulletin & Review, 20*(6). https://doi.org/10.3758/s13423-013-0453-9. Article 6.

Romano Bergstrom, J. C., Howard, J. H., & Howard, D. V. (2012). Enhanced implicit sequence learning in college-age video game players and musicians. *Applied Cognitive Psychology, 26*(1). https://doi.org/10.1002/acp.1800. Article 1.

Roos, L. E., Knight, E. L., Beauchamp, K. G., Berkman, E. T., Faraday, K., Hyslop, K., & Fisher, P. A. (2017). Acute stress impairs inhibitory control based on individual differences in parasympathetic nervous system activity. *Biological Psychology, 125*, 58–63. https://doi.org/10.1016/j.biopsycho.2017.03.004

Ryu, K., Kim, Y., Kim, J., & Woo, M. (2021). False accusation of online games: Internet gaming can enhance the cognitive flexibility of adolescents. *Asian Journal of Sport and Exercise Psychology, 1*(2–3), 116–121. https://doi.org/10.1016/j.ajsep.2021.09.006

Schiebener, J., & Brand, M. (2017). Decision-making and related processes in internet gaming disorder and other types of internet-use disorders. *Current Addiction Reports, 4*(3), 262–271. https://doi.org/10.1007/s40429-017-0156-9

Song, S., Howard, J. H., & Howard, D. V. (2007). Sleep does not benefit probabilistic motor sequence learning. *Journal of Neuroscience, 27*(46). https://doi.org/10.1523/JNEUROSCI.2062-07.2007. Article 46.

Stanmore, E., Stubbs, B., Vancampfort, D., de Bruin, E. D., & Firth, J. (2017). The effect of active video games on cognitive functioning in clinical and non-clinical populations: A meta-analysis of randomized controlled trials. *Neuroscience & Biobehavioral Reviews, 78*, 34–43. https://doi.org/10.1016/j.neubiorev.2017.04.011

Vékony, T. (2021a). Verbal N-back task created with jsPsych [JavaScript] Version v1.0.0. https://github.com/vekteo/Nback_jsPsych. Original work published 2021.

Vékony, T. (2021b). *Alternating Serial Reaction Time Task created with jsPsych* (Version v1.0.0) [Computer software] *Zenodo*. https://doi.org/10.5281/ZENODO.7124730.

Vékony, T. (2022a). Card sorting task created with jsPsych [JavaScript] Version 1.0.1. https://doi.org/10.5281/zenodo.7093470.

Vékony, T. (2022b). *GoNoGo_JSPsych* [JavaScript]. https://github.com/vekteo/GoNoGo_jsPsych (Original work published 2021).

Virag, M., Janacsek, K., Horvath, A., Bujdoso, Z., Fabo, D., & Nemeth, D. (2015). Competition between frontal lobe functions and implicit sequence learning: Evidence from the long-term effects of alcohol. *Experimental Brain Research, 233*(7). https://doi.org/10.1007/s00221-015-4279-8. Article 7.

Warburton, W. A., Parkes, S., & Sweller, N. (2022). Internet gaming disorder: Evidence for a risk and resilience approach. *International Journal of Environmental Research and Public Health, 19*(9), 5587. https://doi.org/10.3390/ijerph19095587

Waris, O., Jaeggi, S. M., Seitz, A. R., Lehtonen, M., Soveri, A., Lukasik, K. M., Söderström, U., Hoffing, R. A. C., & Laine, M. (2019). Video gaming and working memory: A large-scale cross-sectional correlative study. *Computers in Human Behavior, 97*, 94–103. https://doi.org/10.1016/j.chb.2019.03.005

World Health Organization. (2018). International statistical classification of diseases and related health problems (11th revision beta draft). Retrieved from https://icd.who.int/browse11/l-m/en.

Yao, Y.-W., Wang, L.-J., Yip, S. W., Chen, P.-R., Li, S., Xu, J., Zhang, J.-T., Deng, L.-Y., Liu, Q.-X., & Fang, X.-Y. (2015). Impaired decision-making under risk is associated with gaming-specific inhibition deficits among college students with internet gaming disorder. *Psychiatry Research, 229*(1). https://doi.org/10.1016/j.psychres.2015.07.004. Article 1.

Yoon, S., Yang, Y., Ro, E., Ahn, W.-Y., Kim, J., Shin, S.-H., Chey, J., & Choi, K.-H. (2021). Reliability, and convergent and discriminant validity of gaming disorder scales: A meta-analysis. *Frontiers in Psychology, 12*, Article 764209. https://doi.org/10.3389/fpsyg.2021.764209

Zhong, L., Baptista, S., Gattoni, R., Arnold, J., Flickinger, D., Stringer, C., & Pachitariu, M. (2025). Unsupervised pretraining in biological neural networks. *Nature, 644*(8077), 741–748. https://doi.org/10.1038/s41586-025-09180-y

Zhou, W., Zheng, H., Wang, M., Zheng, Y., Chen, S., Wang, M., & Dong, G.-H. (2021). The imbalance between goal-directed and habitual systems in internet gaming disorder: Results from the disturbed thalamocortical communications. *Journal of Psychiatric Research, 134*, 121–128. https://doi.org/10.1016/j.jpsychires.2020.12.058

Zhou, Z., Zhou, H., & Zhu, H. (2016). Working memory, executive function and impulsivity in internet-addictive disorders: A comparison with pathological gambling. *Acta Neuropsychiatrica, 28*(2). https://doi.org/10.1017/neu.2015.54. Article 2.