The Predictive Effect of Cognitive Flexibility and Probability Knowledge on Probability Category Learning

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Abstract
We investigated the predictive effects of learners’ cognitive flexibility and probability knowledge on probability category learning. A number-letter switch task was to measure cognitive flexibility, a self-designed probability knowledge questionnaire to estimate probability knowledge, and two probability category learning tasks (with cues: Coin searching task; no cue: Picture selection task) were analyzed. The regression analysis showed that in the coin searching task, cognitive flexibility alone can predict whether the rules had acquired in probability category learning. In the picture search task, both cognitive flexibility and probability knowledge factors predicted rule acquisition. It reveals that the predictive effect of cognitive flexibility on probability category learning is consistent across tasks, while the predictive effect of probability knowledge varies with specific task characteristics.

Keywords
Cognitive flexibility, Probability knowledge, Probability category learning

Introduction
Classification is an important process and method for understanding our world. Classification in daily life is not always clear-cut. For example, dark clouds don’t always mean rain. The category learning of uncertainty, known as probability category learning, is more difficult than consistent classification learning [1]. Due to the probabilistic properties, there is no “perfect” reaction or one-to-one correspondence between objects and attributes [2]. Learners must accept a certain range of uncertainty, gradually establish the relationship between objects and attributes through continuous classification selection and feedback processing. Research on probability category learning provides important experimental evidence for understanding implicit learning, cognitive flexibility, and feedback information learning [3,4]. Studies using the weather prediction task paradigm found that although subjects could not verbally report the rules of the task, the classification selection of specific objects was higher than random level [5], which meant that probability category learning involved implicit processing [4].

Task cues play an important role in category learning, and the discussion on the cue effect provides some arguments for the debate between explicit and implicit systems in probability category learning [3,6]. The discussion about cues focuses on: firstly, the presence and presentation of cues will affect the probability category learning effect. Previous studies have shown that the effective use of explicit cues can reduce the switch cost and promote the preparation for specific response rules [7]. In the weather prediction task, although the accuracy of both the fixed and random cue position groups was higher than random level, the random group could not correctly estimate the probability of cards predicting sunny weather [6]. Moreover, highly predictive cues could improve learners’ performance. It was the probabilistic matching relationship between the cue and target, not the presentation time of the stimulus, that made the cues highly predictable [8]. Secondly, learners may have various learning effects in the same cue condition. Results have shown that...
learners with high compulsive tendencies stick to their original processing mode, while low compulsive tendency learners adjust processing patterns according to probabilistic changes [9]. Participants with high cognitive flexibility were better able to suppress invalid cues of dominance and efficiently redeploy resources [10] and had better learning performance in probability category learning [11]. We speculate that there may be an interaction between the cue features and learner traits.

The learning of probabilistic categories is associated with individual differences but is not identical to the factors that influence explicit learning [12]. Studies have shown that executive function is associated with rule-based category learning. There is supporting evidence for working memory [13,14] and inhibitory control [15]. Few studies have shown that cognitive flexibility is a good predictor of learning accuracy for rule-based categories [16]. In their study, the regression analysis showed that the performance on the number-switch task, which measured cognitive flexibility, had the highest predictive power (88.7%) for rule-based category learning accuracy. The classification process relies on hypothesis testing to generate, transform, and update possible categories [14], and switching is the core process of cognitive flexibility [17]. We predict that cognitive flexibility is a core factor for probability category learning.

Meanwhile, studies have found that cognitive flexibility plays inconsistent roles in task switching, inhibitory control, and reasoning processes. Individuals’ knowledge and experience could affect their performance in specific tasks [18]. Some studies have revealed that subjects have acquired implicit probabilistic experience and it is constantly updated with the progress of tasks [19]. Learners make use of probabilistic experience to implicitly anticipate the stimulus to be presented [20]. However, there are individual differences in existing probability knowledge and counting ability [21]. In this study, we aim to explore how to measure the level of probability knowledge, and whether probability knowledge enhances the classification learning process during probability category learning.

Most studies have focused on exploring performance differences in probability category learning based on a single factor such as stimulus presentation form, cue location, working memory, inhibitory capacity, etc. [6,22-24]. However, learning often involves multiple strategies [25], and drawing inferential conclusions based on a single task or factor is difficult [2]. This study attempts to analyze the effects of task characteristics (cues) and learner characteristics (cognitive flexibility, probability knowledge) on probability category learning. Two questions will be explored: whether cognitive flexibility and probability knowledge have interactive effects on probability category learning, and whether the effects of cognitive flexibility and probability knowledge on probability category learning differ depending on specific task forms.

Method

Participants

310 college students participated in tasks to assess their cognitive flexibility and probability knowledge. Thirteen datasets were excluded due to repeated responses, incorrect understanding of instructions, and latency of less than 100ms. The remaining 297 participants were sorted based on their switch costs (see 2.2.2). The top 27% with smaller switch costs were considered as high flexibility, while the bottom 27% with larger switch costs were considered as low flexibility. Similarly, based on the scores of the self-developed “probability knowledge questionnaire,” the top 27% were in high probability knowledge level group, while the bottom 27% were in low group. To avoid pre-test influences on the follow-up experiment, participants took part in the probability category learning tasks two weeks later.

Only data from participants who belonged to both subgroups were included in further statistical analysis. Out of 62 participants who completed the cued (coin search) and non-cued (picture selection) probability category tasks, 22 participants were high in cognitive flexibility or probability knowledge, 21 participants were high in both, and 19 participants were low in both.

All participants were right-handed, had normal or corrected-to-normal vision, and had no reported cognitive impairment or mental illness. All participants provided informed consent and were compensated for their participation. The study was approved by the Ethics Committee of ** University.

Experiment tasks

Simple version of Raven’s reasoning test: Considering the difficulty and response latency of the Raven Reasoning Test, a simplified version consisting of items 17-36 of the original test was used to measure participants’ intelligence [26]. The stimuli were presented using E-prime. Participants were given 60 seconds to answer each item, with one point awarded for a correct answer and zero point for an incorrect answer or if the time limit was reached. The number of correct answers was recorded as the participant’s score.

Number-letter switching task (NLST): The number-letter switching task was used to measure participants’ cognitive flexibility [27]. This task aimed to provide a relatively pure measurement of cognitive flexibility by reducing multiple cognitive processing [28].

The stimuli were presented in the form of a number paired with a letter. The number was either odd (3/5/7/9) or even (2/4/6/8), and the letter was either
a vowel (A/E/I/U) or consonant (G/K/M/R). The stimuli were presented in a quadrant at the center of the screen and appeared in a clockwise direction between trials. Participants were instructed to press E for a vowel and I for a consonant when the stimulus appeared in the top two squares, and to press E for an odd and I for an even when it appeared in the bottom two squares. The E and I were counterbalanced between participants. Participants had to achieve an accuracy rate of at least 80% in the practice trials to enter the formal experiment. The formal experiment had 128 trials, and both response latency and accuracy were recorded.

If the judgment criteria between two adjacent trials needed to change, the latter trial was classified as a switch trial, while if the criteria remained the same, it was a repeat trial. The difference between the average correct response latency of switch and repeat trials was calculated as the switch cost. A higher switch cost indicated lower cognitive flexibility.

**Probability knowledge questionnaire (PKQ):** The probability knowledge questionnaire focused on basic probability knowledge, including concepts such as complementary events, independent events, conditional probability, and the equally-likely probability model. The evaluation indexes of the questionnaire are shown in Result 3.1. The final questionnaire included 10 items. A higher score indicated a higher level of probability knowledge.

**Probability category task with cue - coin search task (CST):** The coin search task was similar to that used by Bellebaum, et al. (2008) [29]. The task consisted of three blocks, each comprising 180 trials. Prior to the experiment, participants were informed: (1) The total number of red blocks (4/8) was equal on both sides. (2) A coin was hidden in one of the 12 colored blocks. (3) The task was to press F/J to guess which side the coin was more likely to be hidden in. (4) A triangle or hexagon would appear after each choice to indicate reward or no reward, respectively. (5) There was a “rule” that determined the reward. (6) The more rewards the participant received, the greater actual reward he would receive after the experiment.

According to previous studies, the specific coin location was presented in Block 2 to reduce task difficulty. Following reward feedback, the coin would appear under one of the red blocks in the right column of the selected side, and following non-reward feedback, the coin would appear under a white block in the right column of the selected side. The exact location of the coin was randomized, and the left or right settings were balanced among participants.

There was a probabilistic cue hidden in the task that could maximize the reward. The number of red blocks on each side was either 4 or 8 out of 12 blocks. The possible number of red blocks on the right column was 0/2/4/6, and the corresponding reward probability was 0 or 1/3 or 2/3 or 1. The combinations of the reward probabilities for the two sides were shown in Table 1. Taking the example of the coin appearing in the right column (Figure 1), in the case of the 1/3 (right column of left side) and 2/3 (right column of right side) pairs, it was the correct response to choose the right side, even though there was still a 1/3 chance of receiving no reward feedback.

**Cueless probability category tasks - picture selecting task (PST):** There were hidden cues that could be found and utilized in the CST. Considering that once a cue was correctly identified, the probabilistic attribute of the task might change to frequency. In order to maintain the probabilistic comparison and judgment learning throughout the task, we further designed a picture selection task with the same probabilistic matching pattern as the CST.

The stimuli were E, M, Ξ, W in PST. Each stimulus corresponded to one of the four reward probabilities (0, 1/3, 2/3, 1), and a latin square design was implemented. The four reward modes (Table 2) were counterbalanced across participants. Participants were not provided any information about the probability, and were instructed to press either F or J to indicate whether the stimulus to the left or right of the fixation point was rewarding. The reward probability combinations were identical to those in the CST (see Table 1).

The pre-experiment showed that the task difficulty

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**Table 1:** The combinations of reward probabilities in a single trial and number of trials.

<table>
<thead>
<tr>
<th>Types of stimulus</th>
<th>Number of trails (including left-right balance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reward probability of right column for one side</td>
<td>Reward probability of right column for the other side</td>
</tr>
<tr>
<td>0</td>
<td>1/3</td>
</tr>
<tr>
<td>0</td>
<td>2/3</td>
</tr>
<tr>
<td>1/3</td>
<td>2/3</td>
</tr>
<tr>
<td>1/3</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 2:** Reward Modes in PST.

<table>
<thead>
<tr>
<th>Model</th>
<th>E</th>
<th>M</th>
<th>Ξ</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0</td>
<td>1/3</td>
<td>2/3</td>
<td>1</td>
</tr>
<tr>
<td>Model 2</td>
<td>1</td>
<td>0</td>
<td>1/3</td>
<td>2/3</td>
</tr>
<tr>
<td>Model 3</td>
<td>2/3</td>
<td>1</td>
<td>0</td>
<td>1/3</td>
</tr>
<tr>
<td>Model 4</td>
<td>1/3</td>
<td>2/3</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
was appropriate. The formal procedure of PST is shown in Figure 2. A triangle or hexagon was displayed after the response to indicate reward or no reward, respectively (counterbalanced between participants). There were
540 trials, and participants took a break every 45 trials. The more rewards they received, the greater actual reward they would get after the experiment.

**Experiment procedure**

Learners’ characteristics assessment tasks and probability category learning tasks was included in the experiment. The sRRT, NLST, and PKQ were administered during the assessment. Subsequently, the CST and PST were completed. 310 participants completed the assessment tasks to rate their level of intelligence, cognitive flexibility, and probability knowledge. Participants with high/low cognitive flexibility and probability knowledge were invited to the follow-up CST and PST. To avoid possible interference between two tasks, there was at least a 2-week interval between them, and the order of tasks was balanced among the participants. The participants were asked to complete an open-ended questionnaire to describe the rules they found after the tasks. In PST, they estimated the probability of getting a reward for each of the four stimuli.

**Data analysis**

To explore the learning characteristics over time, we divided each participant’s learning into pre- and post-learning stages. We described participant’s learning curve using a window analysis with a window length of 20 and a step of 1 [29]. The learning baseline was set at 16 correct responses within 20 successive trials (80%). The intersection of the learning curve and baseline was considered the rule acquisition point, and each participant’s learning process was divided into pre- and post-stages accordingly. For participants who did not discover the rule during the task, there was no post-learning stage, and for those who found the rule within a few trials after the task began, there was no pre-learning stage.

Next, a mixed repeated measures ANOVA was conducted to analyze the learning characteristics, with within-factors including learning stage (pre and post), probability pairing (0-1/3, 0-2/3, 1/3-2/3, and 1/3-1), and between-factors including cognitive flexibility level (high and low), and probability knowledge level (high and low).

Finally, logistic regression analysis was used to investigate the predictive effects of cognitive flexibility and probability knowledge on the two probability category learning tasks.

**Results**

**Statistical indicators of the probability knowledge questionnaire**

We conducted several rounds of questionnaire adjustment, modification, and pre-analysis. The probability knowledge questionnaire consists of 10 items, and the evaluation indices are as follows.

**Difficulty:** The difficulty of each question was determined by its average pass rate. Two questions were considered easy with pass rates of 81.0% and 77.9%. Five questions were considered medium difficulty with pass rates ranging from 61.2% to 64.9%, and three questions were considered difficult with pass rates below 45.0%.

**Discriminability:** To calculate discriminability, we ranked participants’ total scores. Those who scored in the upper 27% were placed in the high group, while those in the lower 27% were in the low group. The pass rates for each question (P_H for high group, P_L for low group) were then substituted into the formula \( D = P_H - P_L \) to calculate the discriminability for each item. The results indicated that the question discriminability ranged from 0.3 to 0.7. Referring to the test differentiation criteria proposed by psychometrist Ebel, a distinction of 0.30-0.39 is considered good, and a distinction greater than 0.4 is considered very good. This showed that the discriminability of the probability questionnaire was good.

**Split-half reliability:** To calculate split-half reliability, the questions were first sorted by their pass rates and then split in half based on their odd and even numbers. The correlation coefficient between the odd and even questions was calculated and corrected by the Spearman-Brown formula. The results showed that the split-half reliability of the questionnaire was acceptable (0.61).

**The levels of cognitive flexibility and probability knowledge of the participants**

The descriptive statistics of switch cost and probability knowledge questionnaire scores for 297 participants are presented in Table 3.

62 subjects whose levels of cognitive flexibility and probability knowledge were both in the low or high groups were included in subsequent data analyses. An independent samples t-test showed that the switch cost of the high flexibility group was significantly lower than that of the low flexibility group \( p < 0.000 \). The number of correct answers to the questionnaire in the high

![Table 3: Descriptive statistics of switch cost score and probability score.](image)

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>M</th>
<th>SD</th>
<th>Upper 27th percentile</th>
<th>Lower 27th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch cost</td>
<td>137.5</td>
<td>2085.3</td>
<td>813.4</td>
<td>389.2</td>
<td>523.5</td>
<td>1041.1</td>
</tr>
<tr>
<td>Questionnaire score</td>
<td>20</td>
<td>100</td>
<td>58.4</td>
<td>18.4</td>
<td>40</td>
<td>70</td>
</tr>
</tbody>
</table>
flexibility groups, as well as the high and low probability knowledge groups. 22 out of 30 subjects in the high cognitive flexibility group and 12 out of 32 subjects in the low flexibility group had learned the rule. Pearson chi-square test showed that the number of learners in the high flexibility group was significantly higher than that in the low flexibility group \[ p = 0.005 \]. Similarly, the number of learners in the high probability knowledge group (22 out of 34) was marginally significantly higher than that in the low group (12 out of 28) \[ p = 0.085 \].

**Simple raven reasoning test analysis**

The score of the sRRT was 8.23 ± 3.064. Independent sample t-tests showed that there was no significant difference between the high (8.57 ± 3.104) and low flexibility group (7.91 ± 3.041) \[ p = 0.401 \]. Meanwhile, there was no significant difference between the high (8.71 ± 2.980) and low probability knowledge group (7.64 ± 3.118) \[ p = 0.176 \].

**Coin searching task analysis**

Participants were instructed to select the side that was more likely to result in rewards. During Block 2, participants were presented with specific coin positions. Some participants discovered the hidden cues, which were that the side with more red blocks in the right column (left column for the other half of participants) was more likely to result in rewards. The learning process was analyzed using learning curves, accuracy, and response latency. Regression analysis was used to explore the role of cognitive flexibility and probability knowledge in rule learning.

**Rule acquisition level and learning curve:** Out of 62 participants, 34 had discovered the rule. The learning curves for learners and non-learners are presented in Figure 3. Learners reached the baseline level at around the 250th trial and consistently remained above it. Non-learners’ choices were random throughout the task.

We further compared the differences in the number of learners and non-learners in the high and low cognitive probability knowledge group was significantly higher than the low group \[ p < 0.000 \]. Correlation analysis showed there was no significant correlation between switch cost and probability knowledge score.

**Figure 3:** The learning curve of rule learners and non-learners in CST.
The results showed that only cognitive flexibility had a significant predictive effect on rule learning performance in the coin searching task \[Y = -0.767 \times Z_{\text{cost}}\].

### Picture selection task analysis

**Rule acquisition level and learning curve:** 40 out of 62 participants learned the rule in PST. The learning curves of the learners and non-learners are shown in Figure 4. On average, the correct responses of learners slightly exceeded the baseline from around the 340th trial and remained so until the end of the task.

Regarding cognitive flexibility, the number of learners in the high group (25 out of 30) was significantly higher than that in the low group (15 out of 32) \(p = 0.003\). Similarly, the number of learners in the high probability knowledge group (28 out of 34) was significantly higher than that in the low group (12 out of 28) \(p = 0.001\).

**Accuracy analysis:** The same mixed ANOVA was conducted to analyze the accuracy of PST. The results indicated that the learning stage had a significant main effect \(p < 0.001\), where post-learning accuracy \(0.823 \pm 0.014\) was higher than pre-learning accuracy \(0.637 \pm 0.014\). There was also a significant main effect of probability pairing \(M_{0-1/3} = 0.617 \pm 0.023, M_{0-2/3} = 0.798 \pm 0.015\) was significantly higher than that of the low probability knowledge group \(0.733 \pm 0.019\) \(p < 0.05\). No other main or interaction effects were significant.

**Latency analysis:** The same mixed ANOVA analysis for latency showed that participants reacted significantly faster in the post-learning stage \(398.562 \pm 25.372\) ms than in the pre-learning stage \(562.698 \pm 36.202\) ms \(p < 0.001\). The main effect of probability pairing was significant \(M_{0-1/3} = 502.638 \pm 31.519, M_{0-2/3} = 477.631 \pm 31.347, M_{1/3-2/3} = 490.396 \pm 29.454, M_{1/3-1} = 451.854 \pm 28.091, p < 0.001\). The differences between 0-1/3 and 0-2/3 \(p < 0.05\), 0-1/3 and 1/3-1 \(p < 0.05\), 0-2/3 and 1/3-1 \(p < 0.05\), and 1/3-2/3 and 1/3-1 \(p < 0.05\) were all significant. The high flexibility group \(413.574 \pm 39.396\) ms had significantly smaller latency than the low flexibility group \(547.685 \pm 43.659\) ms \(p < 0.05\). The interaction between learning stage and probability pairing was significant \(p < 0.001\). Simple effect analysis showed that the latency of the four probability pairs was significantly different only in the post stage \(M_{\text{post}_0-1/3} = 435.143 \pm 29.525, M_{\text{post}_0-2/3} = 393.129 \pm 27.643, M_{\text{post}_1/3-2/3} = 416.923 \pm 27.027, M_{\text{post}_1/3-1} = 349.052 \pm 22.168, p < 0.05\). The differences between 0-1/3 and 0-2/3 \(p < 0.05\), 0-1/3 and 1/3-1 \(p < 0.05\), 0-2/3 and 1/3-1 \(p < 0.05\), and 1/3-2/3 and 1/3-1 \(p < 0.05\) were all significant. The other main effects and interaction effects were not significant.

**Regression analysis:** To predict whether a learner could discover the rule in CST, logistic regression analysis was conducted with the standard scores of Raven Reasoning Test, switch cost, and probability knowledge as independent variables. The results are shown in Table 4.
0.805 ± 0.018, \( M_{1/3_2/3} = 0.763 ± 0.018, M_{1/3_1} = 0.736 ± 0.033, p < 0.001 \), and all three probability pairs were significantly different from 0-1/3 \([p < 0.05]\), with marginally significant differences between 0-2/3 and 1/3-2/3 \([p = 0.052]\) or 1/3-1 \([p = 0.077]\). The interaction between learning stage and probability pairing was also significant \([p < 0.05]\). Further simple effect analysis showed that there was a significant difference among the four probability pairings in the pre-learning stage \([p < 0.05]\), with the difference between 0-1/3 (0.580 ± 0.024) and 0-2/3 (0.692 ± 0.027) being significant \([p < 0.05]\). Similarly, the difference among the four probability pairings in the post-learning stage was also significant \([M_{post-0_1/3} = 0.653 ± 0.031, M_{post-0_2/3} = 0.917 ± 0.019, M_{post-1/3_2/3} = 0.892 ± 0.021, M_{post-1/3_1} = 0.831 ± 0.040, p < 0.001]\), with all three pairs being significantly different from 0-1/3 \([p < 0.05]\). The other main effects and interaction effects were not significant.

Latency analysis: For the latency analysis of PST, a mixed ANOVA \([2 \times 4 \times 2 \times 2]\) was conducted. The latency after rule learning (393.898 ± 25.999 ms) was significantly faster than before (491.899 ± 30.303 ms) \([p < 0.001]\). Probability pairing had a significant main effect \([M_{1/3_2/3} = 495.070 ± 29.525 ms, M_{1/3_1} = 430.390 ± 25.193 ms, M_{1/2_3} = 426.107 ± 27.482 ms, M_{1/2_1} = 420.028 ± 29.554 ms, p < 0.001]\). The differences between 0-1/3 and the other three probability pairs were significant \([ps < 0.001]\). The interaction between learning stage and probability knowledge was significant \([p < 0.05]\). Further simple effect analysis showed no significant difference between high and low probability knowledge groups in either pre- or post-learning stages.

Probability estimation of reward feedback: Subjects estimated the reward probability for each stimulus after PST. Those who missed or did not use data for estimation were excluded from analysis. Analysis of 51 datasets showed that the estimations for the four stimuli (0, 1/3, 2/3, and 1) were 0.27, 0.39, 0.62, and 0.64, respectively. Analysis of variance indicated a significant main effect of probability evaluation \([p < 0.001]\). Pairwise comparisons revealed significant differences between every two estimated data points except for 2/3 and 1.

Regression analysis: Taking the standard scores of the Raven’s Reasoning Test, switch cost, and probability knowledge as independent variables, logistic regression analysis was conducted to predict the results of rule learning in PST. The results are shown in Table 5.

Table 5: The regression analysis of switch cost and probability knowledge on the rule acquisition in PST.

<table>
<thead>
<tr>
<th>Index</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>P</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z_{cost}</td>
<td>-0.703</td>
<td>0.319</td>
<td>4.851</td>
<td>0.028</td>
<td>0.495</td>
</tr>
<tr>
<td>Z_{prob}</td>
<td>0.866</td>
<td>0.317</td>
<td>7.432</td>
<td>0.006</td>
<td>2.376</td>
</tr>
<tr>
<td>Z_{raven}</td>
<td>0.302</td>
<td>0.330</td>
<td>0.838</td>
<td>0.360</td>
<td>1.353</td>
</tr>
<tr>
<td>Constant</td>
<td>0.763</td>
<td>0.318</td>
<td>5.765</td>
<td>0.016</td>
<td>2.145</td>
</tr>
</tbody>
</table>

The results indicated that cognitive flexibility had a significant positive predictive effect, and probability knowledge had a significant negative predictive effect on rule learning in PST \([Y = 0.763 - 0.703 \times Z_{\text{cost}} + 0.866 \times Z_{\text{prob}}]\).

Discussion

We examined the predictive effects of cognitive flexibility and probability knowledge on probability category learning with and without cues. The results indicated that cognitive flexibility was the only predictor of learning outcomes in the cued probability category task, while both cognitive flexibility and probability knowledge predicted learning outcomes in the probability category task without cues.

The influence of probability knowledge on probability category learning

Two tasks in this study had equal difficulty in terms of the awareness and application of probability. In CST, the stimulus involved multi-dimensional changes in color, quantity, and position. It was necessary to uncover the hidden cues from seemingly random color blocks and establish a connection between the cue and feedback. If the stimulus was only processed from the bottom-up, relying on working memory, finding the hidden cues was difficult. In PST, subjects had difficulty integrating probabilistic feedback information even though they did not need to expend much cognitive resources to process stimuli. Researchers have found that mastery of domain knowledge could promote the use of strategies within the domain \([30]\). The PST supported this point of view in probabilistic domain knowledge; the high probability knowledge group had more learners than the low probability knowledge group. In contrast to PST, although participants also needed to establish the probability link between the stimuli and reward feedbacks, they might rely on easy frequency processing to make choices in the post-learning stage of CST. In CST, the number of learners was marginally significant \([p = 0.085]\) between the high and low probability knowledge groups, which might be due to the decreased use of probability knowledge in the post-learning period. The results suggest that whether probability knowledge had an impact on probability category learning was related to the continuous dependence on probability processing in tasks.

In both tasks, no information about probability or frequency was explicitly provided in the instructions. In CST, the post-task questionnaire revealed that some participants were able to describe the entire rule explicitly, however the low reward probabilities on both sides decreased their confidence in the rules. In PST, the post-task questionnaire revealed that while most participants were unable to explicitly report the rules accurately, they were able to form differentiated judgments on stimuli pairs except for the probability
pairing of 2/3 and 1. These suggest that learners’ probability knowledge influenced adaptive probabilistic learning, regardless of their awareness of probabilistic rules. In other words, probability knowledge could enhance the learning process implicitly.

The influence of cognitive flexibility on probability category learning

As a core component of executive function, the relationship between cognitive flexibility and learning outcomes has attracted the attention of researchers. Diamond [31] suggested that cognitive flexibility was an important factor that affected intelligence and creativity levels. Cognitive flexibility was found to have a significant predictive effect on children’s academic performance [32], and adults with high flexibility performed better in decision-making and rule-learning tasks [11,33]. Our results consistently showed that the rate of rule acquisition was significantly higher in the high cognitive flexibility group, which providing new evidence that cognitive flexibility had a positive effect on probability category learning.

There are individual differences in learning outcomes among learners for explicit and implicit learning [12]. Although the two tasks in this study could not be matched one-to-one with explicit and implicit learning, we could infer that the CST involved explicit processing and the PST involved implicit processing from the subjects’ reports about the rules. Cognitive flexibility had predictive effects on both tasks, indicating that it was a relatively stable factor affecting the outcome of probability category learning. Moreover, when traditional intelligence tests and cognitive flexibility were included in the regression analysis together, the results only showed the significant predictive effects of cognitive flexibility, further indicating its importance in probability category learning. This may be related to the switch process, which is the core of cognitive flexibility and hypothesis testing in rule learning. Research on brain injuries has shown that schizophrenia patients with reduced striatal response in switching tasks have low effectiveness in detecting rule switching and impaired adaptive behavior after misprediction [34]. Brain structures, including the anterior cingulate cortex, striatum, and fronto-parietal network, are the basis of switch processing and the switch capacity is a key factor for adaptive learning behaviors [35,36].

Conclusion

In probability category learning, cognitive flexibility has a significant predictive effect that is independent of specific task forms. The predictive effect of probabilistic knowledge is influenced by the continuous demand for probability knowledge in the tasks.

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Declaration of Competing Interest

None.

References


