

Deciphering Age Differences in Experience-Based Decision-Making: The Role of Sleep

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Objective: Recent studies have demonstrated that sleep not only facilitates memory consolidation but also benefits more complex cognitive skills such as decision-making in young adults. Older adults use different decision strategies compared with young adults, which leaves the role of sleep in older adults' decision-making unclear. We investigated the age-by-sleep effect on decision-making.

Methods: We recruited 67 young adults (ages 18 to 29 years) and 66 older adults (ages 60 to 79 years) and randomly assigned them into the "sleep" or "wake" study condition. They were given a modified Iowa gambling task to perform before and after a 12-hour interval with sleep or wakefulness.

Results: Using the typical model-free analysis, we found that young adults' between-session performance improved greater than that of older adults regardless of the sleep/wake condition. Furthermore, older adults with longer total sleep time showed a greater improvement in the selection of one "good" deck. To further examine the sleep effect on age-related differences in cognitive processes underlying decision-making, we conducted computational modelling. This more fine-grained analysis revealed that sleep improved feedback sensitivity for both young and older adults while it increased loss aversion for older adults but not for young adults.

Conclusion: These findings indicate that sleep promotes learning-based decision-making performance via facilitating value representation, and such modulation is distinct in young compared to older adults.

Keywords: decision-making, the Iowa gambling task, sleep, aging, computational modelling

Sleep is vital for humans, and we spend about one-third of our lives in sleep. It plays a profound role in a variety of physiological systems that maintain our health and promote cognitive function across domains.^{1,2} Both sleep and cognitive function of older adults alter with advanced age.^{3–5} While previous research has extensively focused on age differences in the sleep-related effects on emotion, memory,^{1,6–8} and executive function,⁹ little is known about age-related differences in sleep modulation effects on decision-making.

Among the widely used decision-making paradigms, the Iowa gambling task (IGT)¹⁰ has been adopted to uncover the relationship between sleep and decision-making, as it involves a feedback learning component that is often influenced by sleep.^{11,12} Specifically, the IGT requires participants to have reinforcement learning ability to distinguish advantageous and disadvantageous decks. The advantageous decks offer small immediate gains but even smaller losses in the long term, resulting in an overall net gain. While the disadvantageous decks produce large

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immediate gains but even larger losses in the long term, leading to an overall net loss. To maximize earnings, participants have to consider gains and losses, long-term and short-term payoffs, as well as uncertainty about outcomes. In sleep studies, poor IGT performance was often reported in the context of sleep deprivation^{13,14} and sleep disorders.^{15,16} Correspondingly, normal sleep was found to be beneficial to IGT performance in young adults. These studies used the “am-pm” experimental design, in which participants had either a 12-hour interval with sleep (in the sleep condition) or with wakefulness (in the wake condition) between the first test and the re-test. For example, Pace-Schott et al¹⁷ found that after a 12-hour interval, participants’ performance, indexed by their net scores, were improved more in the sleep condition compared with that of participants in the wake condition.

Although older adults exhibit cognitive declines and neurobiological impairments with aging, they can still be identified as adaptive decision-makers with the ability to distinguish advantageous decks from disadvantageous decks.^{18–20} However, to achieve this comparable performance as young adults, older adults may utilize different strategies based on the capacity of their cognitive resources. For instance, young adults had more strengths in learning and memory, while older adults had a more accurate representation of gains and losses.¹⁸ Moreover, older adults were more conservative in exploratory behaviour than that of young adults.²¹ Since these age differences were observed in the cognitive processing underlying the IGT, we speculate that the sleep effect on decision-making could be modulated by age.

The typical analysis for the IGT is usually focused on the comparison of net scores between conditions, which is often averaged by blocks of 20 trials.^{22–24} However, this traditional analysis approach does not provide detailed trial-by-trial information, therefore, is insufficient for a more thorough examination of decision strategy. Recently, reinforcement learning (RL) models have been adopted to break down the trial-by-trial performance of the IGT into cognitive components, such as feedback learning, memory, sensitivity, and response consistency,^{25,26} that may enrich our understanding of the cognitive processes underlying decision-making. In this study, we applied the RL models to investigate the sleep effect on decision-making modulated by age.

The overarching aim of the present study is to examine whether sleep contributes to the performance of IGT, and whether and how this potential sleep effect is modulated by age. We conducted both model-free and model-based

analysis to examine decision strategies used by young and older adults. Moreover, we investigated the association between IGT performance and sleep characteristics in order to explore the possible mechanisms underlying the age-by-sleep effect.

Methods

Participants

We recruited 68 young adults (aged 18–29) from a university and 70 older adults (aged 60–79) from adjacent communities. Older adults were independent community-dwelling adults with a mean score of 28.9 ± 1.13 in the minimal state examination (MMSE).²⁷ Participants were all right-handed, had no history of psychiatric, neurological diseases, or sleep disorders, and had normal or corrected-to-normal vision. Five participants were excluded: three older adults with MMSE scores below 25, and two participants (one old and one young) with incomplete data recording. Participants were randomly assigned to the wake or the sleep condition groups. Thus, the sample used for the following analyses included 67 young adults—33 in the sleep condition and 34 in the wake condition—and 66 older adults—32 in the sleep condition and 34 in the wake condition. As shown in Table 1, participants in the wake and sleep conditions were well matched for demographic and neuropsychological characteristics across age groups. With respect to age differences, older adults were generally less educated and more morningness-oriented, and they had generally poorer subjective sleep quality. Considering the significant differences in education and circadian chronotype between the two age groups, we conducted additional analyses to control for these confounding variables. The significance of our results was not affected by these covariates (see [Supplementary Tables S1](#) and [S5](#)).

This study was approved by the ethics committees of the Faculty of Psychology, Southwest University (H17001), and was conducted in accordance with the Declaration of Helsinki. Participants provided informed consent prior to the experiment. Each participant received 40 CNY (ca. 6 USD) for participation in the study, with the opportunity to earn up to an additional 40 CNY based on their performance in the task.

Materials and Procedure

The experiment consisted of two sessions ([Figure 1A](#)). The first session was conducted either in the morning (7:30–9:30 am; wake condition) or in the evening (7:30–9:30 pm;

Table 1 Participants' Characteristics and Neuropsychological Data

	YS (n = 33) M (SD)	YW (n = 34) M (SD)	YS vs YW t (p)	OS (n = 32) M (SD)	OW (n = 34) M (SD)	OS vs OW t (p)	Y vs O t (p)
Age (years)	20.58 (1.58)	20.29 (2.07)	0.63 (0.53)	66.22 (4.48)	67.50 (4.38)	-1.15 (0.26)	-78.97 (2.35×10⁻¹¹²)
Male (%)	0.49	0.47	0.01 ^a (0.91)	0.38	0.38	0.09 ^a (0.76)	0.95 ^a (0.33)
Education (years)	14.64 (1.64)	14.18 (2.11)	1.00 (0.32)	9.00 (2.31)	9.85 (3.04)	-1.28 (0.21)	12.22 (2.14×10⁻²³)
Economic status (5-point)	2.94 (0.56)	3.06 (0.56)	-0.89 (0.38)	2.94 (0.67)	2.85 (0.66)	0.52 (0.61)	0.99 (0.32)
Health status (5-point)	2.24 (0.75)	2.33 (0.78)	-0.48 (0.63)	2.44 (0.84)	2.50 (0.90)	-0.29 (0.77)	-1.28 (0.20)
MMSE	—	—	—	28.72 (1.40)	29.12 (0.77)	-1.45 (0.15)	—
MEQ	48.88 (7.11)	46.91 (7.04)	1.14 (0.26)	61.69 (8.29)	63.59 (5.40)	-1.11 (0.27)	-12.13 (3.59×10⁻²³)
PSQI	4.52 (2.03)	4.03 (1.47)	1.12 (0.27)	5.90 (3.05)	6.44 (3.50)	-0.66 (0.51)	-4.20 (5.00×10⁻⁵)
TST ^b (min)	322.21 (54.34)	—	—	318.31 (72.12)	—	—	0.25 (0.81)
Sleep latency ^b (min)	13.21 (9.99)	—	—	19.69 (18.33)	—	—	-1.78 (0.08)
Sleep efficiency ^b (%)	83.17 (10.80)	—	—	79.80 (9.57)	—	—	1.33 (0.19)

Notes: ^a χ^2 value. ^b Actigraph-measured sleep characteristics.

Abbreviations: M, mean; MEQ, the morningness-eveningness questionnaire; MMSE, the mini-mental state examination; O, older adults; OS, older adults in the sleep condition; OW, older adults in the wake condition; PSQI, the Pittsburgh sleep quality index; SD, standard deviation; TST, total sleep time; Y, young adults; YS, young adults in the sleep condition; YW, young adults in the wake condition. Bold font indicates statistically significant result ($p < 0.05$).

sleep condition), and the second session was conducted 12 hours later (following an interval of wakefulness or sleep). Participants in the wake condition were not allowed to have a nap before the re-test session. All participants were asked to provide a record of their sleep/daily activities of the previous night/daytime prior to each session. To monitor

the sleep of participants in the sleep condition, they were asked to wear an actigraph (BodyMedia FIT LINK) on their non-dominant wrist during sleep. Sleep parameters, including total sleep time (TST), sleep latency, and sleep efficiency were obtained from Sense Wear Software 8.1 (BodyMedia LINK).

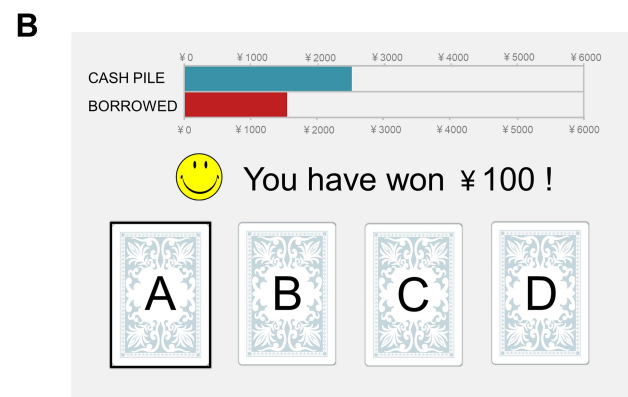
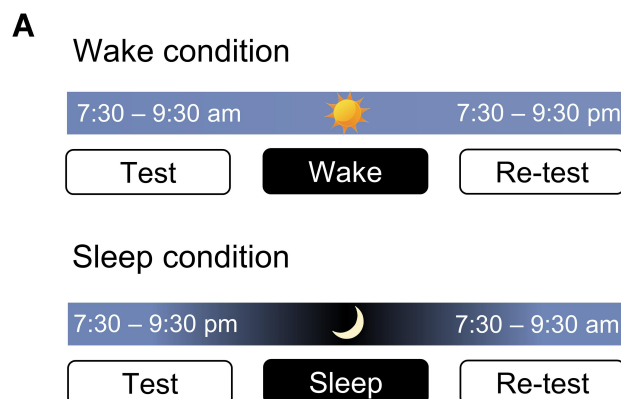


Figure 1 Experimental procedure and design. **(A)** Experimental procedure. The first session was conducted either in the morning (7:30–9:30 am; the wake condition) or in the evening (7:30–9:30 pm; the sleep condition), followed by a re-test session 12 hours later. **(B)** Screenshot of the Iowa gambling task. The green bar shows the amount of money participants gained; the red bar shows the amount of money participants borrowed. In this example, the participant selected deck A and gained 100 CNY.

The Iowa Gambling Task

In the present study, we adopted a well-known experience-based decision-making task, the Iowa gambling task (IGT)^{10,28}. The computerized version of IGT was written with MATLAB 2018a (MathWorks) based on Psychtoolbox (www.psychtoolbox.org). As shown in Figure 1B, in each trial of the task, participants were asked to choose one of four decks (A, B, C and D) on a screen. Two of the decks (A and B) were disadvantageous decks with net losses in the long term, whereas two of the decks (C and D) were advantageous decks with net gains in the long term. Additionally, losses are more frequent in decks A and C (50%) than in decks B and D (10%). Each deck has up to 60 draws and the net gains/losses increase with every 10 draws.²⁹ Specifically, the net profit of decks A and B in the first 10 draws are -250 CNY, and it is increased by -150 CNY every 10 draws; the net profit of decks C and D in the first 10 draws are 250 CNY, and it goes up by 25 CNY every 10 draws. Participants were only told that sometimes they would gain and sometimes they would lose and that some decks might be better than others; they were not told which decks were good or bad. They were required to gain as much as possible, as total gain in the task would be converted into their monetary recompense for the study. There were two bars at the top of the screen, with the green bar showing the amount of money participants gained and the red bar showing the amount of money participants borrowed. The green bar was updated according to the outcome after each selection. If participants' amount of gain was less than 0, a load of 2000 CNY was added to the red bar automatically while the green bar was reset accordingly. Participants were informed of their net outcome (ie, the total amount of money gained minus the total amount of money borrowed) at the end of the task. Participants completed 100 trials in each session, and the features of the four decks were kept the same across the two sessions to avoid reversal learning.

Data Analysis

We calculated the net score for each participant in each session, as net scores have been widely used in the IGT studies to quantify participants' task performance.^{10,30,31} To examine the feedback learning process, the 100 trials were divided into 5 consecutive blocks with each containing 20 trials. A net score was calculated by subtracting the number of draws of the disadvantageous decks from the number of draws of the advantageous decks [(C + D) - (A + B)] for each block. The net scores were examined using

a repeated-measure ANOVA, with age (young, old) and condition (sleep, wake) as between-subject variables, session (test, re-test), and block (1-5) as within-subject variables.

Previous studies identified the decreasing selection of deck B as evidence of sleep beneficial effect on decision-making.^{22,23} Thus, we calculated the proportional change of each deck selection from session 1 to session 2 in order to examine whether the sleep-related improvement was deck-specific. A repeated-measure ANOVA with age (young, old) and condition (sleep, wake) as between-subject variables and deck (A, B, C, D) as a within-subject variable was performed. Next, we conducted correlation analyses between sleep and decision-performance changes. Statistical analyses were performed using SPSS 26.0 (IBM Corporation, Armonk, NY, USA).

Computational Modelling

The IGT is a complex, experience-based, decision-making task involving multiple cognitive processes such as feedback learning, reward sensitivity, loss aversion, time insight, and exploration. Computational modelling is a useful tool for understanding task performance at a more nuanced level. Three commonly used and validated reinforcement learning models of the IGT were applied: the Prospect Valence Learning (PVL)-Decay model,³² the PVL-Delta model³³ and the Value-Plus-Perseverance (VPP) model.³⁴ The main difference between these models is how the expected value of each option updates over time.

The PVL-Decay and PVL-Delta Model

The concepts of PVL models include utility function, learning rule, and choice rule. Outcomes of decisions are evaluated according to the prospect utility function. The utility $u(t)$ of outcome $x(t)$ on the t trial is expressed as:

$$u(t) = \begin{cases} x(t)^\alpha, & x(t) \geq 0 \\ -\lambda |x(t)|^\alpha, & x(t) < 0 \end{cases} \quad (1)$$

where $\alpha(0 < \alpha < 2)$ is a shape parameter, which determines sensitivity to outcome feedback, while $\lambda(0 < \lambda < 10)$ is a loss-aversion parameter, which determines sensitivity to losses versus gains. Higher α means greater sensitivity to feedback (i.e., giving higher subjective value to outcomes). A value of $\lambda < 1$ indicates higher sensitivity to gains other than losses, whereas $\lambda > 1$ represents the opposite.

These two PVL models are identical in utility function and choice rule but are different in learning rule. In the decay rule, the expected value for all decks is discounted in each trial, and the expected value of the selected deck is updated by its current utility. For example, the expected value of the j^{th} deck in the $(t + 1)$ trial, $E_j(t + 1)$, is updated as:

$$E_j(t + 1) = A \cdot E_j(t) + \delta_j(t) \cdot u(t) \quad (2)$$

where $A(0 < A < 1)$ is a decay parameter, which determines how much past expectancy is discounted; $\delta_j(t) = 1$ when the j^{th} deck is the selected deck, otherwise $\delta_j(t) = 0$. However, in the delta rule, only the expected value of the selected deck will be updated, and expected values of unselected decks remain unchanged, which is expressed as:

$$E_j(t + 1) = E_j(t) + A \cdot \delta_j(t) \cdot (u(t) - E_j(t)) \quad (3)$$

where $A(0 < A < 1)$ is a learning rate, which determines the weight of past experiences versus recent experiences. A high learning rate means recent outcomes have greater influence other than past outcomes on the expected value of the selected deck, whereas a low learning rate means the opposite. In addition, $u(t) - E_j(t)$ is the prediction error. The softmax function³⁵ was used as a choice rule to calculate the probability of selecting deck j in $t + 1$ trial:

$$\Pr[D(t + 1) = j] = \frac{e^{\theta \cdot E_j(t+1)}}{\sum_{k=1}^4 e^{\theta \cdot E_k(t+1)}} \quad (4)$$

$$\theta(t) = 3^c - 1 \quad (5)$$

where the sensitivity θ changes over trials depending on the response consistency parameter $c(0 < c < 5)$. Greater c means the continuous selection becomes less random and more determined by expected deck utility. In sum, the PVL models have four free parameters: the feedback sensitivity parameter α , the loss-aversion parameter λ , the learning rate A in the PVL-delta model and the decay parameter A in the PVL-decay model, as well as the choice sensitivity c .

The VPP Model

The VPP model is an updated version of the PVL-delta model, which consists of the same utility function, learning rule and choice rule but combines an additional psychological process, perseverance (ie, win-stay-loss-switch choice behaviour), and is expressed as:

$$P_j(t + 1) = \begin{cases} k \cdot P_j(t) + \varepsilon_p, & x(t) \geq 0 \\ k \cdot P_j(t) + \varepsilon_n, & x(t) < 0 \end{cases} \quad (6)$$

where $k(0 < k < 1)$ is a perseverance decay rate, which determines participants' decay of tendency to select the deck j in each trial; $\varepsilon_p(-\infty < \varepsilon_p < \infty)$ or $\varepsilon_n(-\infty < \varepsilon_n < \infty)$ is the outcome impact parameter, depending on whether the outcome of selected deck j in the t trial is positive (i.e., gain) or negative (i.e., loss). Specifically, positive ε_p or ε_n means a persistent tendency (i.e., to select the same deck in the next trials) while a negative value means a switching tendency (i.e., to select other decks in the next trials). The VPP model also assesses the persistence and maximization of expected utility as two basic but independent psychological processes. A weighted average of these two processes is used in the choice rule to determine the probability of selecting deck j in the $t + 1$ trial (i.e., the next trial), which is expressed as:

$$V_j(t + 1) = \omega \cdot E_j(t + 1) + (1 - \omega) \cdot P_j(t + 1) \quad (7)$$

$$\Pr[D(t + 1) = j] = \frac{e^{\theta \cdot V_j(t+1)}}{\sum_{k=1}^4 e^{\theta \cdot V_k(t+1)}} \quad (8)$$

where $\omega(0 < \omega < 1)$ determines the weight of expected utilities of deck and $1 - \omega$ determines the weight of perseverance process. A value of $\omega > 0.5$ indicates the expected utilities of the deck have more weight while a value of $\omega < 0.5$ indicates the perseverance of the deck has more weight. In sum, the VPP model has eight free parameters: the feedback sensitivity (α), the loss aversion (λ), the learning rate (A), the gain impact (ε_p), the loss impact (ε_n), the perseverance decay rate (k), the choice sensitivity (c), as well as the reinforcement learning weight (ω).

Model Fits and Comparisons

Model fitting and parameter estimation were performed for each session in each group using a hierarchical Bayesian analysis approach based on the implemented algorithms using the hBayesDM R package (<https://cran.rproject.org/web/packages/hBayesDM/index.html>). Four chains were used, each of which comprised 2000 iterations; the initial half of each chain was discarded as burn-in (1000 samples $\times$ 4 chains = a total of 4000 samples).³⁶ Model fits were assessed using the Widely Applicable Information Criterion (WAIC).³⁷ This index is a "more fully Bayesian approach"³⁸ that uses point-by-point log-likelihood posterior predictive density, and a penalty term is used to control the trade-off between goodness of fit and complexity of the

model. Smaller WAIC indicates better model-fit, and the overall fitness is assessed by the sum of WAIC in each group for each model.

Model-based estimates (mean) for parameters were analyzed using repeated-measure ANOVAs with age (young, old), condition (sleep, wake) as between-subject variables, and session (test, re-test) as a within-subject variable. Bonferroni correction with $p < 0.05/8 = 0.0063$ were applied for multiple comparisons. Moreover, we performed correlation analyses between sleep characteristics and parameters estimation from the winning model to investigate individual differences in the relationship between sleep and cognitive processes underlying IGT.

Results

Model-Free Analyses on the Net Score

The net score was examined using a 2 (age: young, old) $\times$ 2 (condition: sleep, wake) $\times$ 2 (session: test, re-test) $\times$ 5 (block: 1–5) repeated-measure ANOVA, with age and condition as between-subject variables, session and block as within-subject variables. As shown in [Figure 2A](#), all groups showed an increased tendency of net score as a function of learning, resulting in significant main effects of block ($F_{4, 130} = 19.18$, $p = 2.48 \times 10^{-12}$, partial $\eta^2 = 0.13$) and session ($F_{1, 130} = 37.55$, $p = 1.01 \times 10^{-8}$, partial $\eta^2 = 0.23$). In addition, there was a significant interaction of age $\times$ session ($F_{1, 130} = 7.78$, $p = 0.006$, partial $\eta^2 = 0.06$). The Bonferroni-corrected simple effect analyses showed that young adults' net scores showed greater between-session increases ($M_{\text{session1}} = 0.004$, $SD = 0.28$; $M_{\text{session2}} = 0.25$, $SD = 0.40$; $p = 3.73 \times 10^{-9}$) than those of older adults ($M_{\text{session1}} = 0.06$, $SD = 0.32$; $M_{\text{session2}} = 0.16$, $SD = 0.25$; $p = 0.02$). No other significant main effects or interactions of net score were observed.

For the proportional change of each deck selection, a 2 (age: young, old) $\times$ 2 (condition: sleep, wake) $\times$ 4 (deck: A, B, C, D) repeated-measure ANOVA with age and condition as between-subject variables, deck as a within-subject variable was performed. The analysis revealed a significant main effect of deck ($F_{3,387} = 17.13$, $p = 5.83 \times 10^{-9}$, partial $\eta^2 = 0.12$) and an interaction of age $\times$ deck ($F_{3,387} = 9.61$, $p = 2.20 \times 10^{-5}$, partial $\eta^2 = 0.07$). Bonferroni-adjusted pairwise comparisons showed that young adults reduced the selection of the disadvantageous deck B more than older adults ($p = 2.56 \times 10^{-4}$) while increased the selection of the advantageous deck C more compared with older adults ($p = 3.40 \times 10^{-5}$; [Figure 2B](#)).

Correlation analyses revealed that the TST was positively correlated with increases in the selection of advantageous deck D in older adults ($r = 0.53$, $p = 0.002$; Bonferroni corrected) but not in young adults ($r = -0.10$, $p = 0.57$; [Figure 2C](#)). The difference between these two correlations was significant ($z = 2.65$, $p = 0.008$). No other significant correlation between sleep characteristics and changes in deck selection survived after multiple comparison correction (see [Supplementary Table S2](#) for all correlation results).

Together, the analyses of net scores suggest that young adults experienced a greater feedback learning effect than older adults in general, manifested as greater performance improvements from session 1 to session 2. Specifically, young adults demonstrated a greater decrease in their selections from disadvantageous deck B and greater increases in their selections from advantageous deck C. However, the evidence of an impact based on condition, ie, sleep versus wake, was relatively weak, only manifesting as the positive correlation between the TST and the increased selection of advantage deck D in older adults.

Computational Modelling

Model Fitting and Comparison

As shown in [Table 2](#) and [Supplementary Figure S1](#), model comparisons suggested that the VPP model ($\text{WAIC}_{\text{sum}} = 59,244.57$) provided the best model-fit relative to the PVL-Decay ($\text{WAIC}_{\text{sum}} = 66,136.71$) and the PVL-Delta model ($\text{WAIC}_{\text{sum}} = 62,746.38$) in all 4 groups and 2 sessions. In addition, we performed model simulation for the VPP model for each session of each participant based on their parameter estimates to evaluate model fit.³⁹ Real data and simulated data of the number of each deck selection in each session showed strong correlations ($ps < 0.001$; [Supplementary Figure S2](#)).

Parameter Comparison

We extracted model parameters from the winning model, ie, the VPP model, to compare specific cognitive processes underlying decision-making assumed by the model among groups. Parameter estimates of the VPP model are provided in [Supplementary Table S3](#), and the other two models are summarized in [Supplementary Table S4](#). In the following, we reported the 2 (age: young, old) $\times$ 2 (condition: sleep, wake) $\times$ 2 (session: test, re-test) repeated-measure ANOVA results of parameter estimates (ie, α , the feedback sensitivity and λ , the loss aversion) that had significant interaction effects of age $\times$ condition $\times$ session after Bonferroni

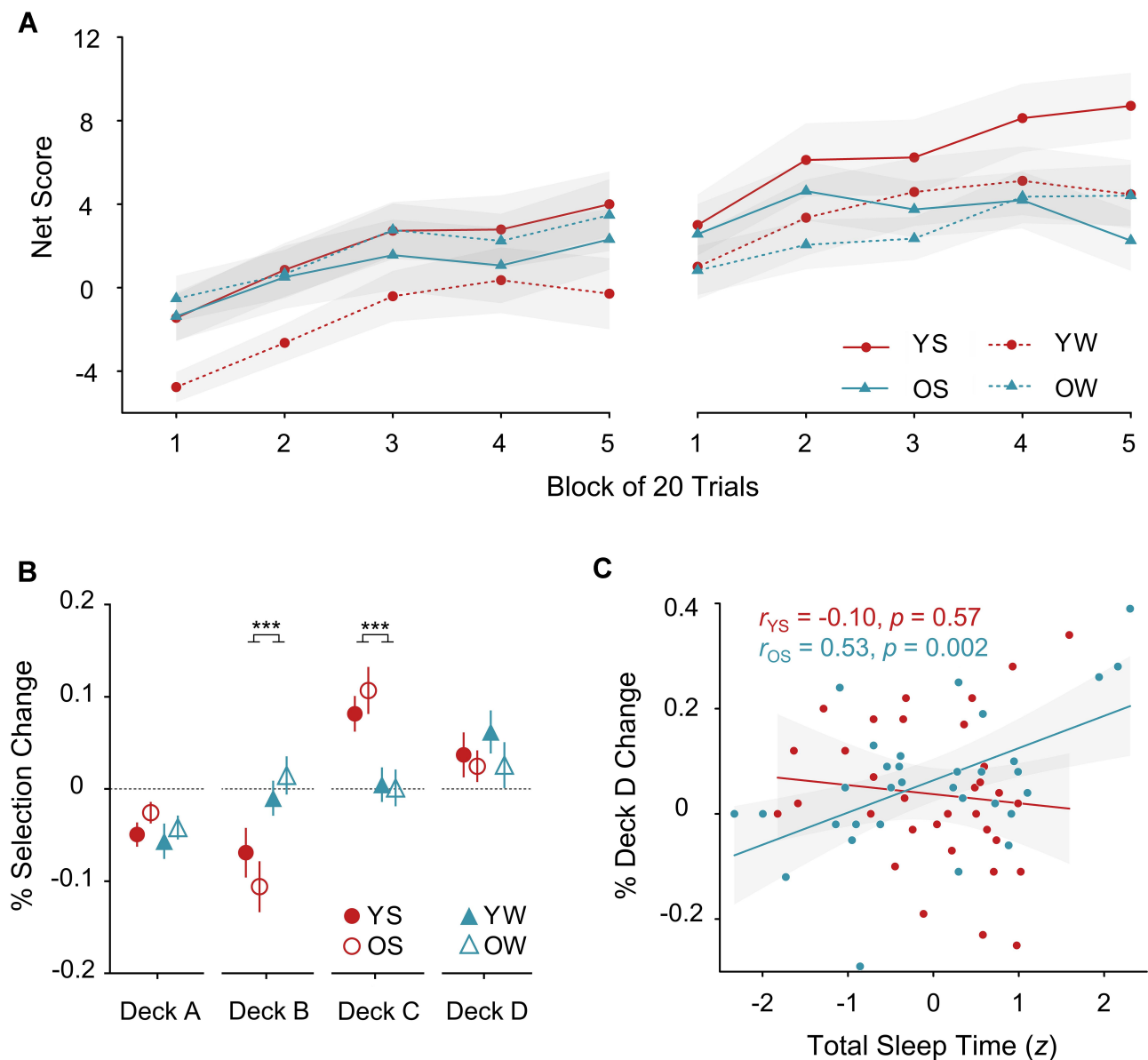


Figure 2 (A) The net score in five 20-trial blocks for four groups in session 1 and session 2, respectively. **(B)** The proportion change in the selection of each deck (A, B, C and D) from session 1 to session 2. Performance improvement is manifested as the decreased selection of disadvantageous decks (A and B) and increased selection of advantageous decks (C and D). **(C)** The correlation between total sleep time and the proportion of selection change of advantageous deck D. *** $p < 0.001$.

Abbreviations: n.s., not significant; OS, older adults in the sleep condition; OW, older adults in the wake condition; YS, young adults in the sleep condition; YW, young adults in the wake condition.

correction, which reflected the mediation effect of age on the association between sleep and decision-making.

α : Feedback Sensitivity

Feedback sensitivity results yielded the significant main effects of session ($F_{1, 129} = 248.57, p = 7.10 \times 10^{-32}$, partial $\eta^2 = 0.66$), condition ($F_{1, 129} = 286.75, p = 1.39 \times 10^{-34}$, partial $\eta^2 = 0.69$) and age ($F_{1129} = 800.62, p = 3.59 \times 10^{-57}$, partial $\eta^2 = 0.86$). Moreover, there was a two-way interaction of age $\times$ condition ($F_{1129} = 360.75, p = 3.47 \times 10^{-39}$, partial

$\eta^2 = 0.74$) and a three-way interaction of age $\times$ condition $\times$ session ($F_{1129} = 359.98, p = 3.85 \times 10^{-39}$, partial $\eta^2 = 0.74$).

As shown in Figure 3, Bonferroni-adjusted pairwise comparisons showed that feedback sensitivity for young adults increased significantly in the sleep condition ($M_{YS1} = 0.07, SD = 0.01; M_{YS2} = 0.10, SD = 0.08; p = 0.002$), but decreased significantly in the wake condition ($M_{YW1} = 0.56, SD = 0.08; M_{YW2} = 0.09, SD = 0.02; p = 1.12 \times 10^{-77}$). For older adults, feedback sensitivity increased significantly in the sleep condition ($M_{OS1} = 0.04, SD = 0.02; M_{OS2} = 0.12, SD = 0.05; p =$

Table 2 Widely Applicable Information Criterion (WAIC) Scores of Each Model for Each Group

	Session 1				Session 2				WAIC _{SUM}
	WAIC _{YS}	WAIC _{YW}	WAIC _{OS}	WAIC _{OW}	WAIC _{YS}	WAIC _{YW}	WAIC _{OS}	WAIC _{OW}	
PVL-Decay	8103.68	8333.15	7934.05	8344.20	7077.46	7584.00	7499.57	7870.27	62,746.38
PVL-Delta	8368.62	8551.21	8067.52	8740.29	8052.83	8060.46	7877.33	8418.45	66,136.71
VPP	7800.61	7982.52	7291.17	7872.58	6763.10	7104.79	7025.38	7404.42	59,244.57

Abbreviations: OS, older adults in the sleep condition; OW, older adults in the wake condition; PVL, prospect valence learning model; VPP, value-plus-perseverance model; YS, young adults in the sleep condition; YW, young adults in the wake condition. Bold font indicates the best fitting model.

7.41×10^{-11}), whereas there was no significant difference between two sessions in the wake condition ($M_{OW1} = 0.02$, $SD = 0.001$; $M_{OW2} = 0.02$, $SD = 0.004$; $p = 0.94$).

λ : Loss Aversion

Loss aversion showed significant main effects with session ($F_{1,129} = 21.91$, $p = 7.00 \times 10^{-6}$, partial $\eta^2 = 0.15$) and age ($F_{1,129} = 106.36$, $p = 1.48 \times 10^{-18}$, partial $\eta^2 = 0.45$). Moreover, there were a significant two-way interaction of age $\times$ condition ($F_{1,129} = 20.56$, $p = 1.30 \times 10^{-5}$, partial $\eta^2 = 0.14$) and a three-way interaction of age $\times$ condition $\times$ session ($F_{1,129} = 20.73$, $p = 1.20 \times 10^{-5}$, partial $\eta^2 = 0.14$).

As shown in Figure 4, Bonferroni-adjusted pairwise comparisons showed that for young adults, there was no significant difference between two sessions in the sleep condition ($M_{YS1} = 0.32$, $SD = 0.02$; $M_{YS2} = 0.34$, $SD = 0.17$; $p = 0.63$), whereas loss aversion was decreased significantly in the wake condition ($M_{YW1} = 0.73$, $SD = 0.46$; $M_{YW2} = 0.05$,

$SD = 0.001$; $p = 4.15 \times 10^{-30}$). For older adults, loss aversion was increased significantly in the sleep condition ($M_{OS1} = 0.02$, $SD = 0.001$; $M_{OS2} = 0.27$, $SD = 0.18$; $p = 1.87 \times 10^{-7}$), whereas there was no significant difference between sessions in the wake condition ($M_{OW1} = 0.12$, $SD = 0.005$; $M_{OW2} = 0.09$, $SD = 0.01$; $p = 0.53$). Unfortunately, no correlation between sleep characteristics and model parameters survived after multiple comparison correction.

Discussion

To the best of our knowledge, this is the first study to investigate age differences in the sleep-related modulation effects on experience-based decision-making. With typical net score analysis, we only found a salient age difference on the feedback learning effect, illustrated as young adults selecting fewer disadvantageous decks and more advantageous decks in the re-test session compared with older adults. Nevertheless, with a more fine-grained

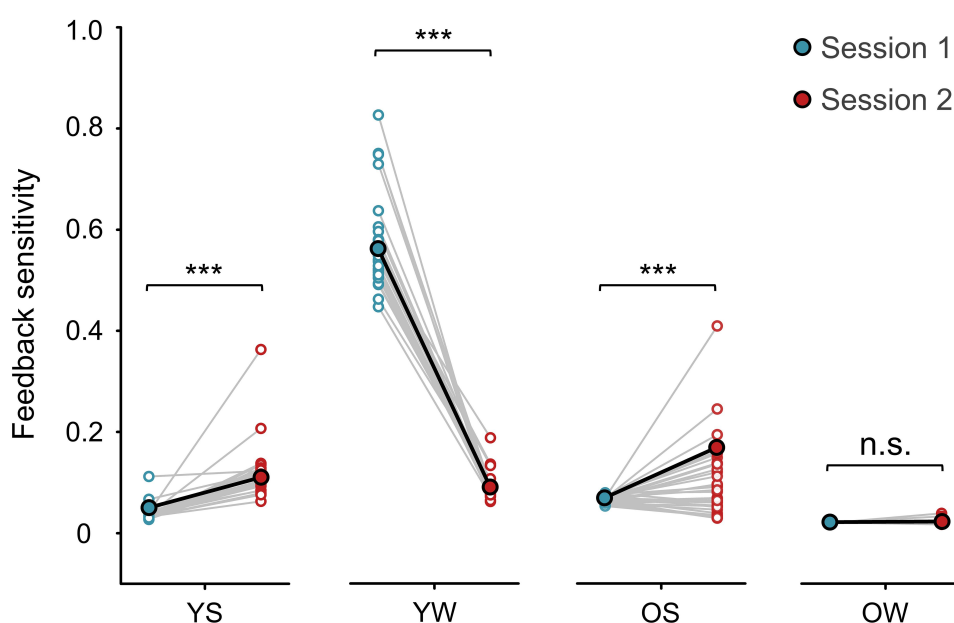


Figure 3 Group-level and individual-level feedback sensitivity α changes after sleep or wakefulness interval for young and older adults. *** $p < 0.001$.

Abbreviations: n.s., not significant; OS, older adults in the sleep condition; OW, older adults in the wake condition; YS, young adults in the sleep condition; YW, young adults in the wake condition.

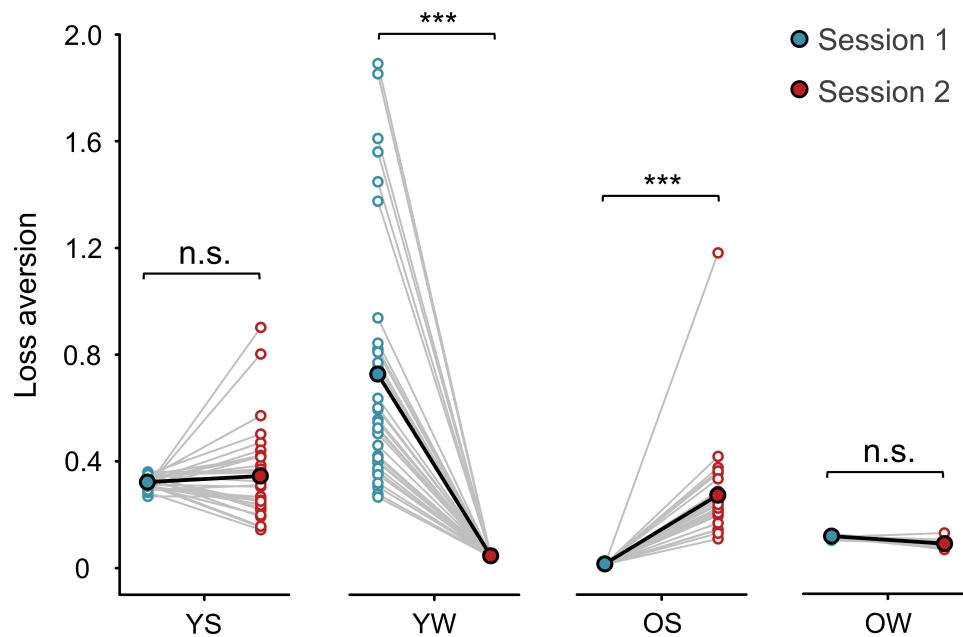


Figure 4 Group-level and individual-level loss aversion λ changes after sleep or wakefulness interval for young and older adults.*** $p < 0.001$.

Abbreviations: n.s., not significant; OS, older adults in the sleep condition; OW, older adults in the wake condition; YS, young adults in the sleep condition; YW, young adults in the wake condition.

analysis considering the underlying cognitive processes, age-by-condition interactions were observed in feedback sensitivity (α) and loss aversion (λ), illustrated by sleep improving feedback sensitivity for both young and older adults (Figure 3) while increasing loss aversion in older adults but not in young adults (Figure 4). Together, these findings indicate that sleep plays a distinct role in the modulation of decision-making in both young and older adults.

Enhancement of Feedback Sensitivity Following Sleep

Due to the complexity of IGT, the behavioural analysis of net scores may not be sufficient to reflect the underlying psychological processes.^{25,26} Therefore, in the present study, we further conducted computational modelling to break down the decision-making process in the IGT into multiple cognitive components, which could then be assessed and associated with the effects of sleep and aging. Consistent with previous studies,^{26,32,34,40} we confirmed that the VPP model provided the best model-fit relative to the other two models (ie, the PVL-Delta and PVL-Decay model).

Among model parameters provided by the winning model, an age-by-condition interaction was observed in the feedback sensitivity. Feedback sensitivity is an index of how sensitive an individual is to the changes in

monetary outcomes. A closer inspection of data revealed that post-test sleep increased both young and older adults' feedback sensitivity in the re-test, while the feedback sensitivity decreased in young adults but was retained in older adults who had a wakefulness interval (Figure 3). According to the synaptic homeostatic hypothesis,^{41,42} the role of sleep is to downscale synaptic strength to a baseline level and allow the organism to learn afresh the next day. In the case of IGT, decision-making is based on information processing of feedback and prior experience. Participants with post-test sleep may have synaptic downscaling to the pre-test level and corresponding promotion of synaptic competition leading to an increase of feedback sensitivity the next morning regardless of age. On the contrary, during wakefulness, individuals interact with the environment and acquire information from it, possibly leading to an increase in synaptic strength in many brain circuits, consuming energy and space; thus, the ability of the brain to acquire new information may be weakened after long-term wakefulness.

Indeed, we found that young adults' feedback sensitivity decreased after a 12-hour period of wakefulness (Figure 3). According to their daily activity records (Supplementary Table S6), young adults were primarily involved in activities with high cognitive load, such as studying in class, doing homework, or playing video games during post-test wakefulness. These activities occupy cognitive resources and may

cumulatively decrease synaptic plasticity, ultimately leading to the declines of feedback sensitivity in the re-test. Using reversal learning paradigms, previous studies found that young adults were less sensitive to feedback under sleep deprivation, showing impairments of adaptive decision-making ability.^{43,44} Similarly, our results suggested that although a 12-hour wakefulness did not affect young adults' net scores in the IGT, it made them less sensitive to feedback. Of note, this wakefulness influence on feedback sensitivity was modulated by age. Older adults' daily activity records showed that they often engaged in relatively low-cognitive-load activities, such as doing housework, walking, and participating in social activities ([Supplementary Table S6](#)). These activities may have less impact on cognitive-dependent synaptic plasticity, therefore allowing us to observe retained feedback sensitivity at re-test in older adults. These findings imply that the alterations of feedback sensitivity not only depend on the length of wakefulness but also the content of it (how people spend that time).

Alteration of Loss Aversion Following Sleep

In the VPP model, loss aversion is an index of how much an individual is averse to losses relative to preference toward gains at the same magnitude. Higher loss aversion suggests that an individual is more sensitive to losses than to gains. The value range of loss aversion in this study is consistent with previous studies.^{32,40} Similar to the findings of feedback sensitivity, our findings showed that loss aversion decreased with post-test wakefulness in young adults but was retained in older adults. On the other hand, sleep sustained young adults' loss aversion whereas it boosted older adults' loss aversion in the re-test. Although the negative information leads to an aversion, a higher loss aversion, helping us be alert to losses and danger, plays a vital role in our survival during evolution. Here, our finding supported that sleep facilitates young adults retaining their alertness to negative information.

As for the older adults, according to the socioemotional selectivity theory (SST), older adults attend to prioritize current goal related to emotional satisfaction as they approach the end of life. One aspect of this optimization may involve reducing negative arousal^{45,46} and a general decrease in sensitivity to negative feedback during information processing.⁴⁷ With regard to decision-making, in line with the prediction from the SST, older adults exhibited a preserved function of the anticipation of rewards but

showed a relative reduction in activation during loss anticipation.⁴⁸ Similarly, findings were found with a reinforcement learning paradigm that older adults showed more decision-making noises compared to younger counterparts when learning from negative feedbacks.^{49,50} The increased noises and decreased anticipation of loss may lead older adults to make more high-risk choices, manifested as choosing more disadvantageous decks in the IGT. Importantly, the current study found that sleep could promote older adults' feedback sensitivity and loss aversion, both of which are essential components of error prediction. Thus, compared with younger counterparts, older adults may need to "sleep on it" more when it comes to an important or difficult decision in daily life.

In addition, the IGT has been used as a testing tool of the somatic marker hypothesis (SMH).^{28,51} The SMH assumes that in complex and uncertainty environments, emotional reactions (ie, somatic markers) produced by previous experience of the emotional feedback following selection could promote rational decision-making in the long term. Specifically, it helps avoiding disadvantageous selections. However, this hypothesis has been disputed in the field.^{52,53} Several researches suggested that with the temporary emotion regulation, participants cannot adopt rational strategies to maximize their long-term profits in the IGT.^{30,54} In line with these findings, we found that sleep facilitated participants' loss aversion; however, this emotion-related regulation did not translate into performance improvement.

Change of Model-Free Index Following Sleep

Our results showed that sleep might not directly contribute to the performance improvement in the IGT in terms of net score in young adults, which is inconsistent with previous studies.^{22,24} The inconsistencies may be attributed to the characteristics of IGT and the relatively low monetary amount involved in our study. For example, Abe et al²⁴ used a variant version of IGT with 10-times higher feedback monetary amounts relative to the original version^{10,28} and fewer trials (reduced from 100 trials to 60 trials). These alterations may increase the task difficulty and correspondingly provide enough room for the subsequent potential post-sleep enhancement. In our study, we adopted the modified version of IGT²⁹ and found there were 6 young adults in the sleep condition reached the

highest net score (ie, 1) in the second block of session 2, implying that the ceiling effect of young adults' performance may lead to a lack of sleep-wake difference in the current study. Indeed, using the original IGT, Pace-Schott et al¹⁷ found that sleep protective effect was only observed in the poor performance participants (ie, remained both advantageous decks by 80 selections) but not in the superior performance participants (ie, had emptied one of the advantageous decks by 80 selections). Together, previous sleep-related learning studies suggested that the beneficial effect of sleep could depend on the degree of prior sleep learning.^{17,55} Although the current study cannot offer direct evidence supporting this hypothesis, the notion of the difficulty of IGT being linked to sleep effect offers a potential avenue for future research aimed at connecting sleep and age interactive effects on decision-making.

We found that older adults with longer TST showed a larger increasing of selection of advantageous deck D, indicating a positive role of sleep in decision-making in older adults. The loss frequency of deck D is lower (10%) compared with another advantageous deck C (90%). Thus, the deck D is a more gain-framed deck. Previous research demonstrated age differences on negative bias in the context of IGT,¹⁸ and our results extended it and showed that this age-related bias also existed in the modulation effect of sleep on decision-making. We did not find any association between sleep characteristics and performance change in young adults. One possible reason is that while the actigraph can provide basic sleep parameters such as TST and sleep efficacy, it cannot recognize specific sleep stages (ie, N1, N2, N3, and REM). The improvement in young adults may be stage-dependent. Furthermore, a recent study showed that the theta activity during REM sleep is positively correlated with performance improvement with deck B in young adults.²³ It is possible that the cortical activity rather than the sleep quantity could predict young adults' decision changes.

Limitations

Despite our novel findings on the effects of sleep and aging on decision-making, some potential limitations of this study need to be taken into consideration. First, we instructed participants to keep their regular sleep and avoid any tea, caffeine, or alcohol consumption during the whole experiment period. Indeed, participants reported zero caffeine or alcohol use in their self-report afterwards. Nevertheless, at-home sleep manipulation is less controllable than lab-based sleep studies. Future research could

repeat this finding in a laboratory environment. Second, young adults exhibited different circadian rhythms and lifestyles compared to older adults, yet our study required them all to complete the IGT at the same times of the day (ie, 7:30–9:30 am in the morning or 7:30–9:30 pm in the evening). Nevertheless, the significance of the results was not changed when we controlled for participants' MEQ scores that reflected morningness/eveningness tendencies ([Supplementary Table S1](#) and [S5](#)). In order to further eliminate the influence of circadian rhythms, future studies could consider to adopt the “am-pm-am” compared with “pm-am-pm” design^{7,17} to control the influence of sleep-wake cycle. Third, although older adults' subjective sleep quality (reflected by PSQI scores) was poorer than that of young adults, objective sleep quality as reflected by the actigraph data did not show any age-related difference. Both groups showed shorter TST than their usual routine. The actigraph-measured short TST may be due to the early time used for the beginning of experiment—7:30 in the morning—which may be different from the habitual wake-up time of participants (especially for young adults). However, participants performed the task more than 30 minutes after getting up, and there was no significant between-session difference in response times for the IGT in sleep groups. Thus, the differences found in the current study might not be attributed to the differences in alertness.

Conclusions

To conclude, as the first study to examine age differences in the sleep-related modulation effect on decision-making, we found that sleep following exposure yielded more optimal decision strategies, reflected as increased feedback sensitivity in both age groups. Of note, this sleep effect was modulated by age such that older adults who had post-test sleep exhibited greater loss aversion, suggesting that, compared with younger counterparts, older adults may need more “sleep on it” time before making decisions in life. Future studies may consider the use of model-based EEG or fMRI to examine the neural mechanisms that potentially underlie the sleep-dependent modulation effect.

Disclosure

Data and MATLAB scripts used in the current study are available from the corresponding authors on reasonable request. This work was supported by the National Natural Science Foundation of China (31971007, 71942004, and 6191101096), the Ministry of Education

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