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The effects of rewards on trial-and-error learning in school-aged children

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Abstract

Humans' ability to rapidly identify appropriate actions in new situations is critical for functional behavior. This skill develops through trial-and-error where humans learn to choose the optimal actions through rewards from previous acts. Here, we used computerized games to test developmental changes in how rewards affect trial-and-error learning. School-aged children (5- to 15-year-olds) played online games while receiving either positive rewards, negative rewards, or no rewards. We tested how the groups differed in performance and play strategy. Children who received negative rewards had higher success rates, fewer attempts, and more efficient strategies. They also showed significant improvement with age, similar to the controls but in contrast to children who received positive rewards. Our findings demonstrate a developmental shift in how rewards affect trial and error and suggest that negative rewards emerge as a powerful cognitive reinforcer during late childhood.

Keywords

Child development, trial-and-error learning, reasoning, rewards, school-aged children, physical cognition

To be functional in a world full of uncertainties, children must learn the skill of discerning beneficial actions from detrimental ones (Van Duijvenvoorde et al., 2008). They do that through trial-and-error learning—a reward-driven process in which future actions are selected based on the outcomes of their previous actions (Decker et al., 2015). These outcomes are evaluated through rewards attributed to specific actions and promote learning by incentivizing corrections of prior mistakes (Schultz et al., 1997).

Previous developmental work indicates that rewards play a central role in late childhood (Ferdinand et al., 2022). Older children and young adolescents (8 to 15 years) show better performance when they are incentivized compared to when they are not, contrary to adults who perform similarly (McGraw, 2015). More specifically, children during mid-adolescence (13–14 years of age) learn faster and are more consistent in tasks that rely on rewards as reinforcers than older children (aged 9–11 years; Crone & Van der Molen, 2004) who might change their choices more frequently (Hämmerer et al., 2011). These findings suggest that during late childhood, children's ability to use rewards as effective reinforcers for learning is gradually increasing, leading to more efficient learning (Galván, 2010).

Rewards during learning can be gains—positive values in successful actions, or penalties—negative values in faulty actions. The type of value plays a role in development. For example, acquiring foundational skills such as walking or talking improves when penalty values are reduced (Han & Adolph, 2021; Ossmy et al., 2024). In contrast, findings in adolescents are inconsistent and change from one task to another (Pauli et al., 2023). For instance, in a task-switching paradigm, 13- to 15-year-olds respond significantly faster to high gains than high losses, while other stages of adolescence (10–12 years or 16–18 years) do not show a similar effect (Ferdinand et al., 2022). Other studies showed that older children and adolescents focus their attention to negative rewards (NR) during learning (Van den Bos et al., 2009). Similarly, findings from game-based learning research show that young children (12-year-olds) avoid using learning assistance tools if the use of those tools can result in a penalty (Sun et al., 2018). Given the importance of rewards and trial-and-error learning for acquiring knowledge about actions, the question is still open as to whether developmental changes in the impact of rewards on trial-and-error learning depends on the type of reward, and if so—how?

We addressed this question by testing school-aged children (5- to 15-year-olds) in an online task—Virtual Tools (see Figure 1(a); Allen et al., 2020; Grandchamp des Raux et al., 2024), which consists of a series of reasoning problems that children had to solve via trial and error (see Figure 1(b)). This online game also allowed us to eliminate confounds from developmental improvements in motor dexterity over a broad age range (Grandchamp des Raux et al., 2024; Ossmy et al., 2022) in which rewards become more

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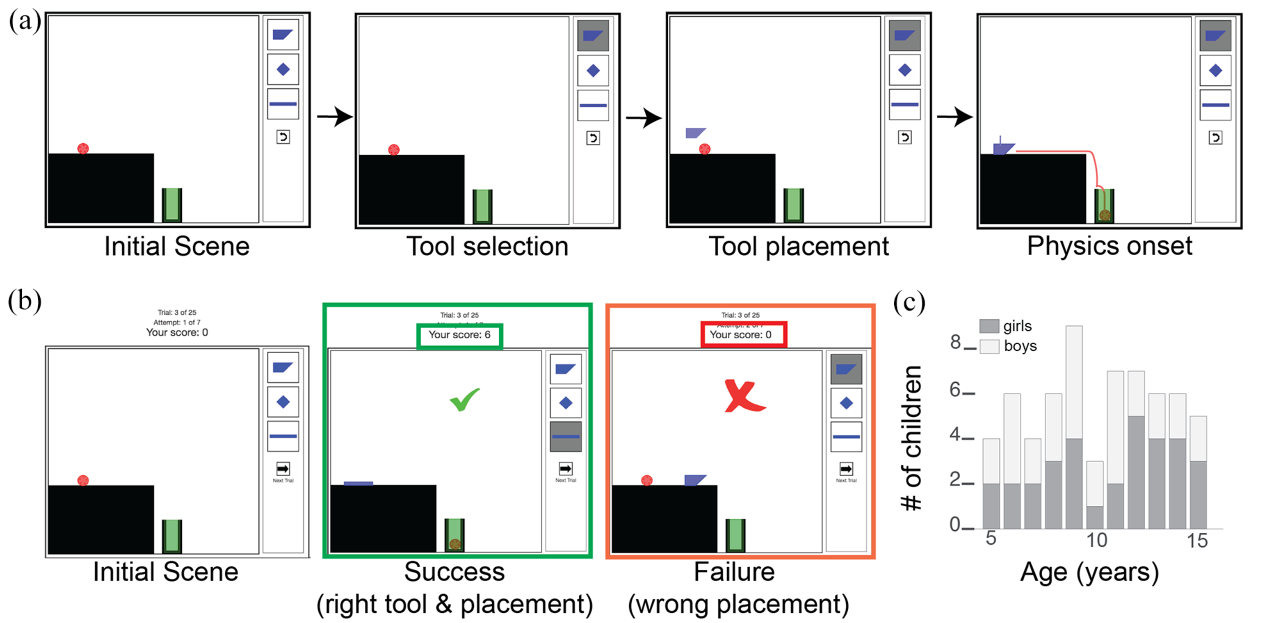

Figure 1. Design of Experiment. (a) Illustrative trial of a Virtual Tools game. Once the initial scene appears (left box), the child must select a tool (blue shapes on the right-hand side of the screen) and place it in the scene (middle boxes). The placement generates object movements based on the laws of physics (right box). (b) Action resulted either in a success (green tick) or failure (red cross). For the positive reward and negative reward groups, the score was updated above the scene. (c) Number of children tested per age and gender.

prominent (Jones et al., 2019). To test the role of rewards, we randomly assigned children to different experimental groups, each with a different reward system. Children in the positive rewards (PR) group received high gains for succeeding and were not penalized for errors. In contrast, children in the negative rewards (NR) group received gains for succeeding with a low number of errors but were highly penalized for errors (see Appendix 1, Table A1). Children in the no-reward group (Control) did not receive any score.

Our first aim was to assess whether PR and NR have different effects on children's trial-and-error learning. We compared children's success rate, number of attempts, and time per attempt. We also tested whether and how different rewards lead to changes in the trial-and-error strategies. To that end, we assessed how many tools children used, how they switched tools from one attempt to another, and how they changed their tool positioning. Frequent tool switching or big changes in positioning indicate poor evaluation of the failed outcome. Based on previous work (McGraw, 2015), we predicted that NR would induce better performance and more efficient strategies.

A second central aim of this study was to test the developmental relations between the type of reward and trial-and-error learning. We compared how performance and strategies changed with age in the three experimental groups. Based on previous literature (Pauli et al., 2023), we expected that NR would elicit stronger developmental effects compared to PR.

Methods

The study was granted ethical approval by the Psychology Ethics Committee at Birkbeck, University of London (reference #2122028).

Participants

We tested 65 children from 5.05 to 15.84 years of age (M = 10.55 years; 33 girls; see Figure 1(c)). The sample size was decided a priori based on previous developmental studies that investigated the effects of rewards on older children (Decker et al., 2015; Gonzalez-Gadea et al., 2015; Scheres et al., 2014; Siegel et al., 2024; Van Mastrigt et al., 2024). Children were recruited from word-of-mouth and advertisements. Two children were excluded because they stopped after a few games. Our only inclusion criteria were age (children had to be between 5 and 15 years of age) and the ability to use the computer for simple functions as moving the mouse cursor and pressing buttons. We did not have any further exclusion criteria. The PR group included 18 children (M = 11.32 years; 10 girls), NR group included 24 children (M = 10.59 years; 14 girls), and the Control group included 23 children (M = 9.89 years; 9 girls).

Task and Procedure

We used 'Virtual Tools'—an online gaming framework (Allen et al., 2020; Grandchamp des Raux et al., 2024)—consisting of a series of two-dimensional games (see Appendix 1, Figure A1). In each game, children needed to select one of three objects ("tools") and place it on the screen to get a red ball into a green area. The tool placement triggers object movements, approximating the physics of the world (Allen et al., 2020, 2021; Grandchamp des Raux et al., 2024). Children could attempt each game up to seven times without a time limit. The game was reset to its "initial state" after each failed attempt (see Figure 1(a)). If the attempt was successful, the children moved to the next game. For each attempt, we recorded which tool children selected, where they placed it, at what time, and whether they succeeded. Children received live feedback at each attempt, and children in the PR and NR groups were updated on their scores after each game (see Figure 1(b)).

Although all the Virtual Tools games shared a similar goal requiring children to apply their physical knowledge, they varied in degrees of difficulty, with a mix of easier, intermediate, and more difficult games (Allen et al., 2021; Allen et al., 2024). In addition, the physical action concepts that underlie the games vary as well (these differences were tested in Grandchamp des Raux et al., 2024). Thus, there is no transfer of knowledge across games where children can learn to solve one game based on previous games. This is supported by previous studies testing children in Virtual Tools (Allen et al., 2024; Grandchamp des Raux et al., 2024).

This online experiment started with an introduction to the study. Children from the PR or NR groups were informed that they would get scores for success and failure during the games. Parents could help their children read the instructions but were explicitly requested to refrain from interfering during the games. After separated consent forms for parents and children, a brief description of the rules of the games was presented on a screen and was customized according to children's groups. The level of comprehension required for the games was adapted to children aged 5 years and above, based on pilot studies in the lab in which we verified whether young children comprehend the instructions and based on previous work showing that children can play these specific online games independently (Allen et al., 2024).

Children also completed a short practice, followed by 23 games that were used in our analyses (see Appendix 1, Figure A1).

Design and Reward System

Children were randomly assigned to one of three groups: (1) PR: children received high gains (positive points) for succeeding within few attempts and slightly reduced gains for success in later attempts or failure; (2) NR: children received moderate gains for success with few errors but were penalized (negative points) for success in later attempts or failure; and (3) Control: children did not receive any score.

Within the PR and NR groups, we used different reward scales within the groups, which varied in magnitude (see Appendix 1, Table A1 for both reward systems). However, expected reward values were not matched across the PR and NR groups to make sure the NR group will still be engaged in the task and for ethical reasons. Children did not receive any additional compensation based on their scores.

Data Processing

For each child, game, and attempt, we recorded the outcome (success/failure) and the time elapsed between the start of the attempt until the placement of the tool. We also recorded which tool was selected and the x and y coordinates of its positioning. Data were then averaged across games per participant, yielding four measures: (1) success rate, (2) number of attempts, (3) time per attempt, and (4) number of tools. We also assessed two additional measures: (5) tool switching and (6) tool-positioning distance. For these last two measures, we only included games where the first attempt failed. To calculate tool switching, we evaluated the percentage of attempts in which the selected tool differed from the previous attempt. For tool-use positioning distance, we averaged the Euclidean distance in pixels between the positioning of the tool in each attempt and the previous one.

Data Analysis

To address our first aim, we used one-way analysis of variance (ANOVA) to test differences between groups in each measure. Then, we addressed the second aim by testing the relation between group and age. We used a linear model fitted through ordinary least squares and created two separate models for each measure. The first model exclusively involved the reward group as an independent variable, while the second model included the reward group, age, and their interaction. We compared their goodness of fit and we extracted the F-test statistics and the associated p-values of the best model.

Post-hoc analysis was performed on the results of the models. To explore the main effects, we estimated the differences between each pair of reward groups while adjusting the p-values for multiple comparisons using the Holm method (Lüdecke et al., 2021; Makowski et al., 2020). In models with significant interactions between reward group and age, we estimated the beta coefficients of age within each reward group and assessed whether these were significantly different from zero ("estimate_slope" function; Makowski et al., 2020).

To evaluate the strength of evidence for our linear models, we also performed a Bayes factor (BF) analysis for each of our key models (test_bf() function from R's performance package; Lüdecke et al., 2021). The BF quantifies the strength of evidence for the observed model relative to its null counterpart. Incorporating BFs alongside the traditional significance testing offers a more rigorous evaluation of the robustness of the findings.

Results

Preliminary analyses showed no significant effect of gender, so we combined boys and girls in subsequent analyses. Overall, children were successful in $M=72.63\%$, $SD=17.61$ of the games and completed each game in $M=3.81$ attempts, $SD=1.09$. Each attempt lasted $M=10.7$, $SD=7.3$ s.

Negative Rewards Led to Better Trial-and-Error Learning

Children in the NR group succeeded more than the other groups (see Figure 2(a)). They succeeded in $M=79.61\%$, $SD=18.39$ of the games, whereas children in the PR group succeeded in $M=66.52\%$, $SD=15.29$ of the games and children in the control group succeeded in $M=70.73\%$, $SD=16.96$ of the games. A one-way ANOVA confirmed a significant difference, $F(2,60)=3.15$, $p=.05$. Post-hoc LSD-corrected tests indicated a significant difference between the NR and PR groups, $p=.04$.

The NR group also needed fewer attempts to succeed (see Figure 2(b)). Those children succeeded in $M=3.35$, $SD=1.16$ attempts whereas children in the PR group succeeded in $M=4.43$, $SD=0.83$ attempts and children in the control group needed $M=3.78$, $SD=1.01$ attempts. A one-way ANOVA confirmed a

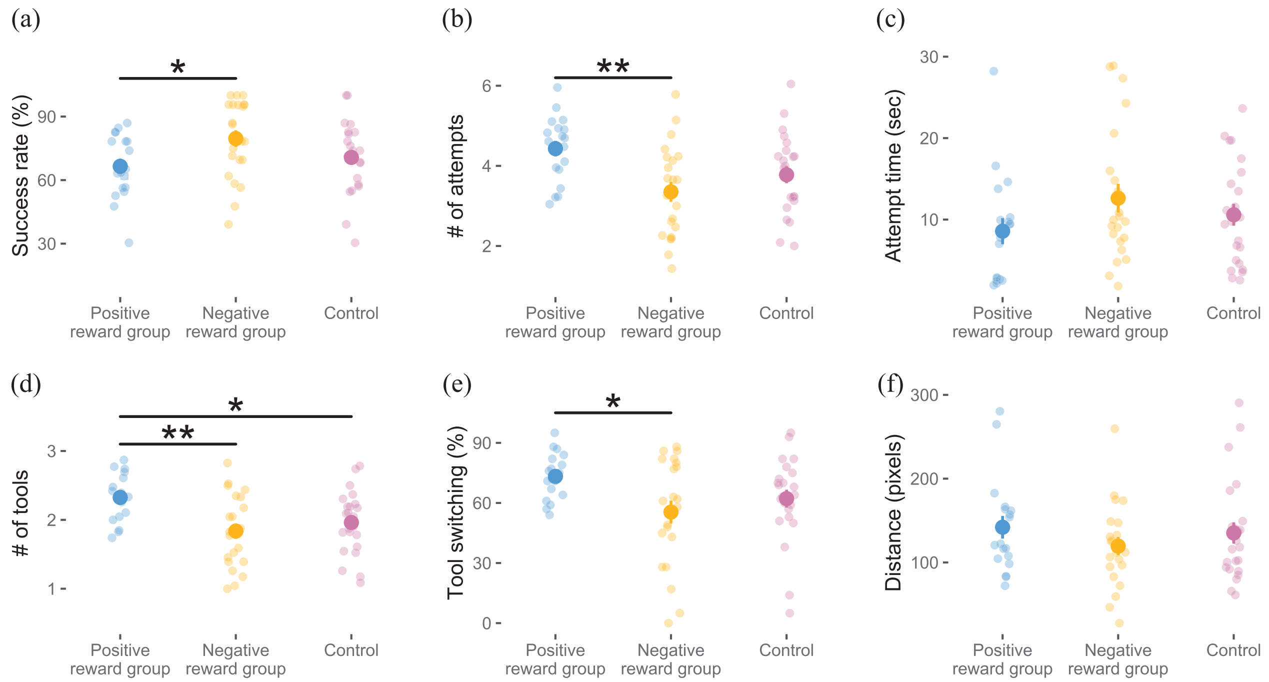

Figure 2. Differences in Performance and Strategies Across Groups. Plots show performance of the positive reward (blue; $N=18$), negative reward (yellow; $N=22$), and control (purple; $N=23$) groups in (a) success rate, (b) number of attempts, (c) time per attempt. Differences in their strategies are shown in the (d) number of tools used, (e) tool switching, and (f) positioning distance. Bright dots represent individual children, dark dots indicate averages across children in the group. Single asterisks (*p < 0.05), double asterisks (**p < 0.01), and triple asterisks (***p < 0.001) denote statistically significant differences.

significant difference, $F(2,60)=5.56$, $p=.01$. Post-hoc LSD-corrected tests indicated significant differences between the NR group and the PR and control groups ($p=.002$ and $p=.046$).

Children in the PR group were the fastest among the groups. Their attempts took $M=8.57$, $SD=6.79$ s (see Figure 2(c)), whereas the control group completed attempts in $M=10.59$, $SD=6.42$ s. The NR group was the slowest, with $M=12.62$, $SD=8.29$ s per attempt. A one-way ANOVA indicated no significant effect between the groups, $F(2,60)=1.56$, $p=.22$.

Age Improvements in Trial-and-Error Learning Depended on the Type of Reward

To address the second aim of the study, we assessed the impact of age within each reward group. Figure 3 shows the added value of including age alongside the reward group in our models. For children's success rate (see Figure 3(a)), the combined model significantly outperformed the model with reward group alone ($\chi^2=25.20$, $p<.01$), as it revealed an interaction between age and reward group ($F(2, 57)=5.31$, $p=<.01$; $\eta_p^2=758.e\text{-}03$) where learning in the NR and control groups were significantly affected by age (coefficient$=3.72$, $t(57)=3.50$, $p<.01$ and coefficient$=3.55$, $t(57)=3.54$, $p<.01$, respectively). In contrast, the performance of the PR group was not affected by age (coefficient$=–0.74$, $t(57)=–0.66$, $p=.51$).

We found similar results for the average number of attempts ($\chi^2=37.85$, $p<.01$). Figure 3(b) shows a significant interaction between age and reward group ($F(2,57)=7.08$, $p<.01$; $\eta_p^2=4.46e\text{-}03$). Children from the NR (coefficient$=–0.26$, $t(57)=–4.40$, $p<.01$) and control (coefficient$=–0.24$, $t(57)=–4.27$, $p<.01$) groups had fewer attempts with age, but not children from the PR group (coefficient$=0.03$, $t(57)=0.51$, $p=.61$). For the average attempt time, including age as a covariate did not increase the explanatory power of the model ($\chi^2=3.23$, $p=.35$).

Type of Reward Affected How Learning Strategies Changed With Age

For the number of tools used, our model ($\chi^2=52.10$, $p<.01$) confirmed a significant interaction between reward group and age ($F(2, 57)=10.50$, $p<.01$; $\eta_p^2=.01$). As shown in Figure 4(a), the number of tools decreased with age in both the NR (coefficient$=–0.12$, $t(57)=–4.93$, $p<.01$) and the control groups (coefficient$=–0.12$, $t(57)=–5.21$, $p<.01$), but not in the PR group (coefficient$=0.02$, $t(57)=0.82$, $p=.41$).

Similar results were found for the average tool-switching across attempts, where the model ($\chi^2=43.49$, $p<.001$) confirmed a significant interaction between reward group and age ($F(2, 57)=7.59$, $p<.01$; $\eta_p^2=2.53e\text{-}03$; see Figure 4(b)), as children in the NR and control groups switched tools less with age (coefficient$=–5.54$, $t(57)=–4.51$, $p<.001$; and coefficient$=–5.46$, $t(57)=–4.8$, $p<.001$, respectively), but children in the PR group did not (coefficient$=0.49$, $t(57)=0.38$, $p=.7$).

Finally, we tested the effects of age on tool-positioning distance and whether it changed across reward groups. Our model ($\chi^2=33.89$, $p<.001$) confirmed a significant interaction between age and reward group ($F(2, 57)=7.58$, $p<.01$; $\eta_p^2=.01$). Children in the NR and control groups showed

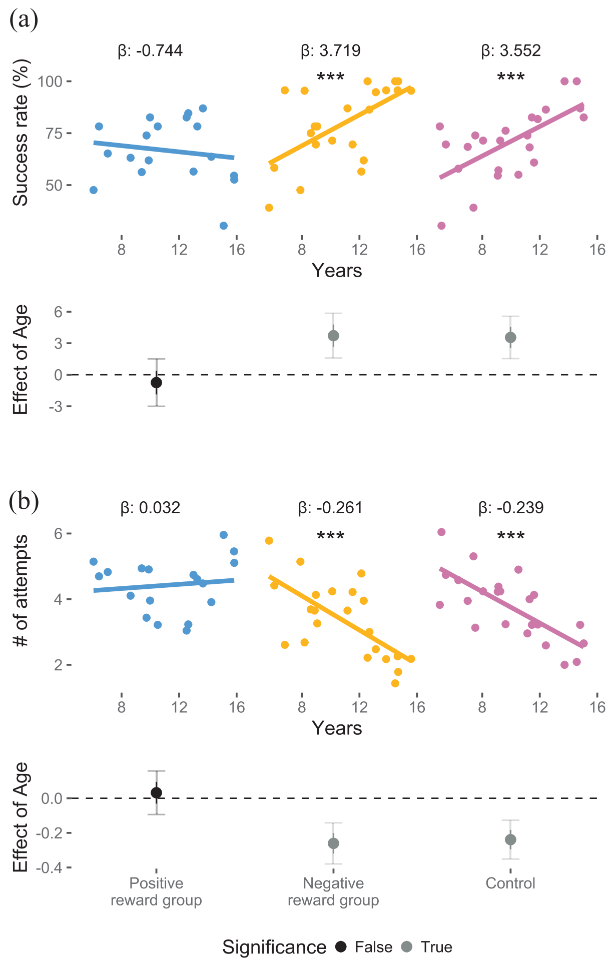

Figure 3. Changes in Performance Across Age. (a) Correlation between children's age and success rate. Each point represents an individual child, and the lines represent the model's estimation of the age-reward group interaction. Asterisks indicate significant correlations. The bottom panels show the estimated beta coefficient for the interaction between age and a specific reward group. The line ranges represent the standard error, while the lighter-colored error bars represent the 95% confidence intervals. Black dots indicate significant interactions and grey dots indicate non-significant interactions. (b) Similar to panel (a) for the correlations between age and the average number of attempts for each group. Single asterisks (*p < 0.05), double asterisks (**p < 0.01), and triple asterisks (***p < 0.001) denote statistically significant differences.

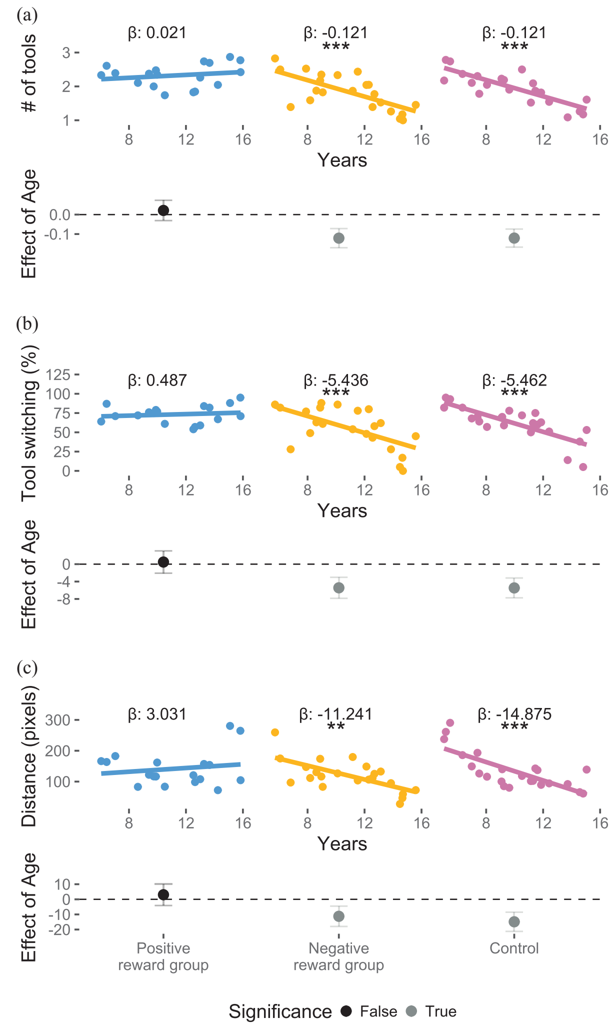

Figure 4. Changes in Strategy Across Age. (a) Correlation between children's age and the average number of tools used. Each point represents an individual child, and the lines represent the model's estimation of the age–reward group interaction. Asterisks indicate significant correlations. The bottom panels show the estimated beta coefficient for the interaction between age and a specific reward group. The line ranges represent the standard error, while the lighter-colored error bars represent the 95% confidence intervals. The color indicates the significance of these interactions. (b) Correlation between age and tool switching. (c) Correlation between age and positioning distance. Single asterisks (*p < 0.05), double asterisks (**p < 0.01), and triple asterisks (***p < 0.001) denote statistically significant differences.

smaller positioning-distance with age (coefficient = –11.24, $t(57) = -3.34$, $p = < .01$; coefficient = –14.87, $t(57) = -4.69$, $p < .001$, respectively) but not the PR group (coefficient = 3.03, $t = 0.85$, $p = .4$; see Figure 4(c)) models that showed significant effects, BFs were consistently high, with the lowest being 75.26 (See Appendix 1, Table A2).

Discussion

This study tested whether positive rewards and negative rewards have different effects on trial-and-error learning among school-aged children. We manipulated children's rewards as they solved online reasoning problems through trial and error. Children who received negative rewards outperformed children who received positive rewards, particularly in terms of developing more efficient strategies with age. In contrast, age-related changes in trial-and-error strategies were absent in children who received positive rewards, suggesting that consequences of errors become more dominant in trial-and-error strategy over development.

Our findings align with previous cognitive research indicating that children's responses to rewards vary significantly with age (Fantino et al., 1983). However, this variation was not consistent across all reward values. Similar to Pauli et al. (2023), we observed in the NR group a pattern indicative of an age-related sensitivity to the consequences of errors where the risk of losing points influenced how older children approached the task. This sensitivity to negative rewards supports theories in cognitive development about shifts in decision-making with age (Crone & Dahl, 2012). Nevertheless, the reduced impact in the PR group suggests that positive reinforcement, typically seen as a reinforcer for engagement (Rahimi et al., 2021) does not always promote a strategic trial-and-error learning.

Our findings challenge some traditional views on the use of positive reinforcement in educational settings, especially for adolescents who may require more than just positive incentives for performing complex problem-solving tasks (Deci et al., 2001; Ryan & Deci, 2000). In that context, our findings support the Self-Determination Theory (Deci et al., 2001; Ryan & Deci, 2000), according to which externally driven motivation, such as that from positive rewards, may not foster deeper learning as effectively as intrinsic motivation. Unlike prior studies employing simplified tasks—such as stable, rule-based, or probabilistic decision-making paradigms—our task required dynamic problem-solving and the flexible application of physical reasoning concepts (Erez et al., 1990; McGraw, 2015; Ryan & Deci, 2000). In tasks that emphasize active tool-use and adapting to changing spatial layouts, penalties may heighten children's sensitivity to errors and encourage more systematic, strategic adjustments. By contrast, positive rewards may fail to provide sufficient information for adapting strategies in such complex, action-oriented contexts. These structural differences might explain why learning from negative rewards emerges more distinctly with age in our findings compared to less ecologically grounded tasks examined in previous research. However, future research is needed to disentangle more precisely whether findings are driven by penalties or by small gains, and how those relate to children's exposure to different types of rewards in their school (McGraw, 2015).

The lack of significant difference in trial-and-error learning strategies between the NR and control groups raises questions regarding the fundamental assumption that external incentives invariably enhance learning outcomes. The similarity in performance between children receiving negative rewards and those in the control group (who were devoid of external incentives), suggests that the presence of rewards does not unilaterally amplify learning efficacy (Filsecker & Hickey, 2014). This is aligned with findings in game-based learning research, which show that the quantity of in-game rewards does not significantly impact learning outcomes (McKernan et al., 2015). In other words, the absence of rewards and the risk for negative consequences both foster a learning environment where children are neither externally reinforced by the allure of gains nor hindered by the pressure of achieving rewards. This environment might, in fact, encourage a more intrinsic or self-driven approach to learning.

Data Availability Statement

Data available at https://github.com/Physical-Cognition-Lab/The-Effects-of-Rewards-on-Trial-and-Error-Learning-in-School-Aged-Children.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Ethical Considerations

This study was approved by the Psychology Ethics Committee at Birkbeck, University of London (reference #2122028) on 01/11/2022. Participants gave informed consent before participating in the study.

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Appendix 1

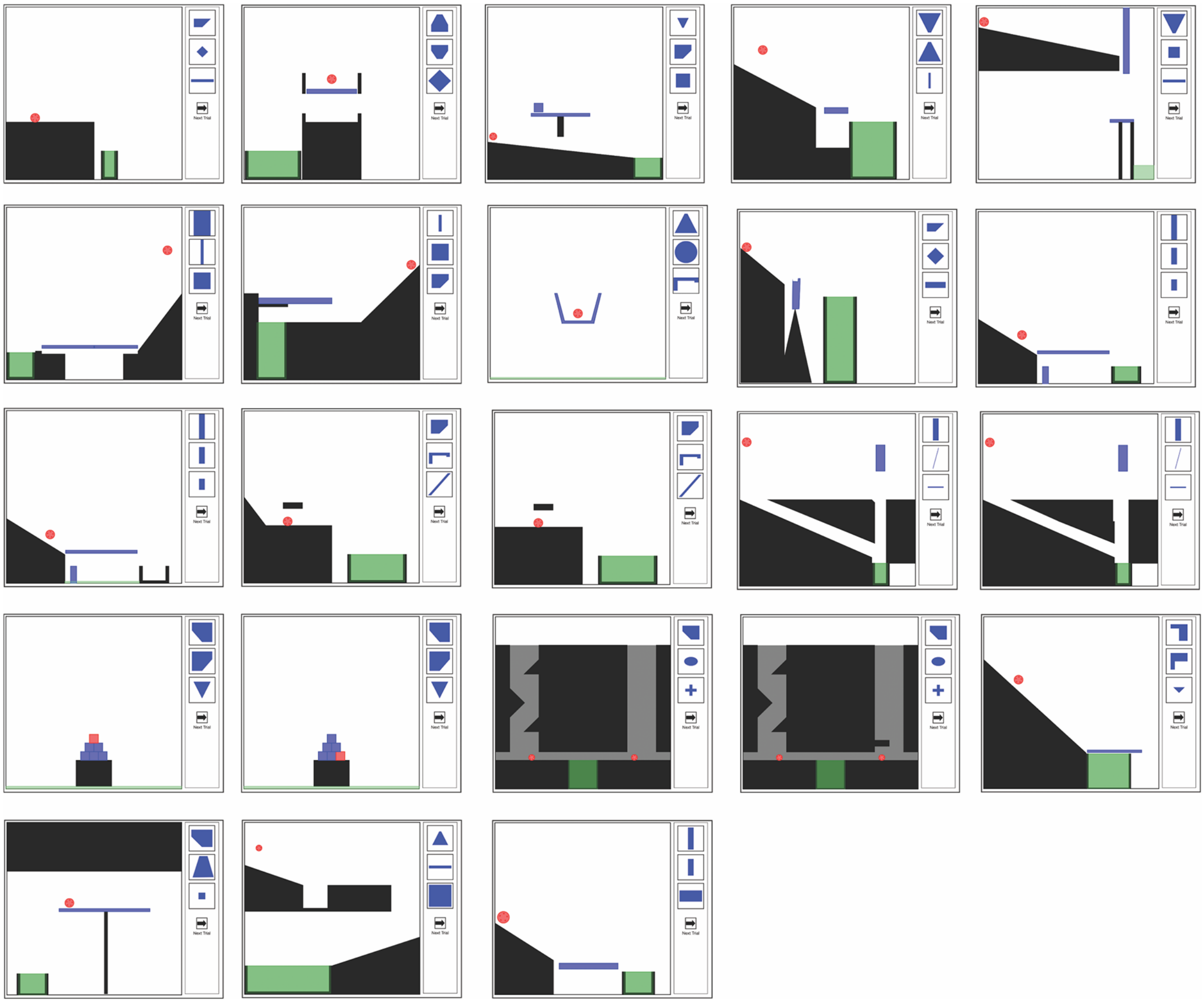

Figure A1. Games Played by the Children. All 23 game environments in the order played by the children.

Table A1. Reward System per Group and Subgroup.

Attempt	Positive reward group					Negative reward group				
	1	2	3	4	5	1	2	3	4	5
1	+8	+16	+24	+32	+40	+6	+4	+10	+5	+6
2	+7	+14	+21	+28	+35	+4	+3	+6	0	+5
3	+6	+12	+18	+24	+30	+2	+2	+2	–1	+4
4	+5	+10	+15	+20	+25	0	+1	–2	–2	+3
5	+4	+8	+12	+16	+20	–2	0	–6	–3	+2
6	+3	+6	+9	+12	+15	–4	–1	–10	–4	+1
7	+2	+4	+6	+8	+10	–6	–2	–14	–5	0
Failed[a]	+1	+2	+3	+4	+5	–8	–3	–18	–6	–1

Note. The reward system for the positive rewards group and the negative rewards group. Each group had five subgroups, which differed in the absolute numbers in the reward system but shared the same conceptual rewarding mechanism. Each row indicates the attempt number in a specific game. The numbers in each cell indicate the score for succeeding in a specific attempt. For example, children in the positive reward group who belonged to Subgroup 1 received +8 points in their score if they solved the games on the first attempt, +7 if they solved on their second attempt, and so on. Children in the positive reward group who belonged to Subgroup 2 received +16 for the first attempt, +14 for their second attempt, and so on.

[a]The numbers in the last row are the scores for failing the game (not succeeding after seven attempts).

Table A2. Bayes Factors for Each Model Included in the Analysis.

Model	Bayes factor
Success rate	75.26
Time per attempt	0.078
Attempt per trial	62,200
Tool switching	57,200
Number of tools	8,040,000
Distance	184.87

Note. The Bayes factor quantifies the strength of evidence for the observed model relative to the null model. Among the significant models, Bayes factors were consistently high, with the lowest being 75.26 for the model predicting success rate, indicating substantial evidence in support of the presence of the effect.