



OPEN Enforcing a high success percentage interferes with reward-based motor learning

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Humans can adapt their movements based on binary reward feedback about success and failure. To engage in such 'reward-based' motor learning, the learner must encounter at least some failures, but it is unclear what percentage of failures is optimal. For learning, we hypothesize that a success percentage of 50% is optimal, as it provides the most information. For motivation, in contrast, we hypothesize that a success percentage of 80% is optimal, since too many failures can reduce motivation. In this study, we simultaneously test the hypotheses on learning and motivation in participants of a wide age range (7 to 58 years) who performed a brief circle-drawing task. The participant's goal in this task was to double the size of the baseline circles drawn with the unseen hand. We assigned participants to a reward scheme that targets either 50% success (moderate success group) or 80% success (high success group). In line with our hypothesis on learning, the results show more motor learning in the moderate success group compared to the high success group. In contrast to our hypothesis on motivation, motivation was not higher in the high success group.

Keywords Reward-based motor learning, Motivation, Success, Learning

Skilled painters can instantly paint an eye, with a size appropriate for the human face. Novices will need some practice before they can do this. Two forms of feedback provide information for learning the right size: the success feedback of hitting the right size (reward feedback^{1–3}, and the spatial deviation from the planned size (the 'prediction error'^{1,4}. Although it was first proposed that the reward feedback is only used in the absence of prediction errors¹, later work showed that these types of feedback jointly contribute to learning^{5–8}. While the prediction errors are difficult to manipulate, a teacher can easily provide reward feedback using their own criterion for success. In this study, we focus on the 'reward-based' motor learning that follows from this reward feedback.

Reward-based motor learning is commonly studied by measuring an increase in performance in a goal-directed task. For instance, reaching a target^{1,2,9}, moving with the right pressure¹⁰, or reaching with the right curvature and direction^{11,12}. Early work suggested that this short-term learning is very well retained¹ but retention of reward-based learning hasn't been extensively studied and short-term increases in performance might be dissociated from long-term learning¹³. We refer to the short-term increases in performance as 'learning.'

Reward-based' motor learning ability increases little after age 7^{14,15} and relies on repeating successful movements and exploring following failure by varying the movement plan¹. As successes are needed to engage in learning, it is common practice for teachers to adapt the reward criterion to a learner's performance, to gradually shape their performance towards the task goal. For instance, a novice painter might receive a more lenient criterion compared to an expert. In doing so, they manipulate not only the success probability but also redefine the task goal or reduce the informativeness of the reward about proximity to the original task goal. Hence, the question of which success percentage one should target is not easily answered. Moreover, the answer might depend on whether one focuses on learning or motivation¹⁶.

To engage participants in reward-based learning, a reward criterion should aim for a balance between success and failure. First, failures are needed to evoke exploration, which pushes movement variability beyond the boundaries of motor noise^{3,17,18}. This allows participants to find the movements that result in reward, even when the rewarded movement is beyond the range of current performance. Second, the success feedback should be informative about the proximity to the target performance, helping to direct behavior towards the task goal. To strike a balance between success and failure, many studies have used a reward criterion that is adapted to the participant's performance to ensure a success percentage of about 50%^{2,7,18–21}. In perceptual learning, an optimal

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success rate of 85% has been proposed²². To our knowledge, no studies have compared reward-based motor learning between conditions using reward criteria that target different success percentages.

While failures are needed to evoke exploration, they also influence motivation, which depends on the probability of and value of success^{23,24}. Failures reduce the probability of success but can also enhance the value of success²³. Hence, some failures should be allowed, but not too many. In educational²⁵ and sports coaching literature²⁶ an 80% success principle has been suggested. Experimental research supports the 80% success principle. In both an interception and a pointing task, an 80% success percentage compared to a 30% success percentage resulted in higher self-reported enjoyment for a computer task^{7,27}. Furthermore, for the self-reported motivation in an online game, we found a curvilinear relationship with the success percentage, which peaked at 80% success, although the play duration peaked at a lower success percentage of about 63%²⁸. Finally, older adults performed more repetitions of a stepping game when the success percentage was 80% compared to when it was 100%²⁹.

When choosing a success percentage, the choice might thus depend on whether the goal is to learn or to motivate: when the goal is to learn, one should use a lower success percentage compared to when the goal is to motivate¹⁶. In this study, we test the influence of success percentage on learning and motivation in a circle-drawing task¹⁵ in which participants learnt to double the size of a circle they drew based on binary reward feedback. Participants were assigned to either a ‘moderate success’ group, which performs the task with a reward criterion that targets 50% success, or to a ‘high success group’, which performs the task with a reward criterion that targets 80% success. We hypothesize that the moderate success group shows the most motor learning, while the high success group shows the most motivation.

Methods
Participants

Participants were visitors of the NEMO science museum who were at least seven years old and reported no injury to the dominant hand. These participants were assigned to either the moderate ($N = 134$) or the high success group ($N = 133$). Of the 134 participants in the moderate success group, 102 participants were measured in the winter of 2023 for previous study¹⁵. The remaining 32 participants were measured in the summer of 2024. All 133 participants in the high success group were measured in the current study. Participants who spoke Dutch were tested in Dutch, whereas other participants were tested in English. In each success group, one participant was excluded for not finishing the experiment. Four participants in the moderate success group and two participants in the high success group were excluded because they did not draw circles, according to our criteria (see data analysis section). Demographics of the included participants are reported in Table 1.

All methods were carried out in accordance with the Declaration of Helsinki, and all experimental protocols (VCWE-2023-100-R2) were approved by the local ethical committee of the Faculty of Behavioural and Movement Sciences, *Vaste Commissie Wetenschap en Ethiek*. Written informed consent was obtained from all subjects and/or their legal guardian.

Task

Motor learning was assessed in a circle-drawing task, which participants performed with an Intuos Medium Wacom drawing tablet and a laptop (Fig. 1a). The participants were seated behind a table and performed a task in which they were instructed to provide a bear named ‘Ollie’ with a nose by drawing a circle of the right size on the Wacom tablet. To remove visual guidance, such that learning relied on post-movement reward feedback, the hand was hidden behind a curtain. The size (S) of the drawn circle at a trial i was approximated by calculating the radius as the mean distance (r) of a spatially resampled trajectory to the trajectory’s center (Fig. 1b). To stimulate exploration, we did not inform participants about the target size (T) which we set to double the baseline size which was the average drawn size on the first five trials:

$$S_{baseline} = \bar{S}_{(1:5)}$$

For the first five trials (baseline), we used an arbitrarily chosen target size of 4.3 centimeters (Fig. 1b).

A trial started with a display of the bear Ollie, with eyes open and without a nose. Once the participant placed the Wacom pen on the tablet, Ollie closed their eyes, and the drawing movement was recorded. The end of the drawing movement was detected once the participant lifted the pen for longer than 500 milliseconds, and at least ten samples of pen position had been recorded. After the drawing movement ended, Ollie opened their eyes and provided reward feedback by showing a happy or sad mouth (Fig. 1a) and playing a ‘bing’ or buzzer sound for 500 ms. After that, the trial ended, and the next trial started.

The reward feedback depended on the success group and was based on the magnitude of the ratio error (e_t) between the size of the drawn circle (S) and a target size (T). We calculated (e_t) as follows:

Group	Age-range (years)	Gender			Handedness			Preferred language	
		Female	Male	Not specified	Left	Right	Not specified	Dutch	English
Moderate success	7–54	64	58	8	14	97	19	67	63
High success	7–58	64	57	10	18	108	5	72	59

Table 1. Participant demographics.

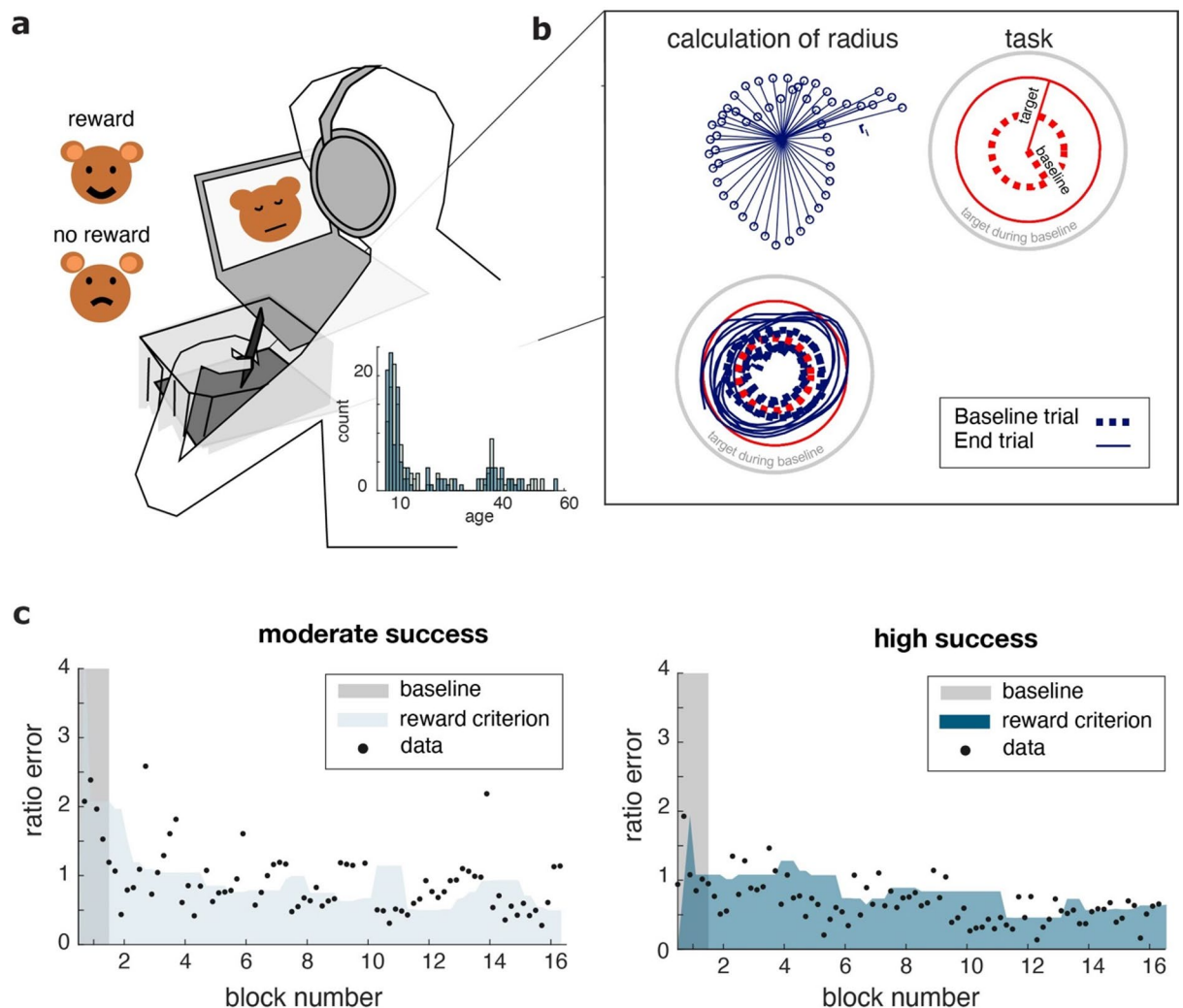


Fig. 1. Methods. (a) Experimental set-up with drawing tablet, laptop, and reward feedback. The histogram shows the age distribution of the participant sample in the two reward groups. (b) Circle size was calculated as the average distance from points on a resampled trajectory (blue dots) to the center. The target size (red line) was double the average circle size in the first five trials (dotted red line). (c) Examples of the trial-to-trial development of the reward criterion for a participant in the moderate (left panel) and high (right panel) success group. We indicate on the horizontal axis the blocks of five trials that we use in our analysis. The reward criterion (shaded area) was continuously adapted based on the participant's performance (black dots).

$$e_t = \text{Max} \left(\frac{T_t}{S_t}, \frac{S_t}{T_t} \right) - 1$$

This way, the ratio error is positive when the drawn size is either too small or too large, and zero when the drawn size is equal to the target size.

To create two success groups, we set two different reward criteria (Fig. 1c). For both groups this criterium was based on the ratio error at trial t compared to the distribution of the ratio errors from the previous ten trials (for the first ten trials, we used the distribution of all earlier trials). For the moderate success group, the reward criterion was the median of this distribution. For the high success group, the reward criterion was 80th percentile of this distribution. Ratio errors smaller than the reward criterion were defined as success. Theoretically, this would result in a success percentage of 50% for the moderate and a success percentage of 80% for the high success group. Exact success percentages would depend on the distribution of the errors.

Procedure

Participants drew 80 circles and were then instructed to call the experimenter, who initiated a 'free phase' to assess the participant's motivation to continue the task. The experimenter indicated that they had to complete some forms and left the participant the option to either wait or continue the task. If the participant chose to continue, they could draw 20 more circles, after which the task ended automatically. We designed this phase to measure motivation, based on the rationale that the decision to continue the task instead of waiting for the

experimenter would imply motivation for the task. The experimenter's behavior was controlled with a protocol that indicated the instructions to the participant. In practice, the experimenters reported that the protocol left too much freedom to execute this phase consistently. Subsequently, the participant completed a motivation questionnaire, which measured motivation to play the game again and included a modified, shortened version of the Intrinsic Motivation Inventory³⁰ that we also used in a previous study⁷, using items from the Interest / Enjoyment, Perceived Competence, Effort, and Pressure / Tension scales. We included these subscales because the experienced success percentage might differentially affect perceived competence and experienced pressure and the resulting enjoyment and effort. The subscales were reduced to one item to accommodate the time constraints involved in running the study in the museum. The following items were answered on a five-point Likert scale either in English or in Dutch:

1. I would like to play this game again / Ik wil dit spel nog een keer spelen (motivation to continue).
2. I enjoyed playing this game / Ik vond het leuk om dit spel te spelen (enjoyment).
3. I was good at this game / Ik was goed in dit spel (perceived competence).
4. I tried my best to score as many points as possible / Ik deed mijn best om zoveel mogelijk punten te scoren (effort).
5. I felt nervous while I was playing this game / Ik voelde me nerveus terwijl ik het spel speelde (pressure/tension).

In this questionnaire, we also collected data on handedness, age in years, and gender. The preferred language was inferred from the questionnaire used (either a Dutch or English version).

Data analysis

Data analysis has been pre-registered: <https://aspredicted.org/qfxm-s32p.pdf>.

We deviated from the pre-registration in three ways:

1. We used a block size of 5 trials instead of a block size of 10 trials to study learning because this better suits the experimental design;
2. The multilevel regression used a logarithmic relationship between learning and block number instead of a linear relationship because learning cannot increase infinitely;
3. We added an analysis in which we compared the increase in variability following failure between groups using a Mann-Whitney U rank-sum test to better understand differences in learning.

We excluded the data from participants who did not finish the entire experiment or who did not draw acceptable circles. A perfect circle has an aspect ratio of 1, meaning that two perpendicular intersections through that circle have equal length, and has zero distance between its start and endpoint. Our definition of an acceptable circle is very lenient and is classified using two criteria. One, the aspect ratio (the largest ratio between two perpendicular intersections of the drawn trajectory) is larger than 0.1 or smaller than 10. Two, the distance between the start and endpoint of the trajectory is smaller than half of the trajectory length. Circles were classified as unacceptable when they failed one or both criteria. Unacceptable circles were removed from the analysis of learning, even though the participant received reward feedback on them during the task. The removed data were not replaced. If more than 20% of the trials of a participant were classified as unacceptable, all data of this participant were excluded from the analysis. We analyzed all data from the drawing task in ratios rather than centimeters.

We measured two key dependent variables: learning and motivation.

Learning was measured based on the ratio in the drawn size (S_t) and the baseline size ($S_{baseline}$). As the participant's task is to double the size, the target ratio is 2.0, and the baseline ratio is 1. We will define the amount of learning within a block (b) of five trials as the median ratio in the block minus the baseline ratio (1). Learning values that differed more than 2.5 times the standard deviation from the mean were treated as outliers and excluded.

Motivation was measured by the average score on the motivation to continue and enjoyment items on the questionnaire, as these two items were correlated ($R = 0.63$) whereas the other items showed inter-item correlations lower than 0.40. The secondary measure of motivation is whether the participant voluntarily engaged in the free phase. As the previous study¹⁵ showed a bimodal distribution of the number of trials played in this phase, indicating that participants either continued or did not, we analyze the behavior in the free phase as a binary decision to continue or not. In addition, we report the scores on the perceived competence, pressure/tension, and effort items for the two success groups.

To test the hypothesis that the moderate success group shows greater learning than the high success group, we performed a multilevel regression with learning as a function of the logarithm of block number and group, including a random slope for participant and using the moderate success group as the reference group. The block number was log-transformed to approximate exponential learning. We incorporated both the main effects of group and block and the interaction between the two, and used the moderate success group as a reference. A negative coefficient for the interaction of block and high success group would provide support for our hypothesis.

We performed a one-sided Mann-Whitney U test to test the hypothesis that motivation is higher in the high success group compared to the moderate success group.

Explorative analyses

The first explorative analysis focused on the influence of success-group on exploration.

We defined exploration as the increase in variability following failure feedback, assuming that variability following success is due to motor noise, and measured variability as trial-to-trial changes in the drawn size^{9,31}. To

accommodate for signal-dependent noise, the trial-to-trial changes from trial t to trial $t + 1$ were normalized by the drawn size on trial t . Having calculated the trial-to-trial changes, we could compare these changes between trials on which success feedback was provided and trials on which failure feedback was provided. Before making this comparison, we accounted for differences between groups in which of the ratio errors received reward feedback. As we used a more lenient reward criterion in the high success group compared to the moderate success group, some successes in the high success group would have been defined as failures in the moderate success group. This difference in sampling successes and failures might bias exploration estimates³¹. We therefore only selected the trials that would have been defined as either a success or a failure in both groups and excluded the other 28% of trials. For this selection, exploration was measured as the median trial-to-trial change following failure minus the median trial-to-trial change following success. To assess whether the success group affected the exploration, exploration was compared between groups with a two-sided Mann-Whitney U rank-sum test.

The second exploratory analysis assessed whether the model fit could be improved by incorporating age and gender by comparing the BIC values of four additional models to the basic model including only success group and the logarithm of block as predictors. We compared four additional models, which included an interaction of the logarithm of block and age, a three-way interaction of the logarithm of block, success group, and age, an interaction of the logarithm of block and gender, and a three-way interaction of the logarithm of block, success group, and gender. A reduction of ten or more points in the BIC was considered a significant improvement. In these exploratory analyses, only the participants who identified as either male or female were included female (N moderate success group = 122, N high success group = 121).

The third exploratory analysis assessed how the rate of learning changed over time by performing a multilevel regression on the learning in a moving window of five blocks with the block number and success group as predictors and a random intercept and slope per participant. If learning would reach asymptote earlier for one of the two success groups, we would expect the regression coefficient for the effect of block to reduce to zero earlier.

Results

All data are reported as average $\pm$ between-participant standard error, unless otherwise specified. Of the trials, $2.3 \pm 3.5\%$ were excluded based on the criterion for not drawing circles. The average success percentage in the moderate success group was 49 ± 5 , whereas the success percentage in the high success group was $72 \pm 6\%$ (Fig. 2a). The reward criterion was not normally distributed across participants. The median average reward criterion across the experiment was $0.69 \pm \text{IQR}0.54$ in the moderate success group and $1.12 \pm \text{IQR}0.69$ in the high success group (Fig. 2b).

For the learning per block, 1.7% of the data were treated as outliers and excluded from the regression analyses. Although the reward criterion in the high success group on average rewarded errors larger than the baseline error, learning increased with block number for both the moderate and high success group (Fig. 2c), evidenced by a positive effect of the logarithm of block on learning ($B = 0.18 \pm 0.02$, $p < 0.001$). The mean learning in the final block was 0.52 ± 0.05 for the moderate success group and 0.40 ± 0.05 for the high success group. As we hypothesized, we found an interaction of block and success group on learning with a negative regression coefficient for the high success group ($B = -0.05 \pm 0.02$, $p = 0.02$). Together, this indicates that participants learned from the reward feedback and that this learning was reduced in the high success group. The model fit could not be improved by including interactions of age or gender. The BIC for the basic model including only the participants who identified as either male or female was 317. The BIC for the model which included an interaction of the logarithm of age and block was 338. The BIC for the model which included a three-way interaction of the logarithm of age, block and success group was 339. The BIC for the model including an interaction of gender and block was 323. The BIC for the model including a three-way interaction of gender, block, and success condition was 320.

In contrast to our hypothesis on motivation, motivation (Fig. 2d) was not higher in the high success group ($U = 7733$, $z = -0.20$, $p = 0.84$, $r = -0.01$), as it was 3.8 on a scale from 1 to 5 in both groups. Neither did the percentage of participants that continued in the free phase differ (respectively 60% and 59%; $X^2 = 0.03$, $p = 0.86$). Mean scores with standard errors per group for each item on the motivation questionnaire are reported in Table 2. Table 2 shows that, consistent with reduced failure, pressure/tension was lower in the high success group, whereas perceived competence was higher. There were no notable differences in motivation to continue, enjoyment, or effort.

Exploratory analyses

In the moderate success group, the median variability following failure was 0.23, whereas the median variability following success was 0.12, indicating that variability almost doubled following failure. In the high success group, the median variability following failure was 0.19, whereas the median variability following success was 0.12, indicating that variability increased by 60%. A Mann-Whitney U test confirmed that the increase in variability following failure was higher for the moderate success group compared to the high success group ($U = 10564$, $z = 2.62$, $p = 0.01$, $r = 0.16$, Fig. 2e), indicating more exploration in the moderate success group. The regression of the learning in a moving window of five blocks (Fig. 3) showed consistently lower learning rates for the high success group and no indication that learning reached an asymptote.

Discussion

In this study, we simultaneously tested the effect of success percentage on motor learning and on motivation. We did so in a circle-drawing task suitable for testing children¹⁵ and tested a large sample with ages between 7 years old and 58 years old. The moderate success group performed the task with 49% success, whereas the high success group performed the task with 72% success. We hypothesized that, compared to the high success group,

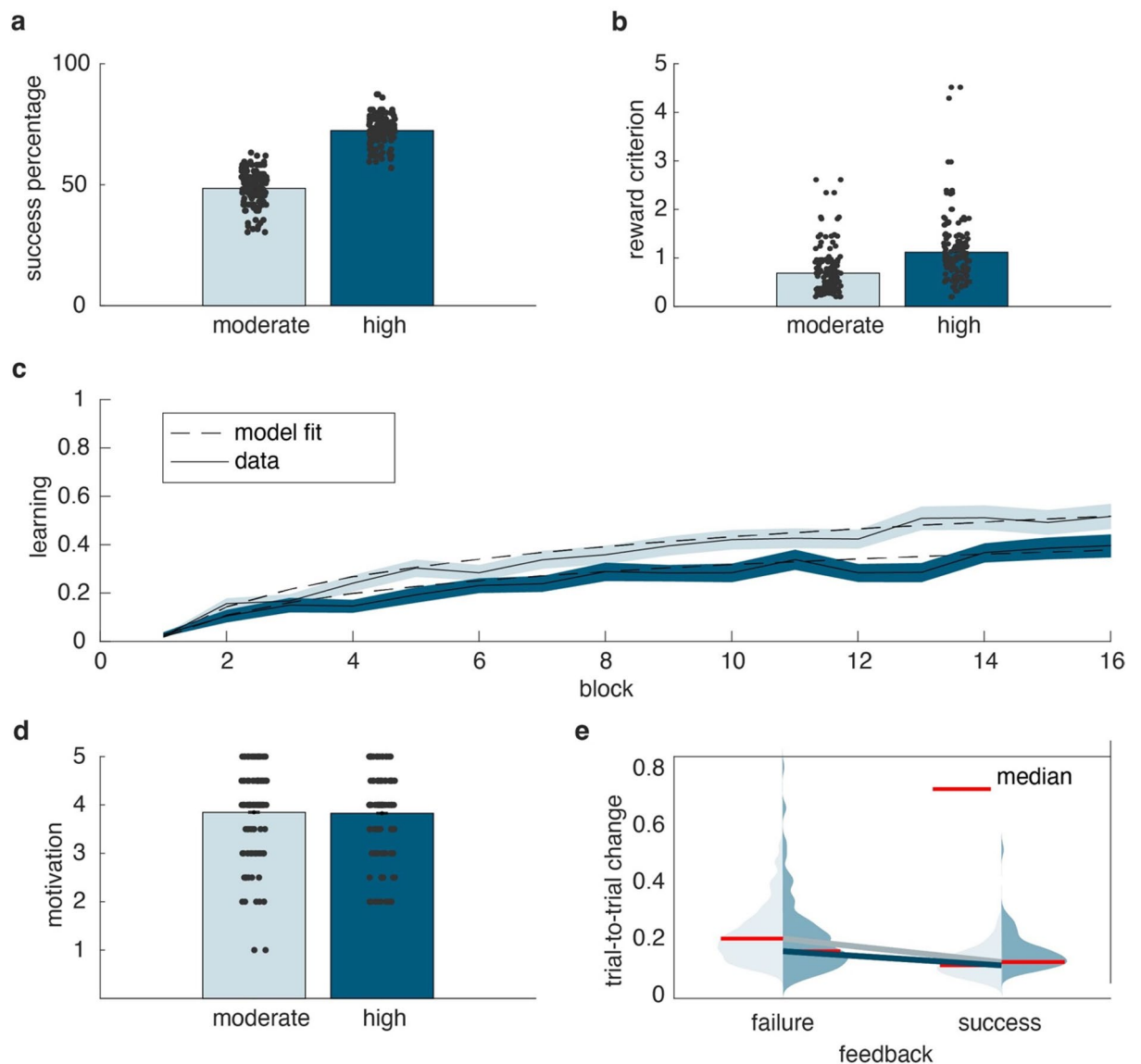


Fig. 2. Results. Data for the moderate success group are shown in light blue, and data for the high success group are shown in dark blue. Black dots represent individual data. **(a)** Mean success percentage. **(b)** Median reward criterion (in ratio error) for the two groups. **(c)** Mean learning (the increase in ratio relative to the baseline block) with standard error as a function of block number. **(d)** Mean motivation with standard error. **(e)** Trial-to-trial change (fraction) following failure and success feedback for the two success groups. Shaded areas show the distribution of the data, and thick red lines represent the median. Thick blue lines connect the medians following failure with the ones following success. For this analysis, we only used trials that would have been defined as a success or failure by both reward criteria.

the moderate success group would show more motor learning but less motivation. In line with the hypothesis on learning, we found that the moderate success group learned more compared to the high success group. In contrast to our hypothesis on motivation, we found no difference between groups in self-reported motivation or 'free phase' participation. Both groups reported similar moderate to high motivation (3.8 on a scale of one to five).

Our finding that the moderate success group learned more than the high success group aligns with the idea that the moderate success group received more opportunities to explore and received more informative success feedback. These opportunities to explore would be 51% in the moderate success group and 28% in the high success group, assuming participants only explored following failure. Furthermore, lower success percentages evoke higher levels of exploration³². Indeed, following failure, the moderate success group increased variability following failure more than the high success group, which is an indication of exploration³¹. Lastly, compared to the high success group, the performance in the moderate success group had to be closer to the target performance to be rewarded. The reward criterion in the high success group rewarded a median ratio error of 1.12 whereas the reward criterion in the moderate success group rewarded a median ratio error of

Success group	Motivation to continue	Enjoyment	Perceived competence	Effort	Pressure/tension
Moderate	3.5 ± 0.09	4.2 ± 0.07	3.7 ± 0.07	4.7 ± 0.06	2.7 ± 0.1
High	3.6 ± 0.09	4.1 ± 0.08	3.9 ± 0.07	4.7 ± 0.06	2.2 ± 0.1
Inter-item correlations					
Motivation to continue		0.64	0.18	0.18	0.12
Enjoyment	0.64		0.23	0.37	0.15
Perceived competence	0.18	0.23		-0.08	-0.08
Effort	0.18	0.37	0.18		0.07
Pressure / tension	0.12	0.15	-0.08	0.07	

Table 2. Mean scores on the motivation items with standard error for the two groups and inter-item correlations, which show that motivation to continue and enjoyment were most related.

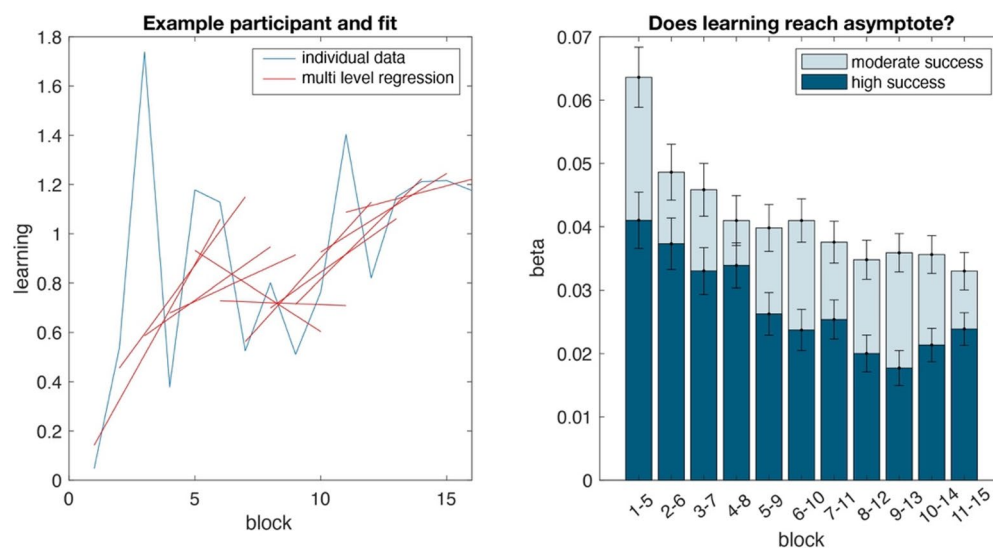


Fig. 3. Left panel: learning per block of five trials for an example participant. The regression line is based on multilevel regression on learning as a function of a moving window of five blocks and success condition. Note that in the multilevel regression we used the linear effect of block instead of the log block that we used in the main analysis. Right panel: the regression coefficient for the effect of block on learning for a moving window of five blocks. For both groups, the beta coefficient is clearly above zero during the whole experiment, so learning did not yet reach an asymptote.

0.69. Other research on perceptual learning, in which the precision of perceptual judgements was assessed, has suggested that the optimal success percentage for learning is 85%²², which would predict better learning in the high success group. We attribute this difference to the fact that the learning metric in the Wilson et al. study²² included variability, whereas the learning metric in our study was based on a reduction of bias. As success absence increases variability, the optimal success percentage might be higher when learning is defined as a reduction of variability²², compared to when learning is defined as a reduction in bias such as we did. An important question is whether the success percentage influenced both the rate and amount of learning, or only one of these parameters. As reward-based learning occurs erratically, with changes in performance being driven by rewarded variability^{1,3,17,18,32} rather than by gradual error correction, the learning curve presented in Fig. 2 represents the average number of participants having reached a certain performance. Its slope can't be interpreted as the learning rate of individual participants. An exploratory analysis that analyzed the group-based learning over a moving window of five blocks showed consistently lower learning rates in the high reward group but no discernable difference in the decay of the learning rate. Hence, the current study is most consistent with the idea that the success percentage influenced the learning rate rather than the amount of learning. Future research, measuring learning on a longer timescale, will have to demonstrate whether the rate of learning, the asymptote of learning, or both are affected by the success percentage. As explicit processes have been found to contribute to reward-based motor learning^{33–35} and explicit processes might involve hypothesis testing besides random exploration³⁶, another interesting question for future research is how the success probability affects such hypothesis testing. In particular, to assess whether the success probability affects the type of exploration strategies used.

Our finding that motivation did not differ between the two success groups is in contrast with the idea that 80% success is optimally motivating^{25,28} and with earlier findings that 80% success resulted in greater motivation

compared to 50% success in a pointing task⁷. The fact that we found no evidence of enhanced motivation in the high success group relative to the moderate success group might be caused by the low sensitivity of the two-item measurement of motivation. Also, in the other studies^{7,28} participants received spatial performance feedback in addition to the score rewards, which might have affected the influence of success percentage on motivation.

Alternatively, the optimally motivating success percentage might depend on the complexity of the task. In information theory, the success percentage determines information, measured as Shannon entropy, with 50% success resulting in the highest information. The highest information might not always be best, though. In the Challenge Point Framework, it has been proposed that the optimal success percentage is the maximum amount of information that can be processed³⁷. Less complex tasks might leave more processing capacity for the successes and failures. The current task was designed to have very low complexity, allowing for reward-based motor learning. The participants were explicitly informed about the task-relevant dimension, rather than having to discover this themselves⁷, and they were rewarded based on a single movement target instead of receiving a different target on each trial^{7,28}.

Study limitations

Study limitations involve the low-precision measurement of motivation with two questionnaire items on a five-point Likert scale and the short duration of the task.

A strong point of our study is that we tested a large sample with a wide age range of 7 to 58 years old and showed that the influence of the success group on learning did not depend on age. To be able to test this number of participants in the museum, we had to limit task duration. The brief task duration of about five minutes limits generalization of the results to learning and motivation on longer timescales. While our previous studies on the effect of success percentage on motivation also employed brief tasks and reported similar levels of motivation^{7,28}, the effect of success percentage on motivation might be stronger for tasks with a longer duration, which allow for a more reliable estimate of the success percentage. Also, the finding of greater learning in the moderate success group might not generalize to tasks that last longer, allowing participants to perform more attempts. Future studies will need to show whether the advantage for the moderate success group holds on a retention test. Our results provide the basis for theoretical predictions on the maintenance of learning. If a high reward criterion, which targets a high success percentage, results in similar or better performance on a retention test than a reward criterion which targets a moderate success percentage, this should be due to improved retention as a result of repeated reward⁵. Finally, it is unclear, however, how the results would generalize to tasks using gradient (non-binary) reward feedback, in which the amount of reward decreases with the performance error. This can be realized by providing categorical feedback^{38–41} or continuous reward feedback^{6,12,42}, the value of which is inversely related to the performance error.

Conclusion

To conclude, we show that participants show more reward-based motor learning when practicing with a success criterion that aims at a moderate success percentage than when practicing with a success criterion that aims at a high success percentage. There was no evidence that motivation differed between groups. Thus, if a novice painter would practice with a digital painting tool which rewards movements that are close to a target movement, the reward criterion shouldn't be too lenient, rewarding only a moderate percentage of movements.

Data availability

The datasets generated during and/or analysed during the current study are available on the Open Science Foundation: <https://osf.io/qtn3k/overview>.

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Wrote the manuscript: KK, NMM, AMML, MRH, JEB, JBJS. Designed the experiment: KK, JBJS, NMM, AMML. Collected the data: NMM, MRH, JEB. Analyzed the data: KK, NMM, MRH. Prepared the figures: KK, NMM. Reviewed the manuscript: KK, NMM, AMML, MH, JEB, JBJS.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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