The Effect of Cognitive Flexibility on Probabilistic Category Learning

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Abstract

This study employed the "Number-Letter Switching Task" to differentiate individuals with high versus low cognitive flexibility, constructed two probabilistic category learning tasks with identical probabilistic pairing patterns but different surface forms, and utilized ERP technology to investigate the characteristics and mechanisms of cognitive flexibility' s effect on probabilistic category learning tasks. The results revealed that in both tasks, the rule acquisition level of the high cognitive flexibility group was superior to that of the low cognitive flexibility group, indicating that cognitive flexibility can facilitate probabilistic category learning. Concurrently, ERP analysis results from different learning stages demonstrated that the advantage of high cognitive flexibility individuals in probabilistic category learning originates from the feedback processing stage.

Full Text

The Effect of Cognitive Flexibility on Probabilistic Category Learning

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Abstract

This study employed a "number-letter switching task" to differentiate individuals with high versus low cognitive flexibility, constructing two probabilistic category learning tasks with identical probability matching patterns but different task formats. Using ERP technology, we investigated the characteristics and mechanisms through which cognitive flexibility influences probabilistic category learning. Results revealed that in both tasks, the high cognitive flexibility group demonstrated superior rule acquisition compared to the low flexibility group,

indicating that cognitive flexibility facilitates probabilistic category learning. Furthermore, ERP analyses across different learning stages showed that the advantage of high cognitive flexibility in probabilistic category learning originates from feedback processing.

Keywords: cognitive flexibility, probability, rule learning, feedback-related negativity (FRN), P300

Introduction

Cognitive flexibility represents a crucial component of executive function that develops on the basis of inhibitory control and working memory (Diamond, 2013). It refers to the capacity to adapt to environmental changes, including maintaining activity in the face of irrelevant changes, with particular emphasis on shifting from original perspectives and understanding objects from multiple viewpoints. This construct overlaps substantially with task switching and creativity (Diamond, 2013). Advanced cognitive processes such as problem-solving and creative thinking depend critically on cognitive flexibility, and research has shown that highly creative individuals can flexibly adjust their cognitive inhibition levels according to task demands (Bai & Yao, 2018) and switch between thinking modes effectively (He et al., 2020). Investigating the mechanisms through which cognitive flexibility operates during problem-solving is essential for understanding higher-order thinking processes and developing effective training methods.

Effective learning in higher-order thinking processes (such as reasoning tasks) depends on the continuous integration of selection and reinforcement to establish abstract stimulus-response rule associations from "stimulus-selection-feedback" chains. Research has documented differential performance between high and low flexibility individuals across various tasks involving advanced thinking. In inductive reasoning tasks, high and low flexibility children show different learning potentials, with low flexibility children requiring more step-by-step prompts to achieve similar learning outcomes as their high flexibility counterparts (Stad et al., 2019). In ambiguous decision-making tasks such as the Iowa Gambling Task (IGT), high flexibility individuals acquire more task-relevant explicit knowledge and demonstrate advantages across decision-making stages including choice evaluation, response selection, and feedback processing (Dong et al., 2016). Ambiguous decision-making essentially represents probabilistic learning under uncertainty. Researchers have also employed the "probabilistic category learning" paradigm to study the acquisition of knowledge about non-deterministic relationships between cues and outcomes, which simultaneously involves elements of probability, categorization, and rule learning (Craig et al., 2011; Schenk et al., 2017; Li et al., 2012). Studies have found that in probabilistic category learning, adolescents with higher IQ levels generate more adaptive learning strategies following positive feedback, accompanied by increased activation in the dorsolateral prefrontal cortex and dorsal anterior cingulate cortex (Bos et al., 2012). Intelligence is intricately linked to executive functions including cognitive flexibility (Alfonso & Lonigan, 2021; Allan et al., 2014). Based on these findings, we hypothesized that learners' cognitive flexibility influences probabilistic category learning.

The role of cues in category learning has also attracted researchers' attention (Newell et al., 2007; Li et al., 2012; Xu et al., 2011), with investigations of cue characteristics providing evidence for the debate between explicit and implicit systems in probabilistic category learning. High-predictability cues can improve learner performance, a response pattern that is independent of stimulus presentation time but constrained by the probabilistic matching relationship between cues and targets (Girardi et al., 2013). The present study examined how the presence versus absence of cues affects learning outcomes in probabilistic category learning. Previous research using switching tasks found that effective utilization of explicit cues reduces switch costs and facilitates preparation for specific response rules (Koch & Allport, 2006). Studies investigating cognitive processing characteristics in special populations (such as individuals with obsessive-compulsive tendencies) under different probabilistic cue conditions revealed that high obsessive-compulsive tendency individuals tend to perseverate on original processing modes, whereas low tendency individuals adjust their processing strategies according to probabilistic changes (Miao et al., 2015). Cognitive flexibility fundamentally reflects individuals' inhibitory control and cognitive shifting abilities, enabling them to suppress dominant but ineffective cues and reconfigure resources efficiently (Lange et al., 2015). This study focused on a normal population to investigate whether high cognitive flexibility individuals can better utilize cues to facilitate learning in cued probabilistic category learning.

Leveraging the high temporal resolution advantage of event-related potential (ERP) technology to examine probabilistic category learning in stages facilitates exploration of learning characteristics at different phases and expands research depth. Zeithamova et al. (2007) proposed that rule-based category learning involves at least two processes: category representation and category criterion formation—namely, perceiving stimuli to form category representations, and processing feedback to establish category criteria. Dong et al. (2016) extended this two-stage model in their study of ambiguous decision-making by dividing learning into choice evaluation, response selection, and feedback processing stages involving stimulus perception, risk selection, and feedback learning, discovering advantages for high cognitive flexibility individuals across all three stages: stronger memory for stimuli, formation of conceptual knowledge about the task, and development of expectations for reward stimuli. Drawing on this research, the present study employed ERP technology to examine characteristics of choice evaluation and feedback processing stages in probabilistic category learning.

Common experimental tasks for measuring cognitive flexibility include the Wisconsin Card Sorting Test (WCST) (Dong et al., 2016) and switching tasks (Deák & Wiseheart, 2015; Erb et al., 2017). Research indicates that switching tasks provide a purer measure of cognitive flexibility (Lange et al., 2018; Lange et al., 2017). Moreover, compared to WCST tasks—which have numerous measurement indicators without consistent key indicators across studies (Feng & Feng, 2019)—the measurement of "switch cost" in switching tasks is relatively uniform across studies and easier to interpret and understand. Therefore, this study used switch cost from a switching task as the basis for distinguishing participants with different cognitive flexibility levels, specifically implementing Rogers' (1995) "number-letter switching task." Additionally, previous research on cognitive flexibility has focused primarily on children and adolescents, likely because cognitive flexibility in these groups is still developing and has greater potential for intervention and improvement. In contrast, college students in early adulthood have relatively stable cognitive flexibility and fluid intelligence levels, making them more suitable for comparing learning characteristics across different cognitive flexibility levels to reveal general features of how cognitive flexibility influences learning, particularly in higher-order thinking processes.

In summary, this study aimed to address three questions: (1) Does cognitive flexibility influence probabilistic category learning? (2) Is the effect of cognitive flexibility on probabilistic category learning moderated by task cues? (3) Which stage of probabilistic category learning is primarily affected by cognitive flexibility? To answer the first two questions, we designed two probabilistic learning tasks with identical probability configurations but different cue characteristics. To address the third question, we employed high temporal resolution ERP technology to examine the learning process in stages.

2.1 Participants

We recruited 310 college students through online and offline channels on campus to complete the "number-letter switching task" for cognitive flexibility assessment. Data from 13 participants were excluded due to consistently repeating one response, misunderstanding instructions, or excessively short reaction times (<100ms), and these individuals did not participate in subsequent experiments. Among the remaining 297 participants (60 male; mean age = 18.7 $\pm$ 1.5 years), none had previously completed tasks identical to those in this study. Based on their performance on the number-letter switching task and willingness to participate in the EEG experiment, 76 individuals were selected. All participants had normal or corrected-to-normal vision, were right-handed, had no cognitive impairments, and no history of psychiatric disorders. The study was approved by the Soochow University Ethics Committee. All participants provided informed consent before the experiment and received monetary compensation upon completion.

2.2.1 Number-Letter Switching Task

We employed the classic "number-letter switching task" paradigm. In each trial, a mixed stimulus consisting of a letter (vowel: A/E/I/U or consonant: G/K/M/R) and a number (odd: 3/5/7/9 or even: 2/4/6/8) was presented in one quadrant of a 2$×$2 grid. Participants were instructed that when the stimulus appeared in the upper two quadrants, they should press the E or I key to judge whether the letter was a vowel or consonant; when it appeared in the lower two quadrants, they should press the E or I key to judge whether the number was odd or even. Participants proceeded to the formal experiment only after achieving at least 80% accuracy in practice. The formal experiment consisted of 128 trials. Reaction time and accuracy were recorded, with switch cost used to differentiate high and low flexibility individuals. Switch cost was calculated as the difference between mean reaction times for correct responses on switch trials and non-switch trials.

2.2.2 Raven' s Progressive Matrices

To measure participants' intelligence levels and control for potential interference from intelligence factors, we administered a shortened version of Raven' s Progressive Matrices. The test consisted of 20 items, with 90 seconds allowed per item. Each correct answer received 1 point, while incorrect answers or timeouts received 0 points.

2.2.3 Uncued Probabilistic Category Learning Task—Picture Selection Task

In the picture selection task, white stimuli were presented on a black background. The experimental materials consisted of four types of stimuli, each associated with a reward probability: 0, 1/3, 2/3, or 1. A Latin square design was used to counterbalance the reward probabilities assigned to each stimulus type across participants. The trial procedure is illustrated in Figure 1. Participants' task was to press the F/J key to select the stimulus on the left/right side that was more likely to yield a reward. Triangular and hexagonal feedback indicated reward or no reward, respectively (counterbalanced across participants). The experiment included four probability pairing levels (0-1/3, 0-2/3, 1/3-2/3, 1-1/3), with the number of trials for each pairing shown in Table 1. The experiment comprised 540 trials total, with a break after every 45 trials. Participants were informed that greater numbers of reward feedback would result in larger monetary compensation upon completion. No probability information was disclosed beforehand; perception of stimulus probabilities and identification of advantageous options required accumulation of feedback information. After the experiment, participants estimated the likelihood of each of the four stimuli yielding a reward when presented individually.

2.2.4 Cued Probabilistic Category Learning Task—Coin Search Task

The coin search task was adapted from Bellebaum et al. (2008). Stimuli were presented on a black background, with 12 colored squares on each side of the fixation point. Participants were informed that one coin was hidden among the 12 squares on each side, and they should press the F/J key to judge which side (left/right) was more likely to yield a reward. After making a selection, triangular and hexagonal feedback indicated reward or no reward (counterbalanced across participants). Greater numbers of reward feedback resulted in larger monetary compensation. The number of red squares on each side was 2, 4, or 6, corresponding to reward probabilities of 0, 1/3, 2/3, or 1. The probability pairings and trial numbers for each condition were identical to the picture selection task (Table 1). With accumulated learning experience, participants would discover the hidden cue: the critical role of the advantageous column. In the example shown in Figure 2, the right column is advantageous, meaning pressing F to select the left column yields a reward probability of 2/6 (1/3), while pressing J to select the right column yields a probability of 4/6 (2/3). The position of the advantageous column (left or right) was counterbalanced across participants. Unlike the picture selection task, this task included three blocks (180 trials each). In Block 2, after reward feedback, the coin' s specific location was revealed: following reward feedback, the coin appeared in a random red square in the selected column; following no-reward feedback, it appeared in a random white square. The left/right configuration was counterbalanced across participants. The trial procedure is illustrated in Figure 2. After the experiment, participants reported the basis for their choices.

The two tasks contained identical probability matching relationships, temporal intervals, and reward feedback patterns to enable cross-task comparisons. However, they differed in several aspects: First, stimulus forms differed to prevent interference or facilitation between task rules in a within-subjects design. Second, task procedures differed: the uncued picture selection task had no block design, whereas the cued coin task included coin location information in Block 2 to reduce task difficulty. Previous research and pilot testing indicated that without coin location cues, the number of participants who would ultimately acquire the rule would be substantially lower. Third, the tasks differed in cued versus uncued design: the picture selection task provided no cues, while the coin search task' s cue was hidden in the comparison of colored square quantities, requiring discovery through learning.

2.3 Procedure

Descriptive statistical analysis of switch costs from the number-letter task ($M \pm SD = 813.41 \pm 389.24$ ms) identified the 27th percentile cutoffs as 525.27 ms and 1041.09 ms. Participants with switch costs below 525.27 ms were invited as high cognitive flexibility participants, while those above 1041.09 ms were invited as low flexibility participants. All volunteers first completed the Raven' s Progressive Matrices, then performed the picture selection task and coin search task in two separate sessions (order counterbalanced across participants) with a two-week interval between EEG recordings.

2.4 Apparatus

EEG data were recorded using Vision Recorder 2.0 (Brain Products, Munich, Germany) with a 64-channel electrode cap. Reference electrodes were placed on bilateral mastoids, with the average of bilateral mastoids used as reference. Horizontal and vertical electrooculograms were recorded from the outer canthus of the left eye and 1 cm above the left eye, respectively. Impedance at all electrode sites was maintained below 5 kΩ, with a sampling rate of 1000 Hz. Offline analysis was conducted using EEGLAB and ERPLAB, with a low-pass filter of 40 Hz and trials containing artifacts exceeding $±$100 V removed.

2.5 Data Collection and Analysis

For behavioral data analysis, to examine the dynamic learning process, we performed a sliding window analysis for each participant with a window length of 20 trials and step size of 1 trial. Additionally, following previous research standards (Bellebaum & Daum, 2008), participants were considered to have acquired the task rule (acquirers) if they achieved at least 16 correct responses out of 20 consecutive trials and maintained this criterion for the remainder of the experiment. This turning point was designated as the acquisition point, allowing division of the experiment into pre-acquisition and post-acquisition phases.

For ERP analysis, to investigate learning characteristics and mechanisms across different learning stages, we divided ERP analysis for both tasks into choice evaluation and feedback processing stages. The choice evaluation stage was time-locked to the onset of the fixation point and bilateral stimuli (the second screen in the trial procedures shown in Figures 1 and 2), with a 200 ms pre-stimulus baseline and analysis epoch of 1200 ms. Observation and analysis revealed maximal ERP differences between bilateral stimuli at frontoparietal and occipital regions. Following previous research (Dong et al., 2016), electrodes P3, P4, Pz, PO3, PO4, and POz were selected for P200 analysis. Due to task-specific differences, the P200 measurement window was 220-280 ms for the picture task and 160-240 ms for the coin search task. Window selection was based on observation of grand-averaged waveforms to center the window on the P200 peak. The feedback processing stage was time-locked to feedback onset, with a 200 ms pre-feedback baseline and ERP analysis epoch of 700 ms. Electrode selection followed previous FRN research, with the average of electrodes Fz, FCz, and Cz in the 200-300 ms window serving as the FRN measure, and the average of electrodes CPz, Pz, and POz in the 300-400 ms window serving as the P300 measure.

3.1 Number-Letter Switching Task

Descriptive analysis of switch costs (X) from 297 participants revealed: Xmin = 137.54 ms, Xmax = 2085.30 ms, Xmean = 813.41 ms, XSD = 389.24 ms. The 27th percentile values were 525.27 ms and 1041.09 ms. Based on these results, high cognitive flexibility participants in the EEG experiment had switch costs below 525.27 ms, while low flexibility participants had switch costs above 1041.09 ms.

3.2 Raven' s Progressive Matrices

Of the 76 participants who completed the EEG experiment, two (one from each flexibility group) were excluded from subsequent analysis due to confusion between reward feedback and response keys. All subsequent analyses were based on the remaining 74 participants. Independent samples t-test on intelligence test scores revealed no significant difference between the high flexibility group (n = 38) and low flexibility group (n = 36) [$t(72) = -0.88$, $p > 0.05$, Cohen' s d = -0.21], indicating equivalent intelligence levels across groups and ruling out intelligence as a confounding factor.

3.3.1 Behavioral Data Analysis: Picture Selection Task

(1) Acquisition Rate and Learning Curves

In the picture selection task, 32 of 38 high flexibility participants (84.21%) acquired the rule, compared to 17 of 36 low flexibility participants (47.22%). The acquisition rate was significantly higher in the high flexibility group [$^2 = 11.31$, df = 1, $p = 0.001$].

Learning curves for the four groups (high flexibility-acquired, high flexibility-unacquired, low flexibility-acquired, low flexibility-unacquired) are shown in Figure 3.

(2) Accuracy

In this study, reward feedback was probabilistic. For example, in the 1/3-2/3 probability pairing, selecting either side could result in reward or no reward, but selecting the right side (2/3 probability) was considered the correct option as it yielded higher reward likelihood.

Among 74 participants (38 high flexibility, 36 low flexibility), six (5 high flexibility, 1 low flexibility) reached the acquisition criterion within approximately 30 trials, resulting in insufficient pre-acquisition trials for analysis. These participants were included only in post-acquisition analyses. Twenty-five participants (6 high flexibility, 19 low flexibility) never reached the acquisition criterion. Repeated measures analysis included only participants with both pre- and post-acquisition phases, yielding a final sample of 43 participants (27 high flexibility, 16 low flexibility).

After removing trials with no response, a 2 (learning phase: pre-acquisition, post-acquisition) × 4 (probability pairing: 0-1/3, 0-2/3, 1/3-2/3, 1-1/3) × 2 (flexibility level: high, low) repeated measures ANOVA on response accuracy revealed significant main effects of learning phase [$F(1,41) = 146.91$, $p < 0.001$, $^2 = 0.78$], with higher accuracy post-acquisition; probability pairing [$F(3,123) = 14.87$, $p < 0.001$, $^2 = 0.27$], with 0-1/3 pairings showing lower accuracy than other conditions ($ps < 0.001$) and 0-2/3 showing higher accuracy than 1/3-2/3 ($p < 0.05$); and flexibility level [$F(1,41) = 6.08$, $p < 0.05$, $^2 = 0.13$], with higher accuracy in the high flexibility group. The learning phase × probability pairing interaction was significant, with differences among the four probability pairings significant in both pre- and post-acquisition phases ($p < 0.001$). No other interactions were significant.

(3) Reaction Time

A 2 × 4 × 2 repeated measures ANOVA on reaction time revealed significant main effects of learning phase [$F(1,41) = 57.24$, $p < 0.001$, $^2 = 0.58$], with faster responses post-acquisition, and probability pairing [$F(3,123) = 10.94$, $p < 0.001$, $^2 = 0.23$], with slower responses for 0-1/3 pairings compared to other conditions ($ps < 0.001$). The 1/3-1 condition was marginally faster than 0-2/3 ($p = 0.085$) and 1/3-2/3 ($p = 0.087$).

(4) Reward Probability Estimation

After the experiment, participants estimated reward probabilities for the four stimuli. Participants who did not provide numerical estimates (using verbal descriptions or rankings instead) were excluded, leaving 63 participants for analysis. Estimated values for the 0, 1/3, 2/3, and 1 probability conditions were 0.27, 0.41, 0.62, and 0.67, respectively. One-way ANOVA revealed a significant main effect of probability [$F(3,251) = 38.18$, $p < 0.001$]. LSD post-hoc comparisons showed significant differences between all pairs except 2/3 and 1.

3.3.2 Behavioral Data Analysis: Coin Search Task

(1) Acquisition Rate and Learning Curves

In the coin search task, 27 of 38 high flexibility participants (71.05%) acquired the rule, compared to 12 of 36 low flexibility participants (33.33%). The acquisition rate was significantly higher in the high flexibility group [$^2 = 10.55$, $df = 1$, $p = 0.001$].

Learning curves for the four groups are shown in Figure 4. Both acquired groups reached their acquisition turning point in the second block (trials 181-360), with the high flexibility group at trial 244 and the low flexibility group at trial 257.

(2) Accuracy

Among 74 participants, three (all high flexibility) reached the acquisition criterion with too few trials for pre-acquisition analysis and were included only in post-acquisition analyses. Thirty-five participants (24 high flexibility, 12 low flexibility) failed to acquire the rule. The repeated measures analysis included 36 participants (24 high flexibility, 12 low flexibility) with both pre- and post-acquisition phases.

A 2 (learning phase) × 4 (probability pairing) × 2 (flexibility level) repeated measures ANOVA on accuracy revealed significant main effects of learning phase

[F(1,34) = 709.73, $p < 0.001$, ^{2} = 0.95], with higher accuracy post-acquisition, and probability pairing [F(3,102) = 10.94, $p < 0.001$, ^{2} = 0.24]. All pairwise comparisons were significant except between 0-2/3 and 1/3-1. The learning phase × flexibility interaction was marginally significant [F(1,34) = 3.05, p = 0.090, ^{2} = 0.08], with simple effects analysis showing significant differences between flexibility groups only post-acquisition [F(1,34) = 12.65, $p < 0.05$, ^{2} = 0.27]. No other main effects or interactions were significant.

(3) Reaction Time

A 2 × 4 × 2 repeated measures ANOVA on reaction time revealed significant main effects of learning phase [F(1,34) = 84.56, $p < 0.001$, ^{2} = 0.71], with faster responses post-acquisition; probability pairing [F(3,102) = 10.03, $p < 0.001$, ^{2} = 0.23], with all pairwise differences significant except between 0-2/3 and 1/3-2/3; and a marginal effect of flexibility [F(1,34) = 3.40, p = 0.074, ^{2} = 0.09], with faster responses in the high flexibility group. The learning phase × probability interaction was significant [F(3,102) = 7.73, $p < 0.001$, ^{2} = 0.19], with simple effects showing significant differences among probability pairings only post-acquisition. The probability × flexibility interaction was significant [F(3,102) = 3.20, $p < 0.05$, ^{2} = 0.09], with simple effects showing significant differences among probability pairings only in the low flexibility group. The three-way interaction was marginally significant [F(3,102) = 2.18, p = 0.100, ^{2} = 0.06].

ERP Results: Picture Selection Task

Among 43 participants with both pre- and post-acquisition phases, seven (4 high flexibility, 3 low flexibility) were excluded from ERP analysis due to excessive artifacts, leaving 36 participants (23 high flexibility, 13 low flexibility) for analysis.

(1) Choice Evaluation Stage

Separate 2 (learning phase) × 4 (probability pairing) × 2 (flexibility level) mixed repeated measures ANOVAs on P200 amplitude (220-280 ms) at electrodes Pz, P3, P4, POz, PO3, and PO4 revealed: At Pz, a marginally significant learning phase × probability interaction [F(3,102) = 2.66, p = 0.052, ^{2} = 0.07], with a marginal difference between pre- and post-acquisition only in the 1/3-1 condition (p = 0.068). At P3, a marginally significant probability × flexibility interaction [F(3,102) = 2.221, p = 0.090, ^{2} = 0.06], with simple effects showing a marginal group difference only in the 0-1/3 condition (p = 0.088). At P4, a marginally significant learning phase × probability interaction [F(3,102) = 2.608, p = 0.056, ^{2} = 0.07], with significant pre-post differences only in the 1/3-1 condition ($p < 0.05$). At POz, a significant learning phase × probability interaction [F(3,102) = 2.79, $p < 0.05$, ^{2} = 0.08], with significant pre-post differences in the 1/3-1 condition ($p < 0.05$). At PO3, a significant main effect of learning phase [F(1,34) = 6.12, $p < 0.05$, ^{2} = 0.15]. At PO4, a significant main effect of learning phase [F(1,34) = 4.99, $p < 0.05$, ^{2} = 0.13] and a marginally significant probability ×

flexibility interaction [$F(3,102) = 2.19$, $p = 0.094$, $^2 = 0.06$], with simple effects showing a marginal group difference only in the 0-1/3 condition ($p = 0.071$).

(2) Feedback Processing Stage

FRN amplitude was analyzed using two approaches. First, a 2 (learning phase: pre/post) × 2 (stimulus probability: high/low) × 2 (reward feedback: present/absent) × 2 (flexibility level) repeated measures ANOVA on the average amplitude (200-300 ms) at frontocentral electrodes Fz, FCz, and Cz revealed: a marginally significant main effect of probability [$F(1,34) = 3.33$, $p = 0.077$, $^2 = 0.09$], with larger amplitude for low versus high probability; a significant main effect of reward [$F(1,34) = 74.05$, $p < 0.001$, $^2 = 0.69$], with larger amplitude for reward versus no-reward feedback; a marginally significant three-way interaction of learning phase × reward × flexibility [$F(1,34) = 3.40$, $p = 0.074$, $^2 = 0.09$], with simple effects showing significantly larger reward than no-reward amplitudes in all conditions ($p < 0.001$); and a marginally significant three-way interaction of learning phase × reward × probability [$F(1,34) = 3.47$, $p = 0.071$, $^2 = 0.09$], with simple effects again showing significantly larger reward than no-reward amplitudes in all conditions ($p < 0.001$). Grand-averaged waveforms and amplitudes for each condition are shown in Figure 5.

To examine expectation effects in probabilistic category learning, we further analyzed expected versus unexpected outcomes. Among the four probabilities (0, 1/3, 2/3, 1), 0 and 1/3 were classified as low-probability conditions, while 2/3 and 1 were high-probability conditions. Receiving reward feedback under high-probability conditions or no reward under low-probability conditions constituted expected outcomes, whereas receiving no reward under high-probability conditions or reward under low-probability conditions constituted unexpected outcomes. Expected amplitude = low-probability no-reward amplitude - high-probability reward amplitude; unexpected amplitude = high-probability no-reward amplitude - low-probability reward amplitude.

A 2 (learning phase) × 2 (expectation: expected/unexpected) × 2 (flexibility level) repeated measures ANOVA on FRN amplitude (200-300 ms at Fz, FCz, Cz) revealed a marginally significant main effect of expectation [$F(1,34) = 3.33$, $p = 0.077$, $^2 = 0.09$], with larger amplitude for unexpected versus expected conditions (Figure 6), and a marginally significant learning phase × flexibility interaction [$F(1,34) = 3.40$, $p = 0.074$, $^2 = 0.09$], though group differences were not significant in either pre- or post-acquisition phases.

For the P300 component (300-400 ms at CPz, Pz, POz), a 2 × 2 × 2 × 2 repeated measures ANOVA revealed: a marginally significant main effect of learning phase [$F(1,34) = 3.30$, $p = 0.078$, $^2 = 0.09$], with larger amplitude pre- versus post-acquisition; a significant main effect of stimulus probability [$F(1,34) = 19.16$, $p < 0.001$, $^2 = 0.36$], with larger amplitude for low versus high probability; a significant main effect of reward feedback [$F(1,34) = 52.80$, $p < 0.001$, $^2 = 0.61$], with larger amplitude for reward versus no-reward feedback;

a significant learning phase × probability interaction [F(1,34) = 10.83, $p < 0.05$, ^{2} = 0.24], with simple effects showing significant pre-post differences only for high-probability conditions; a significant three-way interaction of probability × reward × flexibility [F(1,34) = 5.30, $p < 0.05$, ^{2} = 0.14], though simple effects showed no significant group differences in any condition; and a marginally significant four-way interaction [F(1,34) = 3.18, p = 0.083, ^{2} = 0.09], with simple effects showing a marginally significant group difference only in the pre-acquisition-high-probability-reward condition [F(1,34) = 3.04, p = 0.091, ^{2} = 0.08]. Grand-averaged waveforms and amplitudes are shown in Figure 7.

ERP Results: Coin Search Task

Among 36 participants with both pre- and post-acquisition phases, three (all high flexibility) were excluded due to excessive artifacts, leaving 33 participants (21 high flexibility, 12 low flexibility) for ERP analysis.

(1) Choice Evaluation Stage

Separate 2 (learning phase) × 4 (probability pairing) × 2 (flexibility level) mixed repeated measures ANOVAs on P200 amplitude (160-240 ms) at electrodes Pz, P3, P4, POz, PO3, and PO4 revealed significant main effects of learning phase across all electrodes. At Pz, post-acquisition P200 amplitude was significantly smaller than pre-acquisition [F(1,31) = 6.65, $p < 0.05$, ^{2} = 0.18], with significant reductions for the two conditions with 2/3 probability differences (0-2/3, 1/3-1; $p < 0.05$). At P3, a significant main effect of learning phase [F(1,31) = 9.90, $p < 0.05$, ^{2} = 0.24] and a marginally significant learning phase × probability interaction [F(3,93) = 2.34, p = 0.08, ^{2} = 0.07] showed significantly larger pre- than post-acquisition amplitudes for 0-2/3 and 1/3-1 pairings ($p < 0.05$). At P4, a significant main effect of learning phase [F(1,31) = 12.23, $p < 0.06$, ^{2} = 0.28] was found. At POz, a significant main effect of learning phase [F(1,31) = 11.24, $p < 0.056$, ^{2} = 0.27] showed significant pre-post differences for all pairings except 1/3-2/3 (which was marginal, p = 0.077). At PO3, a significant main effect of learning phase [F(1,31) = 15.93, $p < 0.001$, ^{2} = 0.34] was observed. At PO4, a significant main effect of learning phase [F(1,31) = 16.37, $p < 0.001$, ^{2} = 0.35] was found.

(2) Feedback Processing Stage

FRN amplitude was analyzed using the same two approaches as in the picture task. A 2 (learning phase) × 2 (stimulus probability) × 2 (reward feedback) × 2 (flexibility level) repeated measures ANOVA on FRN amplitude (200-300 ms at Fz, FCz, Cz) revealed: a significant main effect of probability [F(1,31) = 5.31, $p < 0.05$, ^{2} = 0.15], with larger amplitude for low versus high probability; a significant main effect of reward feedback [F(1,31) = 44.26, $p < 0.001$, ^{2} = 0.59], with larger amplitude for reward versus no-reward feedback; a marginally significant reward × flexibility interaction [F(1,31) = 3.38, p = 0.08, ^{2} = 0.10], with simple effects showing significantly larger reward than no-reward amplitudes in both groups ($p < 0.05$); a significant learning phase × probability interaction

[$F(1,31) = 5.38$, $p < 0.05$, $^2 = 0.15$], with simple effects showing larger low- versus high-probability amplitude post-acquisition ($p < 0.05$) and larger amplitude pre- versus post-acquisition for high-probability conditions ($p < 0.05$); and a significant three-way interaction of learning phase × probability × flexibility [$F(1,31) = 6.02$, $p < 0.05$, $^2 = 0.16$]. Post-acquisition, high flexibility participants showed significantly larger amplitude for low versus high probability ($p = 0.001$), and only high flexibility participants showed significantly larger amplitude pre- versus post-acquisition for high-probability conditions ($p = 0.01$). Grand-averaged waveforms and amplitudes are shown in Figure 8.

A 2 (learning phase) × 2 (expectation: expected/unexpected) × 2 (flexibility level) repeated measures ANOVA on FRN amplitude revealed significant main effects of expectation and a marginally significant main effect of flexibility, along with a significant learning phase × expectation interaction. Simple effects analysis showed significant differences between expected and unexpected amplitudes only post-acquisition. The three-way interaction of learning phase × expectation × flexibility was significant, with simple effects showing significantly larger amplitude (more negative) in high versus low flexibility groups for pre-acquisition-expected ($p < 0.05$) and post-acquisition-unexpected ($p = 0.073$) conditions (Figure 9).

For the P300 component (300-400 ms at CPz, Pz, POz), a 2 × 2 × 2 × 2 repeated measures ANOVA revealed: a significant main effect of probability [$F(1,31) = 17.28$, $p < 0.001$, $^2 = 0.36$], with larger amplitude for low versus high probability; a significant main effect of reward feedback [$F(1,31) = 71.16$, $p < 0.001$, $^2 = 0.70$], with larger amplitude for reward versus no-reward feedback; a significant probability × flexibility interaction [$F(1,31) = 8.20$, $p < 0.05$, $^2 = 0.21$], with simple effects showing significant high-low probability differences only in the low flexibility group; and a significant learning phase × probability interaction [$F(1,31) = 4.18$, $p < 0.05$, $^2 = 0.12$], with simple effects showing significant pre-post differences only for high-probability conditions. No other main effects or interactions were significant. Grand-averaged waveforms and amplitudes are shown in Figure 10.

4.1 Learning Characteristics of Probabilistic Category Tasks

Both experimental tasks involved dual processing of rule formation and probability estimation. Participants needed to identify the most probable response criterion applicable to the entire task based on each trial' s "stimulus-response-feedback" chain, and respond accordingly. Compared to typical probability estimation tasks, neither task provided any prior probability information, requiring participants to overcome a response bias toward finding deterministic outcomes and ultimately accept inevitable occasional no-reward feedback (Craig et al., 2011). Post-experiment interviews revealed that even when participants had identified advantageous options, many continued testing alternative response criteria, attempting to find a basis for consistently obtaining reward feedback, confirming the existence of a deterministic cognitive bias.

Learning curves, accuracy, and reaction time analyses indicated that although participants distinguished between stimuli with higher and lower reward likelihoods in the post-learning phase of both tasks, learning was weaker in the uncued picture selection task than in the coin search task. First, learning curves showed that post-acquisition accuracy in the picture task hovered near baseline, reflecting greater uncertainty about task rules compared to the coin search task. Second, accuracy data revealed that in the picture task, post-acquisition accuracy for the 0-1/3 pairing was only 0.67, indicating no clear response preference. This may be because both sides rarely provided positive feedback, preventing participants from establishing a selection basis based solely on the 1/3 reward probability of one side.

Why did learning outcomes differ between the uncued picture selection task and the cued coin search task despite identical probability pairings? The likely reason involves differences in rule representation levels and processing systems. Whether probabilistic category learning relies on explicit verbal systems or implicit procedural processing systems, and the relationship between these systems, remains debated (Lagnado et al., 2006; Li et al., 2016; Xu et al., 2011). In the picture selection task, few participants could clearly report their task basis afterward, and the additional stimulus ranking task was designed to help researchers identify selection tendencies, suggesting implicit processing characteristics. In contrast, most participants in the coin search task could describe their response basis, indicating rule representation reached the explicit system. This benefit derived from the presence of response cues: the difference in red square quantities between sides helped transform the probability problem into a frequency problem, reducing difficulty. This increased task transparency in the later learning stage, and previous research has demonstrated that high task transparency and information volume promote explicit learning characteristics (Liu & Zheng, 2015). In the picture selection task, cues consisted solely of the stimulus materials themselves, preventing acquisition of correct response "shortcuts" through feature associations. Connectionist learning theory proposes two independent learning processes in probability learning: one relying on long-term memory systems to form probability representations implicitly through accumulation, and another relying on short-term memory systems to form probability experience through processing of recent events (Otto et al., 2011). In the picture task, participants could only respond based on previously accumulated vague probability representations and recent trial experience. Notably, implicit and explicit systems may both participate in probabilistic learning (Li et al., 2012). Our results suggest that both uncued tasks relying primarily on implicit processing and cued tasks that can reach explicit levels through cue facilitation can achieve acquisition, but cued probabilistic category learning substantially increases learners' response confidence and demonstrates more stable acquisition. Furthermore, research on high- versus low-probability cue effects found that cues function effectively under high-probability conditions to facilitate selective attention strategy generation (Girardi et al., 2013). Learners initially make selection judgments based on implicit information from inter-trial relationships, but when a particular high-probability relationship or structure is perceived as advantageous, the cognitive system organizes subsequent learning around this cue. In our coin task, the large probability difference between advantageous columns constituted such advantageous information, and results confirmed its learning facilitation (significant pre-post amplitude reductions for the two conditions with 2/3 probability differences: 0-2/3 and 1/3-1). Girardi et al. (2013) further proposed that the mechanism locked to high-frequency cues serves as a switch for endogenous attention component shifting during tasks.

4.2 Cognitive Flexibility Characteristics Across Learning Stages

This study investigated cognitive flexibility effects from choice evaluation and feedback processing perspectives in both uncued (picture selection) and cued (coin search) tasks, finding that cognitive flexibility' s influence on learning relates closely to task characteristics.

In the choice evaluation stage, no evidence of cognitive flexibility effects emerged in the coin task, while in the picture task, only marginal group differences appeared for the 0-1/3 probability pairing at P3 and PO4 electrodes. These results contradict Dong et al.' s (2016) findings of differential performance between high and low cognitive flexibility individuals in the Iowa Gambling Task and fail to support our hypotheses. Researchers have noted that the P200 component analyzed in this stage relates to stimulus perception, attention processing, and short-term memory (Dong et al., 2016; Xing et al., 2017). Although ERP group difference results were similar across tasks, the underlying reasons likely differ. In the uncued picture task, minimal group differences occurred because even high flexibility learners failed to form stable differential representations for all stimulus pairings. In the cued coin task, significant learning phase main effects at multiple electrodes indicated that stimuli were differentially represented. The absence of group differences likely resulted from cue and Block 2 design features that reduced between-group disparities.

In the feedback processing stage, the high cognitive flexibility group showed higher accuracy than the low flexibility group in the picture selection task. For the P300 component, high flexibility group amplitude was marginally larger than the low flexibility group in the pre-acquisition-high-probability-reward condition. The P300 component primarily reflects top-down controlled outcome evaluation processes, with factors attracting more attention allocation—including reward valence and magnitude—influencing P300 amplitude (Wu & Zhou, 2009). High-probability stimuli with reward feedback could rapidly attract high cognitive flexibility learners' attention, allowing them to process such stimuli with fewer cognitive resources. In the coin search task, the high flexibility group showed marginally faster reaction times and significantly higher post-acquisition accuracy than the low flexibility group. For the FRN component, high flexibility group amplitude was marginally larger than the low flexibility group, with significantly larger amplitude in high flexibility participants for pre-acquisition-expected and post-acquisition-unexpected conditions. FRN reflects expectation formation for subsequent possible outcomes based on cue evaluation (Bellebaum & Daum, 2008; Li et al., 2018). In our probabilistic category learning tasks, FRN formation required learners to develop expectations for response outcomes following specific cues based on "stimulus-response-feedback" learning. Data indicated that before behavioral responses reached the acquisition criterion in the coin search task, high flexibility individuals already formed stronger expectations for expected outcomes, while post-acquisition, "high-probability-no-reward" and "low-probability-reward" outcomes were more surprising to them. However, even high flexibility participants failed to form stable expectations for response outcomes across all conditions in the picture selection task, preventing FRN differences from emerging—consistent with behavioral curve differences between tasks.

Our findings demonstrate that in probabilistic category tasks, high cognitive flexibility groups achieve higher rule acquisition rates than low flexibility groups, with ERP results further indicating that this learning advantage is intimately connected to feedback processing. Effective processing of feedback information —whether external explicit feedback or internal implicit feedback—helps learners identify gaps between current and goal states and generate alternative solutions. Flexibility development depends on selecting and using appropriate information to understand the current situation (Spiro, 1988), and learners who can effectively integrate feedback information with problem contexts more easily discover rules and obtain solutions. Research has confirmed that this reflective thinking tendency significantly positively predicts cognitive flexibility (Orakci, 2021). Our results with college student participants indicate that under completely non-intervention conditions, low flexibility learners cannot achieve equivalent learning outcomes as high flexibility learners (similar acquisition rates, similar conflict detection levels) when provided with identical feedback information.

Additionally, from a task difficulty reduction perspective, we included a Block 2 design in the coin search task, which may have directly reduced between-group differences, as learning curves showed acquisition turning points were very close between flexibility groups, with differential evidence emerging only for specific conditions in choice evaluation (e.g., 0-1/3 probability pairing) and feedback processing (pre-acquisition-expected and post-acquisition-unexpected conditions).

4.3 Limitations and Future Directions

This study used two probabilistic category tasks differing in cue presence to explore cognitive flexibility' s role in probabilistic category learning. Further matching of task characteristics would enable more adequate comparative analysis. Building on matched tasks, future research could investigate cognitive flexibility effects using more richly layered cue features.

In conclusion: First, in probabilistic category tasks, high cognitive flexibility groups demonstrate superior rule acquisition compared to low flexibility groups, indicating cross-task advantages for cognitive flexibility. Second, high cognitive flexibility individuals' advantages in probabilistic category learning originate from feedback processing.

References

Alfonso, S. V., & Lonigan, C. J. (2021). Trait anxiety and adolescent's academic achievement: the role of executive function. *Learning and Individual Differences, 85*, 101941.

Allan, N. P., Hume, L. E., Allan, D. M., Farrington, A. L., & Lonigan, C. J. (2014). Relations between inhibitory control and the development of academic skills in preschool and kindergarten: a meta-analysis. *Developmental Psychology, 50*(10), 2368–2379.

Bai, X., & Yao, H. (2018). Differences in cognitive inhibition between persons with high and low creativity: evidences from behavioral and physiological studies. *Acta Psychologica Sinica, 50*(11), 1197–1211.

Bellebaum, C., & Daum, I. (2008). Learning-related changes in reward expectancy are reflected in the feedback-related negativity. *European Journal of Neuroscience, 27*, 1823–1835.

Bos, W. v. d., Crone, E. A., & Güroğlu, B. (2012). Brain function during probabilistic learning in relation to IQ and level of education. *Developmental Cognitive Neuroscience, 2S*, S78–S89.

Craig, S., Lewandowsky, S., & Little, D. R. (2011). Error Discounting in probabilistic category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*(3), 673-687.

Deák, G. O., & Wiseheart, M. (2015). Cognitive flexibility in young children: general or task-specific capacity? *Journal of Experimental Child Psychology, 138*, 31–53.

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

Dong, X., Du, X., & Qi, B. (2016). Conceptual knowledge influences decision making differently in individuals with high or low cognitive flexibility: an ERP study. *PLoS ONE, 11*(8), e0158875.

Erb, C. D., Moher, J., Song, J.-H., & Sobel, D. M. (2017). Cognitive control in action: tracking the dynamics of rule switching in 5-to 8-year-olds and adults. *Cognition, 164*, 163–173.

Feng, X., & Feng, C. (2019). The index predicting power and feedback processing characteristics in the WCST. *Psychology and Behavioral Sciences, 8*(3), 72–78.

Girardi, G., Antonucci, G., & Nico, D. (2013). Cueing spatial attention through timing and probability. *Cortex, 49*, 211–221.

He, L., Li, Y., Zhuang, K., Chen, Q., Sun, J., Yang, W., & Wei, D. (2020). Network connectivity of the creative brain: current knowledge and future directions. *Chinese Science Bulletin, 65*, 25–36.

Koch, I., & Allport, A. (2006). Cue-based preparation and stimulus-based priming of tasks in task switching. *Memory and Cognition, 34*(2), 433–444.

Lagnado, D. A., Newell, B. R., Kahan, S., & Shanks, D. R. (2006). Insight and strategy in multiple-cue learning. *Journal of Experimental Psychology: General, 135*(2), 162–183.

Lange, F., Kip, A., Klein, T., Müller, D., Seer, C., & Kopp, B. (2018). Effects of rule uncertainty on cognitive flexibility in a card-sorting paradigm. *Acta Psychologica, 190*, 53–64.

Lange, F., Seer, C., & Kopp, B. (2017). Cognitive flexibility in neurological disorders: cognitive components and event-related potentials. *Neuroscience and Biobehavioral Reviews, 83*, 496-507.

Lange, F., Seer, C., Müller, D., & Kopp, B. (2015). Cognitive caching promotes flexibility in task switching: evidence from event-related potentials. *Scientific Reports, 5*, 17502.

Li, D., Li, P., & Li, H. (2018). The updated theories of feedback-related negativity in the last decade. *Advances in Psychological Science, 26*(9), 1642–1650.

Li, K., Fu, Q., & Fu, X. (2012). Cognitive and neural mechanisms of probabilistic category learning. *Progress in Biochemistry and Biophysics, 39*(11), 1037–1044.

Li, K., Fu, Q., Sun, X., Zhou, X., & Zhou, X. (2016). Paired-associate and feedback-based weather prediction tasks support multiple category learning systems. *Frontiers in Psychology, 7*, 1–10.

Liu, Z., & Zheng, C. (2015). Information amount and obviousness influence hypothesis generation. *Acta Psychologica Sinica, 47*(12), 1445–1453.

Miao, X., Li, Y., Wang, M., & Zhang, Z. (2015). The information processing flexibility of obsessive-compulsive tendency individuals. *Journal of Psychological Science, 38*(5), 1264–1271.

Newell, B. R., Lagnado, D. A., & Shanks, D. R. (2007). Challenging the role of implicit processes in probabilistic category learning. *Psychonomic Bulletin & Review, 14*(3), 505–511.

Orakci, Ş. (2021). Exploring the relationships between cognitive flexibility, learner autonomy, and reflective thinking tendency. *Thinking Skills And Creativity, In Press.*

Otto, A. R., Taylor, E. G., & Markman, A. B. (2011). There are at least two kinds of probability matching: evidence from a secondary task. *Cognition, 118*, 274-279.

Rogers, R., & Monsell, S. (1995). The costs of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General, 124*, 207-231.

Schenk, S., Lech, R. K., & Suchan, B. (2017). Games people play: how video games improve probabilistic learning. *Behavioural Brain Research, 335*, 208-214.

Spiro, R. J. (1988). Cognitive flexibility theory: advanced knowledge acquisition in ill-structured domains. Paper presented at the Tenth Annual Conference of the Cognitive Science Society, Montreal.

Stad, F. E., Wiedl, K. H., Vogelaar, B., Bakker, M., & Resing, W. C. M. (2019). The role of cognitive flexibility in young children' s potential for learning under dynamic testing conditions. *European Journal of Psychology of Education, 34*, 123-146.

Wu, Y., & Zhou, X. (2009). The P300 and reward valence, magnitude, and expectancy in outcome evaluation. *Brain Research, 1286*, 114-122.

Xu, G., Wen, H., Wei, X., & Mo, L. (2011). The influence of positions of cues on probabilistic category learning. *Acta Psychologica Sinica, 43*(3), 264-273.

Xing, Q., Sun, H., Zhan, D., Hu, J., & Liu, K. (2017). The effect of executive function on verbal insight problem solving: behavioral and ERPs studies. *Acta Psychologica Sinica, 49*(7), 909-919.

Zeithamova, D., & Maddox, W. T. (2007). The role of visuospatial and verbal working memory in perceptual category learning. *Memory and Cognition, 35*, 1380-1398.

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