The Impact of Reward and Punishment Motivation Induction on Working Memory Updating Function in College Students at High Risk for Internet Gaming Disorder

Authors: Gao Yuanxia, Wang Jiangyang, Wang Jiangyang

Date: 2026-04-12T18:03:11+00:00

Abstract

Based on the concern regarding the academic underperformance of college students at high risk for Internet game addiction, this study conducted two multi-factor behavioral experiments to examine the effects of reward and punishment motivation induction on the working memory updating function of these students.

The results showed that college students at high risk for Internet game addiction exhibited longer reaction times and lower accuracy in working memory updating. Under reward motivation induction, both high-risk and low-risk students showed slower reaction times but higher accuracy in working memory updating, indicating an enhanced level of processing. Under punishment motivation induction, the accuracy of both groups improved, although the punishment effect size for high-risk students was smaller than that for low-risk students.

Cross-experimental analysis revealed that, regarding the accuracy of working memory updating, high-risk students performed significantly better under reward motivation induction than under punishment motivation induction, whereas no significant difference was found for low-risk students between the two motivational inductions. The study suggests that the working memory updating function of college students at high risk for Internet game addiction is impaired to a certain extent, and they exhibit reduced sensitivity to punishment during working memory updating tasks.

Full Text

Preamble

The Impact of Reward and Punishment Motivation on Working Memory Updating in College Students at High Risk for Internet Gaming Disorder

Gao Yuanxia[1,2], **Wang Jiangyang**[1] ([1]School of Education Science, Shenyang Normal University, Shenyang 110034) ([2]Faculty of Psychology, Tianjin Normal University, Tianjin 300387)

Abstract

This study aims to explore the characteristics of working memory updating functions in college students at high risk for Internet Gaming Disorder (IGD) under different motivational states induced by reward and punishment. A 2 (Group: High-risk group vs. Control group) × 3 (Motivation type: Reward, Punishment, Neutral) mixed experimental design was employed. The results indicated that in the neutral condition, the high-risk group exhibited significantly lower accuracy and longer reaction times in working memory updating tasks compared to the control group. Under reward and punishment motivation conditions, the performance of the high-risk group improved significantly, showing a "motivation-driven" effect, although their performance remained lower than that of the control group. These findings suggest that while college students at high risk for IGD exhibit deficits in working memory updating, these executive function deficits can be modulated and partially compensated for by external motivational incentives.

---

1. Introduction

Internet Gaming Disorder (IGD) has become a significant public health concern globally, particularly among the college student population. Previous research has consistently shown that individuals with IGD or those at high risk exhibit various cognitive control deficits. Among these, executive function—specifically the "updating" component of working memory—plays a crucial role in regulating behavior and resisting the urge to engage in excessive gaming. Working memory updating refers to the ability to monitor incoming information for relevance to the current task and then appropriately revise the items held in working memory by replacing old, no-longer-relevant information with newer, more relevant information.

Recent theoretical frameworks, such as the I-PACE (Interaction of Person-Affect-Cognition-Execution) model, suggest that the cognitive deficits observed in addiction are not static but are influenced by affective and motivational states. While many studies have documented general executive dysfunction in

IGD, fewer have investigated how these functions fluctuate when external incentives, such as rewards or punishments, are introduced. In the context of gaming, players are constantly exposed to complex reward structures (e.g., leveling up, gaining items) and punishments (e.g., losing points,

摘要

Driven by concerns regarding the academic underperformance of college students at high risk for Internet Gaming Disorder (IGD), this study conducted two multi-factor behavioral experiments to investigate the impact of reward and punishment motivation induction on the working memory updating functions of these individuals. The results revealed that college students at high risk for IGD exhibited longer reaction times and lower accuracy rates in working memory updating tasks compared to their low-risk peers. Under the condition of reward motivation induction, both high-risk and low-risk students showed slower reaction times but increased accuracy, suggesting an enhanced depth of cognitive processing.

Under the condition of punishment motivation induction, accuracy improved for both groups; however, the magnitude of the punishment effect in high-risk students was significantly smaller than that observed in low-risk students. A cross-experimental analysis further revealed that, regarding working memory updating accuracy, high-risk students performed significantly better under reward motivation induction than under punishment motivation induction. In contrast, low-risk students showed no significant difference between the reward and punishment conditions. These findings suggest that the working memory updating function of college students at high risk for IGD is impaired to a certain extent, and these individuals exhibit a specific insensitivity to punishment during working memory updating tasks.

关键词

Abstract

Working memory updating (WMU) refers to the process of monitoring and coding incoming information, replacing old information that is no longer relevant to the current task with new, relevant information. This function is a core component of executive functions and is closely related to higher-level cognitive activities such as fluid intelligence, problem-solving, and reading comprehension. Previous research has indicated that individuals with Internet Gaming Disorder (IGD) exhibit significant deficits in working memory updating. However, most existing studies have focused on the cognitive characteristics of IGD under neutral conditions, while the mechanisms of how motivational information (reward and punishment) influences the updating process in this population remain unclear.

This study aims to investigate the characteristics of working memory updat-

ing in college students with IGD under different motivational conditions. By employing a modified n-back task combined with reward and punishment incentives, we examined the performance differences between an IGD group and a healthy control (HC) group.

1. Introduction

With the rapid development of internet technology, Internet Gaming Disorder (IGD) has become a significant public health concern. IGD is characterized by persistent and recurrent engagement with video games, leading to impairment or distress. One of the hallmark cognitive features of IGD is the impairment of executive functions, particularly working memory updating.

Working memory updating is not merely the storage of information but involves the dynamic manipulation of mental representations. According to the Reward Sensitivity Theory, individuals with addictive behaviors often exhibit hypersensitivity to rewards and hyposensitivity to punishments. In the context of IGD, this imbalance in motivational processing may interfere with basic cognitive processes like updating. While some studies suggest that rewards can enhance cognitive performance in healthy individuals, it remains to be seen whether such incentives can remediate or further exacerbate the updating deficits observed in those with IGD.

2. Methods

2.1 Participants

A total of 60 college students were recruited for this study, divided into an IGD group ($n = 30$) and a healthy control group ($n = 30$) based on their scores on the Young' s Internet Addiction Test (IAT) and the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria for IGD. All participants had normal or corrected-to-normal vision and no history of neurological or psychiatric disorders.

2.2 Experimental Design and Procedure

The experiment utilized a 2 (Group: IGD, HC) × 3 (Motivation Type: Reward, Punishment, Neutral) × 2 (Task Difficulty:

1 引言

In today' s society, characterized by the advanced development of internet technology, online gaming has become a widely popular leisure activity. As of June 2025, the number of online game users in China reached 584 million, accounting for 52% of the total internet population (China Internet Network Information Center, 2025). On one hand, as a recreational activity featuring exquisite graphics and high engagement, online gaming can enrich daily life; on the other hand, it carries risks such as excessive time consumption and potential addiction. Consequently, the number of individuals suffering from online game addiction globally has been increasing annually [?, ?]. Among various age groups, the detection rate of online game addiction among college students is notably high, at approximately 14.8% [?, ?]. Given that online game addiction is a continuous and developing process [?, ?], early identification and intervention for those at high risk of addiction are of critical importance.

In real-world settings, students who find themselves unable to disengage from online games often exhibit poor academic performance [?, ?]. What are the underlying reasons for this phenomenon? Existing research suggests that this may be due to excessive gaming time leading to sleep deprivation, which in turn impairs learning efficiency and academic achievement [?, ?]. However, beyond these surface-level causes, the poor academic performance of college students at high risk for addiction may also stem from deeper cognitive factors. Research indicates that···

Liaoning Provincial Education Science "14th Five-Year Plan" Annual Project (JG25DB426)

Individuals exhibiting symptoms of Internet Gaming Disorder (IGD) typically present with neurobiological alterations, specifically characterized by abnormal connectivity between brain regions involved in executive functions [?, ?]. These neurobiological changes may serve as the underlying mechanism for the cognitive impairments observed in this population, such as deficits in working memory.

Working memory is a prerequisite for completing learning activities and is closely related to academic achievement [?, ?]. The cognitive filtering model assumes that individuals have a limited capacity for processing information; in this framework, working memory acts as a filter that enhances information processing efficiency and improves academic performance by continuously filtering and refreshing information [?, ?]. Within this process, the updating function refers to the ability to continuously refresh the contents of working memory and screen new information, enabling individuals to promptly replace outdated information, extract relevant content, and exclude interference [?, ?].

Given the central role of the updating function within the working memory system, these findings suggest that its impairment may be a direct cause of poor academic performance among college students at high risk for Internet Gaming Disorder (IGD). Specifically, the weakening of the working memory updating function may lead to a slower pace of learning and a decrease in the accuracy of knowledge comprehension. Furthermore, such deficits may prevent individuals from rapidly updating or replacing memories related to online gaming once they have stopped playing.

Consequently, these changes increase the craving for gaming, which ultimately impacts academic performance and daily life. Therefore, the present study focuses on the working memory updating function of college students at high risk for Internet Gaming Disorder (IGD). By analyzing the differences in working memory updating between high-risk and low-risk students, this research aims to explore the specific impact of internet gaming addiction risk on the cognitive function of working memory updating.

Regarding the relationship between the risk of Internet Gaming Disorder (IGD) and working memory updating functions, research has demonstrated that IGD can impair an individual' s working memory. Specifically, individuals with IGD tend to encounter greater difficulties in retaining and updating information [?, ?]. Notably, abnormalities in working memory have also been observed among college students at high risk for IGD, suggesting that working memory impairment may be closely linked to addiction risk [?, ?]. However, some studies have pointed out that daily gaming activities are associated with higher working memory capacity [?, ?], indicating that specific types of gaming may provide beneficial experiences for cognitive development. Furthermore, some evidence suggests that while addicted individuals achieve accuracy rates in working memory tasks comparable to non-addicts, they exhibit significantly faster reaction times—a behavioral pattern associated with enhanced functional connectivity within the reward network [?, ?]. Consequently, the current conclusions regarding the impact of IGD symptoms on an individual' s working memory updating function remain inconclusive, necessitating further research to clarify the specific connection between the two.

Cognitive neuroscience research has identified the frontostriatal circuit as the primary neural substrate associated with both cognitive function and addictive behaviors. Based on this, researchers have proposed a cognitive-neural model of IGD characterized by impaired prefrontal control [?, ?]. Subsequent studies have also found that IGD and working memory share a common neural basis, primarily involving brain regions such as the prefrontal cortex and the striatum [?, ?]. It is possible that IGD adversely affects working memory and its updating functions by altering the volume and activity of these specific brain regions. In studies targeting populations at high risk for IGD, abnormalities in the functional connectivity between the frontal lobe and the limbic system have similarly been identified [?, ?].

At the behavioral level, individuals with Internet Gaming Disorder (IGD) and those at high risk for the condition exhibit poorer performance in cognitive tasks compared to healthy control groups (Jang et al., 2021). Grounded in the theoretical frameworks of cognitive neuroscience and behavioral science, and supported by empirical evidence suggesting that IGD symptoms impair individual working memory, this study proposes Hypothesis 1: Compared to university students at low risk for addiction, those at high risk for internet gaming addiction will demonstrate poorer working memory updating performance, specifically characterized by slower updating speeds and lower updating accuracy.

Furthermore, Social Cognitive Theory posits that motivation extensively influences a wide range of cognitive processes, including working memory, and serves as a primary driver of cognitive function.

Motivation is a critical factor influencing cognitive performance (Schunk & DiBenedetto, 2020). Different motivational states can alter cognitive control strategies, which in turn affect individual behavior. This process primarily functions by inducing motivational states through rewarding or punishing stimuli, which encourages preparation and effort during cognitive processes, thereby enhancing an individual' s cognitive abilities (Yee & Braver, 2018).

Existing research indicates that reward- and punishment-based motivation can effectively improve working memory. Specifically, reward-related stimuli receive prioritized processing in working memory through resource allocation mechanisms (Ricker et al., 2025). Conversely, punishment-related stimuli are more effective at stimulating an individual' s willingness to invest effort, leading to improved cognitive performance under high working memory load conditions (Massar et al., 2020).

Cognitive-behavioral models suggest that individuals engage in online gaming to obtain immediate rewards. Furthermore, populations addicted to online gaming often exhibit dysregulated sensitivity to rewards and punishments, characterized by heightened sensitivity to rewards and diminished sensitivity to punishments (Dong & Potenza, 2014).

This further leads to an increased desire to use the network, resulting in more time spent on gaming. However, this phenomenon primarily occurs in response to stimuli that are directly related or similar to games (Cho et al., 2022). It remains unclear whether this imbalance in reward and punishment sensitivity also manifests within the context of general cognitive tasks.

The specific mechanisms underlying these adjustments require further investigation. Consequently, the present study manipulates reward and punishment motivations to analyze the characteristics of reward and punishment sensitivity in individuals at high risk for Internet gaming disorder during general cognitive tasks.

Under the induction of reward motivation, individuals tend to exert greater effort driven by the desire for rewards [**?**, **?**]. In cognitive tasks, reward motivation not only prioritizes the encoding of relevant information by attracting attention but also enhances the processing of memory representations in the early visual cortex and parietal regions. This, in turn, improves the encoding accuracy of target information within working memory [**?**, **?**]. At the behavioral level, the influence of reward motivation on an individual' s performance in cognitive tasks is typically reflected in two observable indicators: reaction speed and accuracy. Compared to conditions without reward motivation, individuals under the influence of reward motivation flexibly adjust their decision-making processes based on task demands. This often manifests as a speed-accuracy trade-off, where reaction times are prolonged to increase the probability of correct retrieval from working memory [**?**, **?**].

Related research has found that individuals with symptoms of Internet Gaming Disorder (IGD) pay more attention to and are more sensitive to in-game rewards, exhibiting enhanced reward sensitivity [?, ?]. They also demonstrate a preference for immediate rewards and characteristics of active reward-seeking behavior, such as taking risks to pursue high rewards [?, ?]. Furthermore, these individuals show enhanced functional connectivity in reward-related brain regions [?, ?], suggesting that such neural pattern alterations may be associated with an abnormal enhancement of their reward-seeking motivation. Therefore, introducing reward motivation in working memory updating tasks may improve the task performance of individuals at high risk for IGD.

Simultaneously, some studies have found that in general cognitive task contexts, the facilitative effect of reward motivation on cognitive function does not differ significantly between individuals with IGD and non-addicted individuals [?, ?]; both groups exhibit a similar speed-accuracy trade-off during cognitive tasks. Given that individuals with IGD and those at high risk share overlapping structural and functional characteristics in brain regions related to reward networks [?, ?], we propose Hypothesis 2: Reward motivation induction will slow down the working memory updating speed of both high-risk and low-risk college students for IGD, while simultaneously improving the accuracy of their working memory updating.

Under the influence of punishment-induced motivation, individuals tend to enhance cognitive control to mitigate potential penalties due to loss aversion [?, ?]. Furthermore, behavioral evidence suggests that the motivation to avoid punishment exerts a significantly stronger influence on individual performance than the motivation to pursue rewards [?, ?].

Reward motivation and punishment motivation are mediated by distinct neural circuits (Combrisson et al., 2024). Consequently, these two types of motivation exert different influences on an individual' s cognitive performance. It is therefore necessary to study them separately to analyze the specific effects that the induction of reward and punishment motivation has on individual cognitive functions.

Existing research has indicated that punishment motivation can enhance individual accuracy during task performance [?, ?]. However, punishment motivation generally exerts no significant influence on reaction speed, selectively improving conflict processing efficiency only under specific conditions [?, ?]. Individuals with Internet gaming disorder exhibit impairments in their goal-directed systems, leading to a devaluation of punishment and loss outcomes, which renders them less sensitive to such consequences [?, ?].

At the neural level, individuals with internet gaming disorder exhibit excessive responses to reward anticipation while demonstrating blunted neural activity toward monetary losses [?, ?]. Compared to recreational gamers, addicted individuals also display lower cognitive control and reduced activation in the prefrontal cortex and anterior cingulate cortex during the loss feedback stage [?, ?]. These studies consistently suggest that diminished sensitivity to punishment may be a core characteristic of internet gaming addiction and those at high risk for it. Consequently, the facilitative effect of punishment motivation on cognitive function is weaker in these individuals than in non-addicted users.

Furthermore, the transition from impaired goal-directed systems to decreased punishment sensitivity likely represents a psychological and neural mechanism distributed along a continuum across the internet gaming addiction spectrum. Specifically, as the level of addiction risk increases, an individual' s neural responsiveness to loss outcomes and their executive control capacity are expected to decline progressively.

Based on this, we propose Hypothesis 3: Punishment motivation induction can improve the accuracy of working memory updating in both high-risk and low-risk internet gaming addiction college students; however, this improvement effect is weaker for students at high risk of addiction.

Based on these considerations, the present study focuses on the reward and punishment sensitivity of individuals at high risk for Internet Gaming Disorder (IGD) within the framework of cognitive-behavioral models. By examining the roles of reward and punishment motivation in response to non-gaming-related stimuli, this research aims to clarify the behavioral response patterns of high-risk individuals during general cognitive tasks. According to Reinforcement Sensitivity Theory, rewards and punishments activate the Behavioral Approach System (BAS) and the Behavioral Inhibition System (BIS), respectively [**?**, **?**]. When rewards and punishments are presented simultaneously, the activation of one system may inhibit the function of the other, potentially resulting in behavioral performance that is less pronounced than when either stimulus is presented in isolation [**?**, **?**]. Consequently, manipulating both reward and punishment motivations within a single experiment may introduce interactions between variables and potential confounding factors that could compromise research validity.

Therefore, this study utilizes two separate experiments to independently manipulate reward motivation and punishment motivation within a general cognitive task. The objective is to investigate whether differences exist in working memory updating functions between university students at high and low risk for IGD, and to determine whether the induction of reward and punishment motivations significantly impacts these functions in both groups. This research seeks to reveal the underlying mechanisms by which IGD risk influences working memory updating. Furthermore, it provides a new perspective for explaining why high-risk university students often experience poor academic performance, while offering empirical evidence and practical recommendations for educational interventions aimed at improving the academic outcomes of this population.

2.1 被试

First, the required sample size for the study was evaluated using More Power 6.0.4 software. A power analysis for repeated-measures ANOVA was conducted with parameters set at $\alpha = 0.05$, $1 - \beta = 0.8$, and $\eta^2 = 0.06$. The results indicated that a minimum sample size of 78 participants was required. A total of 87 college students (24 females, 63 males) were recruited via posters, which satisfied the research requirements. All participants had no history of medical conditions that would interfere with the experiment and reported no recent sleep or psychological distress (assessed using the Self-Rating Scale of Sleep Status and the Depression-Anxiety-Stress Scale). Based on their scores on the Internet Game Disorder Scale, participants were categorized into a high-risk group for internet gaming addiction (42 participants) and a low-risk group

(45 participants). The mean age of the participants was 21.84 ± 2.60 years. All participants were informed of the recruitment requirements and signed informed consent forms prior to the start of the experiment. Upon completion of the study, they received compensation proportional to their task performance. This study was approved by the Ethics Committee of the School of Education Science at Shenyang Normal University (Approval No. 20230301).

Descriptive statistics for the participants' individual characteristic variables are presented in Table 1 . First, to verify the effectiveness of the group assignment, independent samples t-tests were conducted on the daily gaming time and internet gaming addiction scores of the high-risk and low-risk groups. The results showed that the high-risk group had significantly higher daily gaming time ($t(48) = 13.67$, $p < 0.001$, Cohen' s $d = 3.03$) and internet gaming addiction scores ($t(85) = 26.13$, $p < 0.001$, Cohen's $d = 5.61$) than the low-risk group, confirming the validity of the grouping. Second, to ensure that the grouping was not influenced by gender distribution, a chi-square test of independence was performed. The result was non-significant ($\chi^2(1) = 1.54$, $p = 0.214$), indicating that the experimental grouping was independent of gender distribution. Furthermore, independent samples t-tests were conducted on other potential

confounding variables. The results indicated no significant differences ($ps > 0.05$) between the high-risk and low-risk groups in terms of age ($t(84) = -1.10$), sleep quality ($t(85) = -0.17$), or general psychological distress scores reflecting anxiety, depression, and stress levels ($t(85) = 0.91$). These findings demonstrate that the experimental groups were homogeneous and consistent across these extraneous variables, thereby eliminating the possibility of these factors interfering with the experimental results.

Descriptive statistics of participants' individual characteristics ($M \pm SD$)

Individual characteristic variables

High-risk internet gaming addiction group ($n = 42$)

Low-risk internet gaming addiction group ($n = 45$)

21.52 $±$2.38

22.13 $±$2.78

Daily Gaming Time

5.06 $±$1.94

0.78 $±$0.60

Online Game Addiction Scores

Abstract

With the rapid development of Internet technology, online gaming has become a significant component of modern leisure and entertainment. However, the accompanying phenomenon of online game addiction has emerged as a critical public health concern. This study aims to explore the quantitative assessment of online game addiction scores, analyzing the core dimensions of addictive behavior and their psychological impact. By synthesizing existing diagnostic criteria and psychometric scales, we examine the distribution of addiction scores across different demographic groups and discuss the correlation between high addiction scores and various psychosocial factors.

1. Introduction

Online game addiction, often categorized under the broader umbrella of Internet Use Disorder, refers to the compulsive or uncontrollable use of online games despite negative consequences in personal, social, or occupational spheres. As the gaming industry continues to evolve with more immersive and socially integrated experiences, the risk of developing addictive patterns has increased. To effectively identify and intervene in problematic gaming behavior, researchers have developed various scoring systems to quantify the severity of addiction. These scores serve as essential tools for clinical diagnosis and academic research, providing a standardized metric for evaluating behavioral patterns.

2. Methodology for Scoring Addiction

The assessment of online game addiction scores typically relies on validated psychometric instruments. Most scales are designed based on the diagnostic criteria for Internet Gaming Disorder (IGD) as outlined in the DSM-5 or the International Classification of Diseases (ICD-11).

2.1 Core Assessment Dimensions The calculation of an addiction score generally encompasses several key dimensions: - **Salience:** The extent to which gaming becomes the dominant activity in daily life. - **Withdrawal:** The experience of unpleasant emotions or physical symptoms when gaming is restricted. - **Tolerance:** The need to spend increasing amounts of time gaming to achieve the same level of satisfaction. - **Conflict:** Interpersonal or intrapsychic struggles resulting from excessive gaming. - **Relapse:** Unsuccessful attempts to control or reduce gaming behavior.

2.2 Quantitative Scales Commonly used instruments include the Young' s Internet Addiction Test (IAT) adapted for gaming, and the Game Addiction

Scale (GAS). These scales utilize Likert-type responses (e.g., ranging from 1 "Never" to 5 "Very Often"). The total score is calculated by summing the responses, where higher scores indicate a higher propensity for addiction. For instance, a score exceeding a specific threshold (e.g., $\bar{x} + 2\sigma$) may categorize

59.26 $±$6.33

24.78 $±$5.98

21.74 $±$4.57

21.91 $±$5.03

General Psychological Distress

9.52 $±$9.70

7.89 $±$6.99

2.2 工具

The criteria for identifying individuals at high risk for Internet Gaming Disorder (IGD) were primarily based on diagnostic standards established in previous research [**?**, **?**]. First, a self-administered questionnaire was used to collect basic personal characteristics, such as the participants' daily time spent playing online games and their in-game rankings. Subsequently, an adapted version of the Internet Addiction Test (IAT), originally developed by Young (1999), was employed to screen for the high-risk IGD group. Previous studies have demonstrated that modifying the term "Internet" to "Internet gaming" in the original items effectively identifies and screens populations with gaming addiction [**?**, **?**].

The scale consists of 20 items, each scored on a 5-point Likert scale, with a maximum total score of 100. Participants scoring above 50 were categorized into the high-risk IGD group, while those scoring between 1 and 50 were categorized into the low-risk group. In the present study, the Cronbach' s α coefficient for this scale was 0.93. As this study did not involve clinical diagnosis, participants identified with significant symptoms related to gaming addiction were defined as "high-risk college students for IGD." Their average score on the scale was 58.93 ± 5.75. It should be noted that this classification is not equivalent to a clinical diagnosis of Internet Gaming Disorder.

2.3 实验设计

This study employed a $2 \times 2 \times 3$ mixed experimental design. The between-subjects independent variable was the risk level of internet gaming addiction (high-risk group vs. low-risk group). The within-subjects independent variables consisted of reward motivation induction (present vs. absent) and memory load (1-back, 2-back, and 3-back).

The dependent variable was working memory updating function, which was operationalized using three distinct metrics: updating speed, updating accuracy, and updating performance. Specifically, updating speed was measured by reaction time (recorded in milliseconds, ms); updating accuracy was measured by the percentage of correct responses (accuracy rate, %); and overall updating performance was assessed using the Inverse Efficiency Score (IES), which accounts for the speed-accuracy trade-off.

2.4 实验程序

The reward N-back task developed by Thurm et al. (2018) was employed to examine the working memory updating function of the participants (see [Figure 1: see original paper]). The experiment consisted of a practice phase and a formal experimental phase. The practice phase included 6 blocks, each lasting 40 seconds, while the formal experiment comprised 6 blocks, each lasting 4 minutes. The experimental stimuli consisted of ten digits ranging from 0 to 9.

Participants received a base payment of 10 RMB prior to the experiment. During the session, they were required to perform the reward N-back task under three different memory load conditions. The final compensation received after the experiment was dynamically adjusted based on the task scores achieved.

At the beginning of the task, a difficulty cue was presented, followed by a 5-second blank screen, during which reward and non-reward prompts appeared randomly. When the reward prompt "¥ + ¥" appeared, participants earned 10 points for a correct response, while incorrect or missing responses earned no points. When the non-reward prompt "+ + +"appeared, no points were awarded regardless of the response. The final accumulated points were converted into additional compensation at a rate of 1 RMB per 300 points, with a maximum bonus of 10 RMB. To counterbalancing order effects, a Latin square design was used to arrange the sequence of different memory loads. Across all reward N-back tasks, the prior probability of a "Yes" response in "Yes/No" trials was 30%, and the prior probability of a "Reward" trial in "Reward/No-Reward" conditions was 50%.

The experimental procedure was programmed and presented using E-Prime 2.0, and statistical analysis of the data was conducted using SPSS 22.0. In visual reaction time research, based on the neural conduction time required for visual information processing, reaction times shorter than 200 ms are typically regarded as anticipatory responses [?, ?]. Consequently, responses with reaction times below 200 ms were first excluded (exclusion rate of 1.80%), after which the mean reaction times and accuracy rates for the participants in the reward N-back task were calculated.

2.5.1 不同实验组被试在不同记忆负荷与奖励动机诱发下工作记忆刷新速度的差异

The descriptive statistical results for participants' reaction times in the working memory updating task across different experimental conditions are presented in . The results of the repeated measures analysis of variance (ANOVA) revealed a significant main effect for participant type, $F(1, 85) = 5.04$, $p = 0.027$, $\eta_p^2 = 0.06$. Specifically, the high-risk group for addiction exhibited

significantly longer reaction times than the low-risk group. This suggests that in the rewarded N-back task, individuals at high risk for Internet gaming addiction demonstrate slower working memory updating speeds compared to those at low risk. The main effect of reward motivation was also significant, $F(1, 85) = 4.03$, $p = 0.048$, $\eta_p^2 = 0.05$, with participants showing significantly longer reaction times under reward-motivated conditions than under non-reward conditions. This indicates that the induction of reward motivation leads to a deceleration in working memory updating speed. Furthermore, the main effect of memory load was highly significant, $F(2, 84) = 237.19$, $p < 0.001$, $\eta_p^2 = 0.74$. Post-hoc tests revealed that reaction times under the 1-back load were significantly shorter than those under the 2-back and 3-back loads, and reaction times for the 2-back load were significantly shorter than those for the 3-back load. These findings indicate that as memory load increases in the rewarded N-back task, participants' working memory updating speed gradually slows down.

The interaction between participant type and reward motivation [$F(1, 85) = 0.02, p = 0.878$], the interaction between participant type and memory load [$F(2, 84) = 1.00, p = 0.354$], and the interaction between memory load and reward motivation [$F(2, 84) = 0.08, p = 0.920$] were all non-significant. Additionally, the three-way interaction between participant type, memory load, and reward motivation [$F(2, 84) = 0.04, p = 0.959$] did not reach statistical significance.

1-back

2-back

3-back

Descriptive statistics ($M \pm SD$) for working memory updating task performance across experimental groups under conditions with and without reward motivation: High-risk group for Internet Gaming Disorder ($n = 42$).

Low-risk group for Internet Gaming Disorder ($n = 45$).

With reward motivation

Without reward motivation

With reward motivation

Without reward motivation

658.51$±$125.93

653.19$±$133.61

581.64$±$109.36

575.38$±$108.01

95.93$±$4.65

93.95$±$4.56

97.16$±$2.13

95.80$±$2.24

Inverse Efficiency Score

In the field of performance evaluation and data envelopment analysis, the Inverse Efficiency Score (IES) serves as a critical metric for assessing the relative productivity and resource utilization of decision-making units (DMUs). Unlike traditional efficiency measures that focus on the ratio of weighted outputs to weighted inputs, the inverse efficiency score provides a reciprocal perspective, often used to identify the extent of potential improvements or to stabilize mathematical models in specific optimization contexts.

Theoretical Framework

The concept of inverse efficiency is rooted in the duality of linear programming. In a standard input-oriented model, efficiency is defined by the ability of a DMU to minimize inputs while maintaining a constant level of output. Conversely, the inverse efficiency score represents the factor by which inputs would need to be increased—or outputs decreased—to reach the efficiency frontier from the opposite direction. This metric is particularly useful when analyzing "worst-case" scenarios or when the objective is to minimize the "waste" rather than maximize the "gain."

Mathematical Representation

Mathematically, if we denote the standard efficiency score of a unit as θ, where $0 < \theta \leq 1$, the inverse efficiency score is typically represented as:

$$IES = \frac{1}{\theta}$$

In this formulation, an IES of 1 indicates a perfectly efficient unit on the frontier. As the value of IES increases beyond 1, it indicates a higher degree of inefficiency. For example, an IES of 1.25 suggests that the unit is 25% less efficient than the benchmark, or that its inputs are 1.25 times higher than what is theoretically required to produce its current output level.

Applications in Machine Learning and Optimization

In modern computational research, the inverse efficiency score is frequently employed as a loss function component or a regularization term. By utilizing the inverse, researchers can transform a maximization problem into a minimization problem, which is often more compatible with standard gradient descent algorithms used in deep learning. Furthermore, in multi-objective optimization, the inverse efficiency score helps in balancing trade-offs between conflicting performance indicators, ensuring that no single metric disproportionately dominates the evaluation process.

Practical Implications

The use of inverse efficiency scores allows for a more granular sensitivity analysis. It highlights the vulnerability of specific DMUs to fluctuations in resource availability. In industrial engineering and economic modeling, this score is instrumental in identifying "bottleneck" units that require significant structural adjustments to approach the production possibility frontier. By

646.24$±$35.21

653.64$±$34.96

636.78$±$14.16

639.73$±$15.45

797.05$±$152.61

791.81$±$153.89

728.67$±$135.35

724.47$±$137.92

88.81$±$7.31

87.17$±$7.36

92.96$±$4.71

91.64$±$4.37

Inverse Efficiency Score

In the field of performance evaluation and data envelopment analysis, the Inverse Efficiency Score (IES) serves as a critical metric for assessing the relative productivity and resource utilization of decision-making units (DMUs). Unlike traditional efficiency measures that focus on maximizing output for a given set of inputs, the inverse efficiency perspective provides a complementary framework for understanding the potential for input reduction or output expansion from a reciprocal standpoint.

Theoretical Framework

The concept of inverse efficiency is mathematically derived from the reciprocal of the standard efficiency score. If we denote the technical efficiency of a DMU as θ, where $0 < \theta \leq 1$, the inverse efficiency score is typically represented as $1/\theta$. This transformation allows researchers to quantify the magnitude of inefficiency in terms of a multiplier. For instance, an inverse efficiency score of 1.25 suggests that the unit requires 25% more resources than an efficient benchmark to produce the same level of output, or conversely, that its output could be increased by 25% using current input levels if it were operating on the frontier.

Applications in Machine Learning and Optimization

In the context of machine learning and algorithmic optimization, inverse efficiency scores are frequently employed to evaluate model performance relative to computational complexity. When training deep learning architectures, the IES can help identify models that achieve high accuracy but at a disproportionately high computational cost. By analyzing the trade-off between error rates and resource consumption (such as FLOPs or memory usage), researchers can utilize the IES to select models that offer the best balance of performance and practical feasibility.

Methodological Advantages

The primary advantage of utilizing the inverse efficiency score lies in its interpretability regarding "waste" or "excess." While standard efficiency scores are bounded between 0 and 1, making them ideal for ranking, the IES provides a linear representation of the distance to the production frontier. This makes it particularly useful for:

- **Sensitivity Analysis:** Determining how fluctuations in input variables affect the overall inefficiency of a system.
- **Resource Allocation:** Identifying specific DMUs that require the most significant interventions to reach optimal performance levels.
- **Benchmarking:** Establishing clear targets for underperforming units by calculating the exact reciprocal of their current productivity levels.

As shown in , the relationship between standard efficiency and inverse efficiency is non-linear, meaning that as a unit' s efficiency drops, its inverse efficiency score grows at an increasing rate

863.24$±$75.97

874.45$±$78.90

821.11$±$43.89

827.40$±$41.50

893.08$±$185.02

890.76$±$191.67

848.86$±$158.56

844.29$±$153.82

77.19$±$9.48

77.17$±$9.58

83.18$±$7.54

82.49$±$7.59

Inverse Efficiency Score

In the context of performance evaluation and data envelopment analysis (DEA), the **Inverse Efficiency Score** (IES) is a metric used to assess the relative inefficiency or the "distance" of a decision-making unit (DMU) from the production frontier from an alternative perspective. While standard efficiency scores typically range from 0 to 1 (where 1 represents full efficiency), the inverse efficiency score provides a reciprocal measure that can be more intuitive for analyzing cost-related metrics or specific optimization problems.

Theoretical Framework

The traditional efficiency score, often denoted as θ, measures the ratio of weighted outputs to weighted inputs. In an input-oriented model, it represents the maximum proportional reduction in inputs required to achieve a given level of output. Conversely, the inverse efficiency score is defined as:

$$IES = \frac{1}{\theta}$$

Where: - θ is the standard efficiency score calculated via DEA or stochastic frontier analysis (SFA). - $IES \geq 1$, where a value of 1 indicates a fully efficient unit, and values greater than 1 represent increasing levels of inefficiency.

Applications in Machine Learning and Optimization

In modern computational research, the inverse efficiency score is frequently utilized as a loss function component or a regularization term. By transforming the efficiency metric into a value that scales positively with inefficiency, researchers can more easily integrate it into gradient-based optimization frameworks.

1. **Model Evaluation**: In deep learning models designed for resource allocation, the IES serves as a penalty term. As the model deviates from the optimal frontier, the IES increases, providing a clear signal for backpropagation.

2. **Benchmarking**: When comparing multiple algorithms, the IES allows for a linear interpretation of performance gaps. For instance, an IES of 1.2 suggests that a system is using 20% more resources than the theoretical optimum.

Advantages of the Inverse Metric

The primary advantage of using the inverse efficiency score lies in its mathematical properties during sensitivity analysis. While standard efficiency scores are bounded between $(0, 1]$, the inverse score maps to $[1, \infty)$. This expansion of the scale allows for a more granular differentiation between highly inefficient units, which might otherwise cluster near the lower bound of a standard efficiency scale.

Furthermore, in economic modeling, the IES often aligns more closely with "cost-plus" interpretations, where the score directly reflects the multiplier of excess input consumption. This makes the results

1144.83$±$152.59

1140.64$±$149.37

1054.47$±$100.34

1059.58$±$105.52

2.5.2 不同实验组被试在不同记忆负荷与奖励动机诱发下工作记忆刷新准确性的差异

The descriptive statistics for the accuracy of working memory updating across different experimental conditions are presented in . Repeated measures analysis of variance (ANOVA) revealed a significant main effect of participant type, $F(1, 85) = 11.81$, $p = 0.001$, $\eta_p^2 = 0.12$, with the high-risk addiction group showing significantly lower accuracy than the low-risk group. This indicates that participants at high risk for internet gaming addiction have lower working memory updating accuracy than those at low risk. The main effect of reward motivation was also significant, $F(1, 85) = 36.98$, $p < 0.001$, $\eta_p^2 = 0.30$, as accuracy was significantly higher in the reward-motivated condition than in the non-reward condition. This suggests that reward motivation enhances working memory updating performance compared to conditions without such motivation. Furthermore, the main effect of memory load was significant, $F(2, 84) = 308.47$, $p < 0.001$, $\eta_p^2 = 0.78$. Post-hoc tests indicated that accuracy in the 1-back condition was significantly higher than in the 2-back and 3-back conditions, and accuracy in the 2-back condition was significantly higher than in the 3-back condition. These results demonstrate that in the rewarded N-back task, working memory updating accuracy gradually decreases as memory load increases.

The interaction between participant type and reward motivation was not significant [$F(1, 85) = 0.06$, $p = 0.803$], nor was the three-way interaction between participant type, memory load, and reward motivation [$F(2,84) = 1.40$, $p = 0.250$]. However, the interaction between participant type and memory load was significant, $F(2,84) = 5.36$, $p = 0.009$, $\eta_p^2 = 0.06$. Simple effects analysis revealed that the accuracy of the high-risk addiction group was significantly lower than that of the low-risk group across all three memory load conditions ($p_1 = 0.045$, $p_2 = 0.001$, $p_3 = 0.002$). Notably, the difference in accuracy between the high-risk and low-risk groups in the 1-back condition was smaller than the differences observed in the 2-back and 3-back conditions (Cohen' s $d_1 = 0.45$, Cohen' s $d_2 = 0.73$, Cohen' s $d_3 = 0.67$), while the differences in the 2-back and 3-back conditions were comparable. This suggests that in the rewarded N-back task, the negative impact of internet gaming addiction risk on working memory updating accuracy intensifies as memory load increases and remains relatively stable under medium-to-high memory loads.

The interaction between memory load and reward motivation was significant, $F(2,84) = 6.15$, $p = 0.005$, $\eta_p^2 = 0.07$. Simple effects analysis showed that

in the 1-back and 2-back conditions, accuracy was significantly higher when reward motivation was present compared to when it was absent (Cohen' s $d_1 = 0.46$, Cohen' s $d_2 = 0.23$), $ps < 0.001$. In the 3-back condition, however, there was no significant difference in accuracy between the reward-motivated and non-reward conditions (Cohen' s $d = 0.04$), $p = 0.335$. These findings indicate that while reward motivation can improve working memory updating accuracy in tasks with low-to-medium memory loads, this facilitative effect is no longer evident in tasks with high memory loads.

2.5.3 不同实验组被试在不同记忆负荷与奖励动机诱发下工作记忆刷新表现的差异

Based on the results described above, it is evident that individuals exhibited a speed-accuracy trade-off during the working memory updating task. Specifically, under the induction of reward motivation, participants showed longer reaction times but higher accuracy compared to the no-reward condition. Consequently, the Inverse Efficiency Score (IES)—calculated as the ratio of reaction time to accuracy—was employed to control for the influence of the speed-accuracy trade-off on the experimental results (Statsenko et al., 2020; Townsend & Ashby, 1983). This measure allows for a more accurate analysis of participants'working memory updating performance by representing the time expended to achieve a correct response during the experiment.

Descriptive statistics for the inverse efficiency scores of participants across different experimental conditions are presented in . The results of the repeated-measures ANOVA revealed a significant main effect of participant group, $F(1,85) = 12.00$, $p = 0.001$, $\eta_p^2 = 0.12$, indicating that the processing efficiency of the high-risk addiction group was significantly weaker than that of the low-risk group. This suggests that in the rewarded N-back task, participants at high risk for Internet gaming disorder performed worse in working memory updating than those at low risk. The main effect of reward motivation was also significant, $F(1,85) = 4.48$, $p = 0.037$, $\eta_p^2 = 0.05$, with processing efficiency being significantly stronger under reward motivation than in the no-reward condition. This indicates that reward motivation improved working memory updating performance compared to the absence of such motivation. Furthermore, the main effect of memory load was significant, $F(2,84) = 1148.16$, $p < 0.001$, $\eta_p^2 = 0.93$. Post-hoc tests showed that processing efficiency was significantly higher under the 1-back load than under the 2-back and 3-back loads, and significantly higher under the 2-back load than the 3-back load. This demonstrates that in the rewarded N-back task, working memory updating performance gradually declined as memory load increased.

The interaction between participant group and reward motivation $[F(1,85) < 0.01, p = 0.996]$, the interaction between memory load and reward motivation $[F(2,84) = 1.19, p = 0.292]$, and the three-way interaction between participant group, memory load, and reward motivation $[F(2,84) = 1.12, p = 0.309]$ were all non-significant. However, the interaction between participant group and memory load was significant, $F(2,84) = 7.57$, $p = 0.004$, $\eta_p^2 = 0.08$.

Simple effects analysis revealed that across all three memory load conditions, the processing efficiency of the high-risk addiction group was significantly weaker than that of the low-risk group ($p_1 = 0.043, p_2 = 0.001, p_3 = 0.002$). Furthermore, the difference in processing efficiency between the high-risk and low-risk groups was smaller in the 1-back condition compared to the 2-back and 3-back conditions (Cohen' s $d_1 = 0.46$, Cohen' s $d_2 = 0.74$, Cohen' s $d_3 = 0.68$), while the differences in the 2-back and 3-back conditions were comparable. These findings suggest that the negative impact of Internet gaming addiction risk on working memory updating performance intensifies as memory load increases and remains relatively stable under medium-to-high memory load tasks.

2.6 讨论

Experiment 1 revealed that in the rewarded N-back task, college students at high risk for Internet gaming disorder (IGD) exhibited slower working memory updating speeds and lower updating accuracy compared to those at low risk for addiction. These findings support Hypothesis 1, suggesting that Internet gaming addiction exerts a negative impact on working memory updating functions and that high-risk individuals suffer from impaired updating capabilities.

These results are consistent with previous research indicating that behavioral addictions, much like substance addictions, cause significant damage to an individual' s working memory (Brand et al., 2014). Similar to diagnosed Internet gaming addicts, individuals at high risk for addiction experience adverse effects on their working memory, manifesting as processing difficulties in both retaining and updating information (Weinstein, 2017).

Compared to conditions without reward motivation, the induction of reward motivation led to slower working memory updating speeds in both high-risk and low-risk college students but simultaneously improved their updating accuracy, thereby validating Hypothesis 2. While these results demonstrate that reward motivation induction has a positive effect on working memory updating performance, they also confirm the effectiveness of the monetary reward manipulation used in this experiment. Previous studies have noted that reward motivation can improve working memory accuracy by optimizing the allocation of cognitive resources (prioritizing reward-related information) and adjusting response strategies (increasing decision-making caution), though often at the expense of response speed (Grogan et al., 2022). The present study also found that participants engaged in a speed-accuracy tradeoff during the rewarded N-back task, and that the facilitative effect of reward motivation on updating accuracy was greater than its effect on updating speed for both groups. Consequently, while reward motivation slowed updating speed and increased accuracy, it ultimately enhanced overall working memory updating performance. Furthermore, the facilitative effect of reward motivation did not differ significantly between high-risk and low-risk students. This suggests that high-risk individuals do not exhibit excessive reward-seeking behavior nor significant reward avoidance in this context. In cognitive tasks and daily life, the sensitivity of high-risk college students to common rewards may not differ significantly from that of low-risk individuals.

3.1 被试

The experimental participants were the same as those in Experiment 1. This study employed a single-session N-back task as a measurement tool for working memory updating functions; notably, this design is categorized as a cognitive assessment rather than a training intervention [**?**, **?**]. Consequently, to ensure that the N-back task performed in Experiment 1 did not exert any carryover effects on Experiment 2⋯

To minimize the impact on the N-back task and avoid the practice and fatigue effects associated with consecutive experimental sessions, a gap of one to two weeks was maintained between Experiment 1 and Experiment 2.

3.2 工具

The experimental tools utilized were identical to those employed in Experiment 1. Given that the previously administered scales maintain a temporal validity of one week or longer, a second round of testing was not conducted for this phase. Instead, the researchers conducted interviews with the participants to determine whether any significant or unusual circumstances had occurred within the preceding one to two weeks.

3.3 实验设计

A $2 \times 2 \times 3$ mixed experimental design was employed for this study. The between-subjects independent variable was the risk level of online game addiction (high-risk group vs. low-risk group). The within-subjects independent variables consisted of punishment motivation induction (present vs. absent) and working memory load (1-back, 2-back, and 3-back). The dependent variables and their respective scoring methods were identical to those utilized in the previous experiment.

3.4 实验程序

A penalized N-back task, corresponding to the rewarded N-back task, was employed (see Figure 2 [Figure 2: see original paper]). The experiment consisted of both practice and formal sessions. The practice session included 3 blocks of 40 seconds each, while the formal experiment comprised 6 blocks, each lasting 4 minutes. The experimental stimuli consisted of 10 numerical digits ranging from 0 to 9. Participants received a base payment of 15 RMB before the experiment. During the session, they were required to perform the penalized N-back task under three different memory load conditions. The final compensation was dynamically adjusted based on the task scores achieved after the experiment.

At the beginning of each task, a difficulty cue was presented, followed by a 5-second blank screen during which penalty and no-penalty prompts were randomly displayed. When the penalty prompt "¥−¥" appeared, 10 points were deducted for incorrect or missing responses, while no points were deducted for correct responses. When the no-penalty prompt "——" appeared, no points were deducted regardless of the response. The total points deducted were converted into monetary penalties at a rate of 1 RMB per 300 points, with a maximum deduction of 10 RMB. To balance for order effects, a Latin square design was used to arrange the sequence of different memory load conditions. In all penalized N-back tasks, the prior probability of a "Yes" response in the "Yes/No" trials was 30%, and the prior probability of a "Penalty" condition in the "Penalty/No-penalty" trials was 50%.

The experimental procedure was programmed and presented using E-Prime 2.0, and statistical analysis was conducted using SPSS 22.0. For the entire dataset, responses with reaction times shorter than 200 ms were first excluded (an exclusion rate of 1.39%). Subsequently, the reaction times and accuracy rates of the participants in the penalized N-back task were calculated.

3.5.1 不同实验组被试在不同记忆负荷与惩罚动机诱发下工作记忆刷新速度的差异

The descriptive statistics for participants' working memory updating reaction times across different experimental conditions are presented in . Results from the repeated-measures ANOVA revealed a significant main effect of participant type, $F(1, 85) = 5.80$, $p = 0.018$, $\eta_p^2 = 0.06$, indicating that reaction times for the high-risk addiction group were significantly longer than those of the low-risk group. This suggests that in the penalized N-back task, individuals at high risk for Internet gaming disorder exhibit slower working memory updating speeds compared to low-risk individuals. Additionally, the main effect of memory load was significant, $F(2, 84) = 221.33$, $p < 0.001$, $\eta_p^2 = 0.72$. Post-hoc tests showed that reaction times under the 1-back load were significantly shorter than those under 2-back and 3-back loads, and reaction times for the 2-back load were significantly shorter than those for the 3-back load. These findings indicate that working memory updating speed gradually slows as memory load increases within the penalized N-back task.

The main effect of punishment motivation $[F(1, 85) = 2.32, p = 0.131]$ and the interaction between participant type and punishment motivation $[F(1, 85) = 0.56, p = 0.456]$ were both non-significant.

Furthermore, the interaction between participant type and memory load $[F(2, 84) = 0.72, p = 0.449]$, the interaction between memory load and punishment motivation $[F(2, 84) = 0.08, p = 0.924]$, and the three-way interaction between participant type, memory load, and punishment motivation $[F(2, 84) = 0.04, p = 0.951]$ were all found to be non-significant.

1-back

2-back

3-back

Descriptive statistics ($M \pm SD$) of working memory updating task performance for different experimental groups under conditions with and without punishment motivation: High-risk group for Internet Gaming Disorder ($n = 42$).

Low-risk group for Internet Gaming Disorder ($n = 45$).

With punishment motivation

Without punishment motivation

With punishment motivation

Without punishment motivation

653.83$±$125.08

650.44$±$133.32

582.32$±$107.58

575.08$±$108.24

94.36$±$3.99

93.31$±$4.06

97.98$±$1.73

95.80$±$2.71

794.73$±$129.85

792.00$±$134.08

725.34$±$144.97

720.34$±$145.21

86.45$±$7.46

85.55$±$7.60

91.82$±$6.77

90.67$±$5.58

891.02$±$136.59

890.98$±$133.10

846.79$±$177.27

840.93$±$187.04

74.07$±$10.13

74.17$±$9.77

83.67$±$8.39

82.64$±$8.24

3.5.2 不同实验组被试在不同记忆负荷与惩罚动机诱发下工作记忆刷新准确性的差异

The descriptive statistics for the accuracy of working memory updating across different experimental conditions are presented in . The results of the repeated-measures ANOVA revealed a significant main effect of participant type, $F(1, 85) = 22.75$, $p < 0.001$, $\eta_p^2 = 0.21$, with the high-risk addiction group showing significantly lower accuracy than the low-risk group. This indicates that in the penalized N-back task, individuals at high risk for Internet gaming addiction exhibit lower accuracy in working memory updating compared to those at low risk. The main effect of punishment motivation was also significant, $F(1, 85) = 26.31$, $p < 0.001$, $\eta_p^2 = 0.24$, where accuracy under punishment-motivated conditions was significantly higher than under non-punishment conditions. This suggests that punishment motivation enhances the accuracy of working memory updating compared to neutral conditions. Furthermore, the main effect of memory load was significant, $F(2, 84) = 311.36$, $p < 0.001$, $\eta_p^2 = 0.79$. Post-hoc tests indicated that accuracy in the 1-back condition was significantly higher than in the 2-back and 3-back conditions, and accuracy in the 2-back condition was significantly higher than in the 3-back condition. This demonstrates that in the penalized N-back task, the accuracy of working memory updating gradually decreases as memory load increases.

The three-way interaction between participant type, memory load, and punishment motivation was not significant, $F(2, 84) = 0.80$, $p = 0.442$. However, the interaction between participant type and punishment motivation was significant, $F(1, 85) = 4.25$, $p = 0.042$, $\eta_p^2 = 0.05$. Simple effects analysis revealed that for both groups, accuracy was significantly higher when punishment motivation was induced compared to when it was absent ($p_1 = 0.025$, $p_2 < 0.001$). Nevertheless, the difference in accuracy between the punishment-induced and non-punishment conditions was smaller in the high-risk addiction group than in the low-risk group (Cohen' s $d_1 = 0.09$, Cohen' s $d_2 = 0.30$). This indicates that the facilitative effect of punishment motivation on working memory updating accuracy is weaker in individuals at high risk for Internet gaming addiction than in low-risk individuals.

The interaction between participant type and memory load was significant, $F(2, 84) = 10.07$, $p < 0.001$, $\eta_p^2 = 0.11$. Simple effects analysis showed that across all three memory load conditions, the accuracy of the high-risk addiction group was significantly lower than that of the low-risk group ($ps < 0.001$).

Specifically, the difference in accuracy between the high-risk and low-risk addiction groups was smaller in the 2-back condition compared to the 1-back and 3-back conditions (Cohen' s $d_1 = 0.78$, Cohen' s $d_2 = 1.00$, Cohen' s $d_3 = 1.01$), while the differences in the 1-back and 3-back conditions were comparable. This suggests that the negative impact of Internet gaming addiction risk on working memory updating accuracy is relatively weaker in tasks with moderate memory load and stronger in tasks with low or high memory loads.

The interaction between memory load and punishment motivation was significant, $F(2, 84) = 4.14$, $p = 0.021$, $\eta_p^2 = 0.05$. Simple effects analysis revealed that in the 1-back and 2-back load conditions, accuracy was significantly higher when punishment motivation was induced than when it was absent (Cohen' s $d_1 = 0.46$, Cohen' s $d_2 = 0.14$; $p_1 < 0.001$, $p_2 = 0.002$). In the 3-back load condition, however, there was no significant difference in accuracy between the punishment-induced and non-punishment conditions (Cohen' s $d = 0.05$, $p = 0.187$). This indicates that while punishment motivation can improve the accuracy of working memory updating in tasks with low-to-moderate memory loads, this effect is no longer evident in tasks with high memory loads.

3.6 讨论

Experiment 2 revealed that the induction of punishment motivation improved the accuracy of working memory updating in both high-risk and low-risk internet gaming addiction groups among college students. However, this improvement was significantly weaker in the high-risk group, thereby validating Hypothesis 3. Previous research has demonstrated that loss framing can stimulate cognitive effort [**?**, **?**]. When punishment motivation is induced, participants' aversion to potential losses typically leads to more accurate performance in working memory tasks.

While moderate punishment motivation generally facilitates cognitive function, addicts often exhibit diminished sensitivity to punishment. This reduced sensitivity impairs their ability to learn from errors following negative feedback, leading to generally lower performance in cognitive tasks involving punishment motivation [?, ?, ?]. Consequently, the facilitative effect of punishment motivation on working memory updating accuracy is less pronounced in college students at high risk for internet gaming addiction.

Prior studies have noted that, compared to non-addicts, individuals with internet gaming addiction are characterized by decreased sensitivity to negative feedback [?, ?]. When punishment motivation is induced, these individuals may fail to accurately assess risky outcomes due to this insensitivity. Therefore, when utilizing incentive-based motivation to intervene or train working memory updating functions in students with internet gaming addiction or those at high risk, it is advisable to prioritize reward motivation over punishment motivation to better leverage the positive effects of motivational induction.

4 跨实验分析

Since the participants were the same for both experiments, the data from Experiment 1 and Experiment 2 were merged to better analyze the differences between reward-induced and punishment-induced motivation on the working memory updating functions of college students at high risk for Internet gaming disorder. Prior to merging the data, a difference test was conducted on the reaction times and accuracy rates of the working memory updating tasks under the no-reward motivation condition in Experiment 1 and the no-punishment motivation condition in Experiment 2. The results indicated no significant difference in reaction times between the no-reward condition ($M = 745.55, SD = 136.86$) and the no-punishment condition ($M = 743.83, SD = 129.23; t(86) = 0.19, p = 0.854, \text{Cohen' s } d = 0.01$). However, a significant difference was found in accuracy rates ($t(86) = 3.30, p = 0.001, \text{Cohen' s } d = 0.17$), where accuracy under the no-reward condition ($M = 88.10, SD = 5.64$) was significantly higher than under the no-punishment condition ($M = 87.11, SD = 6.25$). This discrepancy may be attributed to the facilitative effect of reward motivation in Experiment 1.

The facilitative effect of reward motivation on the accuracy of participants' working memory updating may have carried over to the tasks performed under the no-reward motivation condition. Therefore, when merging the experimental results, it was necessary to use the mean performance scores from the no-reward condition in Experiment 1 and the no-punishment condition in Experiment 2 as the baseline for the "no incentive" condition. This approach allows for a more accurate representation of the participants' working memory updating performance in the absence of any motivational induction.

4.1 不同实验组被试在奖惩动机诱发下工作记忆刷新速度的差异

The results of the repeated measures analysis of variance (ANOVA) for reaction times revealed a significant main effect of participant type, $F(1, 85) = 6.02$, $p = 0.016$, $\eta_p^2 = 0.07$. Specifically, reaction times for the high-risk addiction group ($M = 780.31$, $SD = 120.00$) were significantly longer than those of the low-risk addiction group ($M = 717.20$, $SD = 119.91$). This indicates that in both reward and punishment N-back tasks, individuals at high risk for Internet gaming disorder exhibit a significant increase in reaction times during working memory updating compared to the low-risk group. Thus, these findings robustly demonstrate that high-risk subjects possess slower working memory updating speeds than low-risk subjects. The main effect of incentive motivation (reward vs. punishment) was not significant, $F(1, 85) = 0.34$, $p = 0.592$. However, the main effect of memory load was significant, $F(2, 84) = 320.67$, $p < 0.001$, $\eta_p^2 = 0.79$. Post-hoc tests showed that reaction times under the 1-back load ($M = 615.93$, $SD = 116.30$) were significantly shorter than those under the 2-back ($M = 758.98$, $SD = 139.91$) and 3-back ($M = 868.09$, $SD = 148.56$) loads; furthermore, reaction times for the 2-back load were significantly shorter than those for the 3-back load. This suggests that across both reward and punishment conditions, participants' reaction times for working memory updating significantly increase as memory load rises. Consequently, it can be robustly concluded that working memory updating speed gradually slows down as the cognitive load increases.

No significant interaction effects were observed. Specifically, the interaction between participant type and incentive motivation [$F(2, 84) = 0.02, p = 0.907$], the interaction between participant type and memory load [$F(2, 84) = 1.21, p = 0.292$], and the interaction between memory load and incentive motivation [$F(4, 82) = 0.02, p = 0.976$] were all non-significant. Furthermore, the three-way interaction between participant type, memory load, and incentive motivation was also not significant [$F(4, 82) = 0.04, p = 0.952$].

4.2 不同实验组被试在奖惩动机诱发下工作记忆刷新准确性的差异

The results of the repeated measures analysis of variance (ANOVA) conducted on accuracy revealed a significant main effect of participant type, $F(1, 85) = 18.37$, $p < 0.001$, $\eta_p^2 = 0.18$. Specifically, the working memory updating accuracy of the high-risk addiction group ($M = 85.90$, $SD = 6.28$) was significantly lower than that of the low-risk addiction group ($M = 90.78$, $SD = 4.15$). This indicates that in both reward and punishment N-back tasks, individuals at high risk for Internet gaming addiction exhibited significantly reduced working memory updating accuracy compared to the low-risk group. These findings provide robust evidence that high risk for Internet gaming addiction is associated with impaired performance.

The working memory updating accuracy of high-risk participants was lower than that of low-risk participants. There was a significant main effect of incentive motivation, $F(2,84) = 24.27$, $p < 0.001$, $\eta_p^2 = 0.22$. Post-hoc tests revealed that accuracy under reward motivation ($M = 89.27$, $SD = 5.53$) was significantly higher than under punishment motivation ($M = 88.16$, $SD = 6.53$) and the no-incentive condition ($M = 87.58$, $SD = 5.81$). Furthermore, accuracy under punishment motivation was significantly higher than in the no-incentive condition. This suggests that in the N-back task, both reward and punishment motivation improve working memory updating accuracy compared to no incentive, though the effect of reward motivation is greater than that of punishment motivation.

The main effect of memory load was significant, $F(2,84) = 363.06$, $p < 0.001$, $\eta_p^2 = 0.81$. Post-hoc tests showed that accuracy in the 1-back condition ($M = 95.94$, $SD = 3.25$) was significantly higher than in the 2-back ($M = 89.76$, $SD = 6.56$) and 3-back ($M = 79.58$, $SD = 9.13$) conditions; accuracy in the 2-back condition was also significantly higher than in the 3-back condition. This indicates that in reward and punishment N-back tasks, participants' working memory updating accuracy significantly decreases as memory load increases. Thus, it can be robustly demonstrated that as memory load rises,

The three-way interaction between participant type, memory load, and incentive motivation was not significant, $F(4,82) = 1.97$, $p = 0.120$. However, the interaction between participant type and incentive motivation was significant (see [Figure 3: see original paper]), $F(2,84) = 12.53$, $p < 0.001$, $\eta_p^2 = 0.13$. Simple effects analysis revealed that for the high-risk addiction group, accuracy under reward motivation was significantly higher than under punishment motivation and no incentive ($Cohen's\ d_1 = 0.37$, $Cohen's\ d_2 = 0.34$, $ps < 0.001$), while there was no significant difference between the punishment and no-incentive conditions ($Cohen's\ d = 0.03$, $p = 0.518$). In the low-risk addiction group, accuracy under both reward and punishment motivation was significantly higher than under no incentive ($Cohen's\ d_1 = 0.31$, $Cohen's\ d_2 = 0.30$, $ps < 0.001$), with no significant difference between reward and punishment conditions ($Cohen's\ d = 0.01$, $p = 0.892$). This suggests that among high-risk Internet gaming addiction participants, only reward motivation enhances working memory updating accuracy; in contrast, for low-risk participants, both reward and punishment motivation improve accuracy, demonstrating equivalent utility.

No incentive motivation

participants' working memory updating accuracy gradually decreases.

High-risk Internet gaming addiction group; Low-risk Internet gaming addiction group (Note: Error bars represent ± 1 standard deviation; the same applies below.)

The interaction between participant type and memory load was significant (see [Figure 4: see original paper]), $F(2,84) = 8.79$, $p = 0.001$, $\eta_p^2 = 0.09$. Simple effects analysis found that across all three memory load conditions, the accuracy of the high-risk group was significantly lower than that of the low-risk group ($p_1 = 0.001$,

$p_2 = 0.001$, $p_3 < 0.001$). Furthermore, the difference in accuracy between the high-risk and low-risk groups was greater in the 3-back condition than in the 1-back and 2-back conditions ($Cohen's\ d_1 = 0.90$, $Cohen's\ d_2 = 0.75$, $Cohen's\ d_3 = 0.78$), while the differences in the 1-back and 2-back conditions were comparable. This indicates that the negative impact of Internet gaming addiction risk on working memory updating accuracy is relatively stable in low-to-medium memory load tasks and further intensifies in high memory load tasks.

High-risk Internet gaming addiction group; Low-risk Internet gaming addiction group

2-back

3-back

The interaction between memory load and incentive motivation was significant [Figure 5: see original paper], $F(4, 82) = 4.70$, $p = 0.003$, $\eta_p^2 = 0.05$. Simple effects analysis revealed that in the 1-back load condition, accuracy under both reward and punishment motivation was significantly higher than in the no-incentive condition ($Cohen'sd_1 = 0.52$, $Cohen'sd_2 = 0.43$, $ps < 0.001$); however, there was no significant difference in accuracy between reward and punishment motivation ($Cohen'sd = 0.09$, $p = 0.248$). In the 2-back load condition, accuracy under reward motivation was significantly higher than under both punishment motivation and no incentive ($Cohen'sd_1 = 0.25$, $Cohen'sd_2 = 0.32$, $ps < 0.001$), while no significant difference was found between the punishment and no-incentive conditions ($Cohen'sd = 0.05$, $p = 0.308$). Similarly, in the 3-back load condition, accuracy under reward motivation remained significantly higher than under punishment motivation and no incentive ($Cohen'sd_1 = 0.13$, $Cohen'sd_2 = 0.12$, $p_1 = 0.034$, $p_2 = 0.009$), but there was no significant difference between the punishment and no-incentive conditions ($Cohen'sd = 0.02$, $p = 0.622$).

These results indicate that in low memory load tasks, both reward and punishment motivation can enhance the accuracy of working memory updating. However, in tasks involving medium-to-high memory loads, the effect of punishment motivation on improving working memory updating accuracy is no longer significant, and only reward motivation continues to facilitate performance.

No incentive

1-back

1-back

2-back

3-back

5 总讨论

Through two experiments, this study demonstrates that the risk of Internet Gaming Disorder (IGD) has a negative impact on the working memory updating function of college students. In the study, college students at high risk for IGD exhibited significantly poorer performance in working memory updating compared to those at low risk. Specifically, high-risk individuals showed longer updating latencies and lower accuracy, indicating that the risk of IGD impairs the working memory updating function.

This finding advances the understanding of poor academic performance among high-risk college students from a superficial behavioral mechanism—where time is simply crowded out—to a deeper cognitive mechanism involving impaired cognitive abilities. Given the same cognitive load, the memory performance of high-risk students may remain at a lower level. Specifically, the weakening of the working memory updating function leads to a reduced capacity for knowledge acquisition and comprehension. Furthermore, the inability to rapidly update relevant memories upon ceasing gameplay creates persistent cognitive interference, which in turn hinders learning efficiency. Additionally, both experiments incorporated varying

memory loads, requiring participants to perform task switching between different conditions [?, ?]. Individuals with addictive symptoms typically require greater investment of executive control and attention during task switching [?, ?], which may serve as another reason for the slower speed and lower accuracy of working memory updating observed in high-risk college students.

Synthesizing the results of Experiment 1 and Experiment 2, a comparison of working memory updating under reward-motivated and punishment-motivated conditions reveals that, among high-risk college students, the facilitative effect of reward motivation on updating accuracy is greater than that of punishment motivation. In contrast, for low-risk college students, reward and punishment motivations exhibit equal utility in promoting updating accuracy. These results align with social cognitive theory regarding the role of motivation in enhancing individual cognitive performance [?, ?]. Previous research has noted that, compared to neutral conditions, both reward and punishment motivations increase activation in the frontoparietal regions associated with working memory processing [?, ?]. Furthermore, individuals with IGD exhibit dysregulated sensitivity to rewards and punishments during real-time gameplay, characterized by enhanced prefrontal neural responses to game rewards and weakened neural responses to negative in-game events [?, ?]. The present study did not observe an enhanced sensitivity to reward motivation in high-risk students, possibly because both the high-risk and low-risk groups were active gamers who are relatively familiar with rewards in both gaming and daily life. Previous studies on reward sensitivity have often utilized gaming-related stimuli and found abnormal reward processing in IGD individuals within those contexts. Specifically, game-related cues can directly activate the reward circuitry of addicted individuals and form automated processing mechanisms [?, ?]. This mechanism leads to a processing bias toward game rewards [?, ?], manifested as the automatic capture of and persistent attraction to game-related rewards. However, in general cognitive tasks and daily life, high-risk individuals may not differ significantly from low-risk individuals in their sensitivity to common social rewards (such as monetary incentives). Moreover, this study found that high-risk students exhibit a characteristic weakening of sensitivity to punishment motivation. Relevant functional magnetic resonance imaging (fMRI) research also indicates that individuals with IGD show reduced loss aversion, which is associated with abnormal functional connectivity in limbic centers—comprising the left inferior frontal gyrus, right caudate nucleus, and right hippocampus—and particularly with enhanced bottom-up neuromodulation from the right hippocampus to the left inferior frontal gyrus [?, ?]. This reduced sensitivity to loss may extend to the processing of general punishment signals. Therefore, in practice, reward motivation may offer a greater advantage than punishment motivation when utilizing motivational induction for the intervention and training of working memory updating functions in students with or at high risk for IGD.

This study demonstrates that the reward and punishment sensitivity of high-risk individuals in working memory updating tasks is not entirely identical to that of IGD individuals in gaming-stimulus contexts. This result extends the transfer range and temporal characteristics of reward and punishment sensitivity dysregulation in the IGD population. Previous research has shown that individuals with IGD exhibit significantly enhanced neural sensitivity to in-game rewards (e.g., points, virtual items, achievements) while remaining relatively insensitive to in-game punishments (e.g., failure, time limits, virtual losses), which may cause them to persist in gaming despite negative consequences [?, ?]. In high-risk individuals, reward motivation can improve working memory updating accuracy, but the magnitude of this improvement does not differ significantly from that of low-risk individuals, suggesting that reward sensitivity in non-gaming contexts is not significantly enhanced. Similarly, punishment motivation can improve updating accuracy, but the degree of improvement is smaller than that seen in low-risk individuals. This study further indicates that

high-risk individuals are less sensitive to punishment motivation in cognitive contexts. This mirrors the punishment sensitivity of IGD individuals in gaming contexts, suggesting that the weakened punishment sensitivity of IGD and high-risk groups partially transfers to general cognitive tasks. Furthermore, the alteration of punishment sensitivity in high-risk individuals appears to precede changes in reward sensitivity. This result provides a new perspective for understanding the complexity of addictive behaviors and offers cognitive markers for early identification of addiction.

Additionally, this study found that memory load moderates the effects of IGD risk and motivational induction on working memory updating accuracy. In high-load tasks, the negative impact of IGD risk on updating accuracy was most pronounced. Moreover, as memory load increased, the facilitative effect of reward and punishment motivation on accuracy weakened, becoming non-existent under high-load conditions. These results reveal differences in cognitive processing among high-risk individuals under varying cognitive loads, providing evidence for a comprehensive understanding of how motivation affects performance in complex cognitive tasks. On one hand, high-load tasks require greater utilization of working memory updating functions; since these functions are impaired in high-risk students, high-load tasks further highlight the negative impact of IGD risk, thereby reducing performance. On the other hand, memory load can regulate cognitive resources [**?**, **?**]. When memory load is low, motivational induction can increase attention and facilitate updating; however, when load is high, the facilitative effect of motivation tends to saturate and is partially offset by the high levels of attention and effort required by the task itself [**?**, **?**], rendering the motivation ineffective. This suggests that when addressing the academic difficulties of high-risk students, one must consider not only the effects of motivation but also the specific load characteristics of the learning tasks.

Finally, this study has limitations that warrant further investigation. First, the research only examined the impact of motivational induction on the working memory updating of high-risk individuals at the level of immediate response. Existing research suggests that the facilitative effect of punishment motivation on cognitive function may not be as persistent as that of reward motivation [**?**, **?**]. Future research could explore the mechanisms by which immediate versus delayed motivation affects various cognitive functions in high-risk individuals from a temporal perspective, as well as the duration of these facilitative effects. Second, the study manipulated motivation only as a binary variable (presence vs. absence).

Future research could consider manipulating multi-dimensional motivational factors—such as reward/punishment expectancy, magnitude, and probability—to more precisely characterize the cognitive processing patterns of individuals at high risk for IGD across motivational dimensions.

6 结论

High-risk university students with Internet Gaming Disorder (IGD) exhibit a certain degree of impairment in their working memory updating functions. Compared to low-risk students, those at high risk for IGD demonstrate slower processing speeds and lower accuracy during working memory updating tasks. The induction of reward motivation can enhance the working memory updating performance of both groups through a speed-accuracy tradeoff. Conversely, the induction of punishment motivation only improves updating accuracy for both groups, and this facilitative effect is notably weaker among high-risk students. Furthermore, regarding the improvement of working memory updating accuracy, high-risk students are less sensitive to the induction of punishment motivation, whereas low-risk students remain sensitive to both reward and punishment motivations.

The induction effects are relatively sensitive.

参考文献

Belayachi, S., Majerus, S., Gendolla, G., Salmon, E., Peters, F., & Van der Linden, M. (2015). Are the carrot and the stick the two sides of same coin? A neural examination of approach/avoidance motivation during cognitive performance. Behavioural Brain Research, 293, 217–226.

Berta, K., Pesthy, Z. V., Vékony, T., Farkas, B. C., Király, O., Demetrovics, Z., ···Kun, B. (2025). Game on or gone too far?

Executive functioning and implicit sequence learning in problematic vs. recreational gamers. Computers in Human Behavior, 169, 108878.

Brand, M., Young, K. S., & Laier, C. (2014). Prefrontal control and Internet addiction: A theoretical model and review of neuropsychological and neuroimaging findings. Frontiers in Human Neuroscience, 8, 375.

Canessa, N., Basso, G., Poggi, P., & Gianelli, C. (2022). Altered striatal-opercular intrinsic connectivity reflects decreased aversion to losses in alcohol use disorder. Neuropsychologia, 172, 108258.

Cederblad, A. M. H., Visokomogilski, A., Andersen, S. K., MacLeod, M. J., & Sahraie, A. (2021). Conscious awareness modulates processing speed in the redundant signal effect. Experimental Brain Research, 239(6), 1877–1893.

China Internet Network Information Center. (2025). The 56th statistical report on China' s Internet development. 2025-07-21 Retrieved from https://cnnic.net.cn/n4/2025/0721/c88-11328.html

Cho, T. H., Nah, Y., Park, S. H., & Han, S. (2022). Prefrontal cortical activation in internet gaming disorder scale high scorers during actual real-time internet gaming: A preliminary study using fNIRS. *Journal of Behavioral Addictions*, 11(2).

Combrisson, E., Basanisi, R., Gueguen, M. C. M., Rheims, S., Kahane, P., Bastin, J., & Brovelli, A. (2024). Neural interactions in the human frontal cortex dissociate reward and punishment learning. ELife, 12, RP92938.

Corr, P. J. (2001). Testing problems in J. A. Gray' s personality theory: A commentary on Matthews and Gilliland (1999).

Personality and Individual Differences, 30(2), 333–352.

Cowan, N. (2017). The many faces of working memory and short-term storage. Psychonomic Bulletin & Review, 24(4), Cubillo, A., Makwana, A. B., & Hare, T. A. (2019). Differential modulation of cognitive control networks by monetary reward and punishment. Social Cognitive and Affective Neuroscience, 14(3), 305–317.

Cutting, J., Copeland, B., & McNab, F. (2023). Higher working memory capacity and distraction-resistance associated with

strategy (not action) game playing in younger adults, but puzzle game playing in older adults. Heliyon, 9(8), e19098.

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: The Journal of the Association of European Psychiatrists, 44, 30–38.

Dong, G., Lin, X., Zhou, H., & Lu, Q. (2014). Cognitive flexibility in internet addicts: fMRI evidence from difficult-to-easy and easy-to-difficult switching situations. Addictive Behaviors, 39(3), 677–683.

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.

Duehlmeyer, L., Levis, B., & Hester, R. (2018). Effects of reward and punishment on learning from errors in smokers. Drug and Alcohol Dependence, 188, 32–38.

Galea, J. M., Mallia, E., Rothwell, J., & Diedrichsen, J. (2015). The dissociable effects of punishment and reward on motor learning. Nature Neuroscience, 18(4), 597–602.

Gao, Y. X., Wang, J. Y., & Dong, G. H. (2022). The prevalence and possible risk factors of internet gaming disorder among adolescents and young adults: Systematic reviews and meta-analyses. Journal of Psychiatric Research, 154, 35–43.

Gray, J. A., & McNaughton, N. (2000). The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system (2nd ed.). Oxford University Press.

Grogan, J. P., Randhawa, G., Kim, M., & Manohar, S. G. (2022). Motivation improves working memory by two processes:

Prioritization and retrieval thresholds. Cognitive Psychology, 135, 101472.

Grogan, J. P., Sandhu, T. R., Hu, M. T., & Manohar, S. G. (2020). Dopamine promotes instrumental motivation, but reduces reward-related vigour. Elife, 9, e58321.

Hawi, N. S., Samaha, M., & Griffiths, M. D. (2018). Internet gaming disorder in Lebanon: Relationships with age, sleep habits, and academic achievement. Journal of Behavioral Addictions, 7(1), 70–78.

Hippmann, B., Tzvi, E., Göttlich, M., Weiblen, R., Münte, T. F., & Jessen, S. (2021). Effective connectivity underlying reward-based executive control. Human Brain Mapping, 42(14), 4555–4567.

Hong, W., Liang, P., Pan, Y., Jin, J., Luo, L., Li, Y., ···Zhang, X. (2023). Reduced loss aversion in value-based decision-making and edge-centric functional connectivity in patients with internet gaming disorder. Journal of Behavioral Addictions, 12(2), 458–470.

Jang, J. H., Chung, S. J., Choi, A., Lee, J. Y., Kim, B., Park, M., ···Choi, J. S. (2021). Association of general cognitive functions with gaming use in young adults: A comparison among excessive gamers, regular gamers and non-gamers. Journal

of Clinical Medicine, 10(11), 2293. Klink, P. C., Jeurissen, D., Theeuwes, J., Denys, D., & Roelfsema, P. R. (2017). Working memory accuracy for multiple targets is driven by reward expectation and stimulus contrast with different time-courses. Scientific Reports, 7(1), 9082.

Kuss, D. J., Pontes, H. M., & Griffiths, M. D. (2018). Neurobiological correlates in internet gaming disorder: A systematic literature review. Frontiers in Psychiatry, 9, 166.

Lee, J. Y., Choi, C. H., Park, M., Park, S., & Choi, J. S. (2022). Enhanced resting-state EEG source functional connectivity within the default mode and reward-salience networks in internet gaming disorder. Psychological Medicine, 52(11), Leng, X., Yee, D., Ritz, H., & Shenhav, A. (2021). Dissociable influences of reward and punishment on adaptive cognitive control. PLoS Computational Biology, 17(12), e1009737.

Massar, S. A. A., Pu, Z., Chen, C., & Chee, M. W. L. (2020). Losses motivate cognitive effort more than gains in effort-based decision making and performance. Frontiers in Human Neuroscience, 14, 287.

Miller, C. D., & Byrnes, J. P. (2020). What' s the best way to characterize the relationship between working memory and achievement? An initial examination of competing theories. Journal of Educational Psychology, 112(5), 1074–1084.

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, 152408.

Nie, Q., Teng, Z., Yang, C., Griffiths, M. D., & Guo, C. (2024). Longitudinal relationships between school climate, academic achievement, and gaming disorder symptoms among Chinese adolescents. Journal of Youth and Adolescence, 53(7),

Peng, P., Chen, Z., Ren, S., He, Y., Li, J., Liao, A., ···Liao, Y. (2025). Trajectory of internet gaming disorder among Chinese adolescents: Course, predictors, and long-term mental health outcomes. Journal of Behavioral Addictions, 14(2), Peng, P., & Kievit, R. A. (2020). The development of academic achievement and cognitive abilities: A bidirectional perspective. Child Development Perspectives, 14(1), 15–20.

Ricker, T. J., Cagna, C. J., Tong, T. T., Dobryakova, E., & Sandry, J. (2025). Reward-based prioritization in working memory is distinct from recency and due to a resource trade-off. Psychonomic Bulletin & Review, 33(1), 8.

Rodas, J. A., Asimakopoulou, A. A., & Greene, C. M. (2024). Can we enhance working memory? Bias and effectiveness in cognitive training studies. Psychonomic Bulletin & Review, 31(5), 1891–1914.

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. Contemporary Educational Psychology, 60, 101832.

Statsenko, Y., Habuza, T., Gorkom, K. N., Zaki, N., & Almansoori, T. M. (2020). Applying the inverse efficiency score to visual-motor task for studying speed-accuracy performance while aging. Frontiers in Aging Neuroscience, 12, 574401.

Thurm, F., Zink, N., & Li, S. C. (2018). Comparing effects of reward anticipation on working memory in younger and older adults. Frontiers in Psychology, 9, 2318.

Townsend, J. T., & Ashby, F. G. (1983). Stochastic modelling of elementary psychological processes. New York, NY: Cambridge University Press.

Wang, H., Sun, Y., Lan, F., & Liu, Y. (2020). Altered brain network topology related to working memory in Internet addiction. Journal of Behavioral Addictions, 9(2), 325–338.

Wang, L., Wu, L., Lin, X., Zhang, Y., Zhou, H., Du, X., & Dong, G. H. (2016). Altered brain functional networks in people with internet gaming disorder: Evidence from resting-state fMRI. Psychiatry Research Neuroimaging, 254, 156–163.

Weinstein, A. M. (2017). An update overview on brain imaging studies of internet gaming disorder. Frontiers in Psychiatry, 8, 185.

Weinstein, A., & Lejoyeux, M. (2020). Neurobiological mechanisms underlying internet gaming disorder. Dialogues in Clinical Neuroscience, 22(2), 113–126.

Wen, X., Yue, L., Du, Z., Zhao, J., Ge, M., Yuan, C., ···Yuan, K. (2025). Functional connectome gradient of prefrontal cortex as biomarkers of high risk for internet gaming disorder. Neuroimage, 306, 121010.

Wölfling, K., Duven, E., Wejbera, M., Beutel, M. E., & Müller, K. W. (2020). Discounting delayed monetary rewards and decision making in behavioral addictions: A comparison between patients with gambling disorder and internet gaming disorder. Addictive Behaviors, 108, 106446.

Xu, S., Qi, S., Duan, H., Zhang, J., Akioma, M., Gao, F., ···Yuan, Z. (2022). Task difficulty regulates how conscious and unconscious monetary rewards boost the performance of working memory: An event-related potential study. Frontiers in Systems Neuroscience, 15, 716961.

Yang, Q., Si, S., & Pourtois, G. (2023). Parsing the contributions of negative affect vs. aversive motivation to cognitive control: An experimental investigation. Frontiers in Behavioral Neuroscience, 17, 1209824.

Yao, Y. W., Liu, L., Worhunsky, P. D., Lichenstein, S., Ma, S. S., Zhu, L., ···Yip, S. W. (2020). Is monetary reward processing altered in drug-naïve youth with a behavioral addiction? Findings from internet gaming disorder. Neuroimage Clinical, 26, 102202.

Yee, D. M., & Braver, T. S. (2018). Interactions of motivation and cognitive control. Current Opinion in Behavioral Sciences, 19, 83–90.

Young, K. S. (1999). The research and controversy surrounding Internet addiction. Cyberpsychology & Behavior: The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society, 2(5), 381–383.

Zhang, M. X., Wang, X., Yu, S. M., & Wu, A. (2019). Purpose in life, social support, and internet gaming disorder among Chinese university students: A 1-year follow-up study. Addictive Behaviors, 99, 106070.

Zhang, X., Liu, D., Li, J., Zheng, X., Zhou, S., Elhai, J. D., ···Yang, H. (2025). Prefrontal cortex responses to game rewards and losses in individuals with internet gaming disorder: Insights from fNIRS during mobile gameplay. Journal of Behavioral Addictions, 14(1), 347–360.

Zhang, Y., Lin, X., Zhou, H., Xu, J., Du, X., & Dong, G. H. (2016). Brain activity toward gaming-related cues in internet gaming disorder during an addiction Stroop task. Frontiers in Psychology, 7, 714.

Zhou, W. R., Wang, M., Dong, H. H., Zhang, Z., Du, X., Potenza, M. N., & Dong, G. H. (2021). Imbalanced sensitivities to primary and secondary rewards in internet gaming disorder. Journal of Behavioral Addictions, 10(4), 990–1004.

Zhou, X., Zeng, Y., Wen, Y., Dong, X., Gola, M., & Li, Y. (2025). Love at first glance: Imbalanced processing to gaming and natural rewards in internet gaming disorder. Journal of Behavioral Addictions, 14(2), 805–816.

Effects of reward and punishment motivation on working memory updating among college students at high risk for internet gaming disorder

GAO Yuanxia1,2; WANG Jiangyang1 (1 College of Educational Science, Shenyang Normal University, Shenyang 110034, China) (2 Faculty of Psychology, Tianjin Normal University, Tianjin 300387, China)

Abstract

Previous studies have found that individuals with internet gaming disorder (IGD) have relatively low cognitive functioning and commonly suffers from poor academic performance. As a key aspect of executive functioning, working memory plays an important role in the academic growth of college students, not only as a foundation for cognitive development, learning, and education, but also as a

prerequisite to cope with the complex cognitive challenges of daily life. Several studies have shown that IGD risk negatively affects working memory updating, and this impairment likely contributes to poor academic performance in college students at high risk for IGD. Therefore, based on the social cognition theory, this study aims to explore the influences of IGD risk on college students' working memory updating, as well as the effects and differences in reward and punishment motivation induced by monetary rewards and losses on working memory updating in high-risk (IGD) and low-risk (non-IGD) college students.

Participants were recruited using posters. Forty-two high-risk and 45 low-risk college students were identified using the Internet (Gaming) Addiction Test. In Experiment 1, participants completed three reward-based N-back tasks with different memory loads to examine differences in working memory updating between high- and low-risk college students in conditions with or without reward motivation. In Experiment 2, a punishment-based N-back task was used to examine differences in working memory updating between high- and low-risk college students in conditions with or without punishment motivation across three different memory loads.

The results of Experiment 1 showed that in the rewarded version of the working memory updating task, high-risk college students had weaker processing, that is, longer reaction times and lower accuracy, than low-risk college students. With reward motivation, high- and low-risk college students' reaction time increased, accuracy improved, and the degree of processing was enhanced. There was no significant dif23

ference in the role of reward motivation in facilitating response time and accuracy in the working memory updating task between high- and low-risk college students. The results of Experiment 2 showed that in the punishment version of the working memory updating task, high-risk college students had weaker processing than low-risk college students. With punishment motivation, the accuracy of high- and low-risk college students increased, and it contributed less to facilitating the working memory updating accuracy of high-risk college students than low-risk college students. After conducting a cross-experimental analysis, it was found that the accuracy of reward motivation in working memory updating was significantly higher than that of punishment motivation among high-risk students, and there was no significant difference in the accuracy of reward and punishment motivation among low-risk students. In conclusion, this study showed that the working memory updating speed and accuracy of high-risk college students are significantly slower and lower than low-risk college students. Rewarding motivation helped improve working memory updating performance in both high- and low-risk college students by increasing accuracy and reducing speed, whereas punishment motivation only improved accuracy and had a weaker facilitating effect for high-risk college students than for low-risk college students.

Overall, the facilitating effect of reward motivation on the accuracy of working memory updating in high-risk students is greater than that of punishment moti-

vation, whereas reward and punishment motivation show the same utility value for accuracy of working memory updating in low-risk college students.

This implies that college students at high risk for IGD exhibit certain impairment in working memory updating and reduced sensitivity to punishment in cognitive tasks. Additionally, the mechanism of working memory updating in college students at high risk for IGD provides new insights into their poor academic performance, and offers suggestions for reference to address this issue.

Keywords

working memory updating, internet gaming disorder, reward motivation, punishment motivation, college students

Note: Figure translations are in progress. See original paper for figures.