Task difficulty influences the strategy of learning a new visuomotor task

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Abstract

Introduction: Task difficulty affects the amount of interpretable information from a task, which is thought to interfere with motor learning. However, it is unclear whether task difficulty in itself is a stimulus for motor learning because the experimental evidence is mixed in support of the optimal challenge point framework that predicts one specific level of nominal task difficulty to produce the greatest magnitude of motor learning.

Purpose: We determined the effects of functional task difficulty on motor skill acquisition, retention, and transfer.

Methods: Healthy young participants (n=36) learned a mirror star-tracing task at a low, medium or hard difficulty level defined by the bandwidth of the star. We measured skill acquisition, retention and transfer to untrained difficulty levels, as well as the perceived mental workload during the task.

Results: Task difficulty affected motor performance, but did not affect motor learning and transfer. The groups that practiced at the medium and hard difficulty levels used a learning strategy based on errors, supporting the optimal challenge point framework, whereas learning at the low difficulty was independent of errors.

Conclusion: The optimal challenge point framework does not capture the complex relationship between task difficulty and motor learning. Task difficulty affects the performers' approach to learn a task but did not affect the magnitude of skill acquisition, retention or transfer. Previously reported effects of task difficulty on the magnitude of motor learning are probably mediated by perceived mental workload. The data have implications on how athletes learn new motor skills and patients re-learn injury-affected motor skills during rehabilitation.

Running title

Effects of task difficulty on motor learning

Keywords

Motor Learning; Motor Control; Challenge Point; Errorful Learning; Errorless Learning; Mental Workload

Introduction

Motor learning is important during the lifespan and can be defined as “a problem-solving process in which the goal of an action represents the problem to be solved” (1). To solve this problem, the performer selects the most suitable action plan from the many available options and ‘learns’ the task. Sources of information available during and after each attempt to perform the task help pick the right action plan and this information forms the basis of motor learning (1–3). Based on Fitt’s law, the amount of interpretable information derived from a task depends on the difficulty of the task (4).

Task difficulty is a broad concept and can be seen as a summed manifestation of all task characteristics (4,5). A task is difficult if it cannot be mastered in a single session and has multiple degrees of freedom (6). With increasing task difficulty, the number of errors tends to increase. The information content embedded in the errors shapes the action plan and helps to improve performance. However, our information capacity is limited and when exceeded, the performer chooses an incorrect action plan and errors and poor performance ensue (2,4,7). High task difficulty can lead to information overload, which is thought to interfere with motor learning (1,4).

The central tenet of the optimal challenge point framework is this information processing underlying motor learning. The framework posits that a specific level of task difficulty produces the greatest magnitude of motor learning. This level is called the optimal challenge point and depends on two types of task difficulty: nominal and functional. Nominal task difficulty includes experimental constraints of a task independent of the context or performer, whereas functional task difficulty refers to the challenge level of the task relative to the performer. Functional task difficulty is therefore not only influenced by nominal task difficulty, but also by the skill level of the performer and the context in which the task is performed (1).

Since the introduction of the optimal challenge point framework, most experiments to test its assumptions have been based on the effects of external manipulations of functional task difficulty on motor learning, for example by manipulating practice schedules (8–11). Little is known about the relationship between functional task difficulty and motor learning when functional task difficulty is mainly driven by the nominal difficulty of a task. . The framework predicts that motor learning increases up to a certain level of nominal task difficulty, beyond which further increases in difficulty are counterproductive and learning does not improve and can in fact deteriorate (1).

However, the experimental evidence is mixed for the presence of an optimal level of nominal task difficulty. In a postural control task, the optimal challenge point occurred at a medium difficulty level. Difficulty in this task was manipulated by changing the stability of the ground surface (12). In a sequence key-press task, where difficulty was manipulated by the information given about the next key, the most difficult level corresponded to the optimal challenge point. However, there are also studies reporting no optimal point of task difficulty. In a tracing task, the bandwidth represented task difficulty and affected warm-up decrements, but not the rate of improvements (13). In a dart-throwing task, motor learning was also independent of difficulty level, i.e., target size (14).

Individual differences as well as differences in difficulty manipulations between studies can underlie these inconsistencies. Most studies attempted to control for individual differences by implementing novel tasks and doing group-level analysis. However, the challenge point framework as well as recent work emphasize that individual characteristics affect the perceived difficulty level (1,15). Although the amount of available information from a task is directly related tonominal task difficulty, the amount of interpretable information also depends on individual characteristics such as initial skill level and information processing capacity (16,17). Therefore, a task with a medium level of nominal task difficulty can be easy for someone with a high initial skill level, while someone with a low initial skill level can perceive the task as hard. In addition, since there is no unifying definition of task difficulty, most studies quantify nominal task difficulty in terms of performance outcomes, e.g. longer movement times or higher error scores with increasing difficulty. However, expressing it this way, a level of difficulty that is hard in one task can correspond to a level of difficulty that is medium or easy in another task. In addition to the nominal task difficulty, the functional task difficulty should be also taken into account. Recently, the measure of mental workload through the National Aeronautics and Space Administration Task Load Index (NASA-TLX) has been put forward as a subjective measure of functional task difficulty (12,15,18). Designed to measure mental workload in pilots, the NASA-TLX is a valid index of mental workload in a variety of contexts, including motor learning (19).

Beyond the magnitude of improvement and the perceived workload, the magnitude and direction of transfer are behaviourally also relevant measures of motor learning. Transfer is the conveyance of the learned skill from one to another difficulty level. Until now, experimental evidence favours no particular direction of transfer (20). Based on the optimal challenge point framework, it is expected that transfer from a hard to an easy task is greater than from an easy to a hard task (1). In reaching, where difficulty was defined as distance to the target and transfer was defined as performance on a target distance not included in the acquisition phase, this expectation was indeed confirmed (10). However, in a stick balancing task, transfer from an easy to a more difficult task was more beneficial than the other way around (11).

Altogether, experimental evidence is mixed and inconclusive in support of an optimal challenge point for motor skill learning. Because athletes are constantly on the lookout to increase training effectiveness, a better understanding of how functional task difficulty can be measured and how it affects motor learning can contribute to more efficient training protocols. If an optimal challenge point indeed exists, training at the optimal difficulty level would increase the effectiveness of training and decrease learning time. In addition, patients in rehabilitation would likely recover functions impaired by an injury faster and to a greater extent if they practiced the impaired function at the optimal difficulty level. Using a reductionist approach, we implemented a new visuomotor mirror-star tracing task in a homogeneous population (healthy young adults). In this task, we measure performance in terms of speed and accuracy. Using this approach, differences in functional task difficulty are mainly driven by the nominal task difficulty while still taking individual differences in account.

The purpose of this study was to determine the effects of functional task difficulty on motor skill acquisition, retention, and transfer. Based on the optimal challenge point framework, we tested three hypotheses: 1) motor skill practice at a medium or hard versus a low difficulty level of the same task will produce greater motor skill acquisition and retention in terms of speed and accuracy, 2) the learning benefit gained from a specific difficulty level depends on the initial skill level as predicted by the optimal challenge point framework, and 3) motor skill transfer is difficulty-dependent so that the optimal direction of transfer is from hard to easy.

Methods

Participants

Healthy and right handed (21) young adults aged 18-30 years (N = 36; 38.9 % male; age: 22.97 ± 2.43 years; height: 175.67 ± 9.97 cm; weight: 68.44 ± 13.61) participated in the study. Exclusion criteria were the use of medication that affects neural functioning, movement restrictions with and pain in the right hand or arm, presence of a neurological condition and familiarity with the task. Participants gave written informed consent to the study protocol, which was approved by the ethical committee of Human Movement Sciences at the University Medical Centre of Groningen.

Design

Participants were randomly assigned to one of three groups based on the nominal difficulty of the motor skill they subsequently practiced: Motor Practice with Low Difficulty (P-LD), Motor Practice with Medium Difficulty (P-MD) or Motor Practice with High Difficulty (P-HD). Participants visited the lab on two consecutive days. On Day 1, visuomotor performance was measured (baseline), followed by motor practice at the assigned difficulty level for 160 trials . After practice, the post- and transfer tests were administered. Participants also rated how difficult they perceived the execution of the motor skill using the National Aeronautics and Space Administration Task Load Index (NASA-TLX) (18). On Day 2, ~24 h after practice, the baseline and transfer measurements were repeated to quantify skill retention.

Task

Based on pilot experiments, we adopted and modified the star-tracing task (22,23). The modifications compared with previous studies consisted of: 1) performing the task on a 24 by

16.95 cm Apple iPad Air; 2) visualizing the iPad surface through a mirror to make the task even more challenging, and 3) creating three levels of tracing difficulty by changing the bandwidth of the star (13). Participants sat in a chair and placed both hands on the surface of a table in front of them. The iPad was placed on the table top in front of the participant. The task was to trace, by holding a stylus in the right-dominant hand, a symmetrical pentagon-shaped star as fast and accurately as possible. Participants looked at their moving hand in a mirror placed vertically 14 cm beyond the back edge of the iPad. A sheet of cardboard placed horizontally above the participant's hand and below the chin, prevented participants from seeing the hand tracing the star. The length of each of the five sides of the pentagon was 10.5 cm. The width of the wall of the star was set to 3 (Hard Difficulty, HD), 5 (Medium Difficulty, MD), or 7 mm (Low Difficulty, LD). Participants were instructed to trace the star by moving the stylus within the bandwidth formed by the walls of the star. The non-dominant left hand rested on the table next to the iPad. Fig 1 shows the setup. While executing the task, the star was visible to the participant and a blue dot represented the start and end point of the tracing path. When ready, the participant was asked to place the stylus on the blue dot, after which a beep signalled the start of the trial. Because frequency of knowledge of results (KR) and knowledge of performance (KP) can affect motor performance and learning (24,25), KP was available during each trial by maintaining visibility of the star. In addition, KR was kept at 100% for each group, by presenting the movement time and error percentage after each trial. Before the start of the test, participants familiarized themselves with the task by performing one trial at each difficulty level. For the pre-, post- and retention tests, participants traced the star at the assigned difficulty level 10 times. Motor practice consisted of four blocks of 40 trials at the assigned difficulty level. Transfer was quantified as performance at the untrained difficulty levels, comprising ten trials each. The order of the difficulty levels in the transfer task was block randomized across participants.

NASA-TLX

The NASA-TLX was administered at the end of Day 1, using the official NASA-TLX IOS application on the iPad. Participants rated six dimensions related to perceived effort completing the motor task with their assigned difficulty on a scale from 0 to 100: Mental demand, Physical demand, Temporal demand, Performance, Effort and Frustration. In addition, to determine the weighting of each dimension, participants completed pairwise comparisons across all pairs of the six dimensions. Weightings were given to each dimension based on the number of times a dimension was chosen as most relevant. Total workload scores were computed by multiplying the weighting with the rating score of each dimension, summing the scores across all dimensions and dividing by 15 (18).

Data analysis

Visuomotor data were analysed with custom made Matlab scripts (The Mathworks, Natick, Massachusetts, USA, version R2016b). Raw position data were manually checked for correctness before interpolating at 60 Hz. Because participants at times made large errors unrelated to motor performance at the start and end of a trial, these initial and final segments were excluded from the analyses. Visuomotor performance was quantified as the error percentage and movement time per trial, in order to capture both speed and accuracy. Movement time was defined as the time it took for participants to complete the full path of the pentagon one time. Error percentages were computed as the percent of samples outside of the bandwidth (S_{error}) per trial (total samples S_{total}: 660 ± 346), according to the equation:

$$\%Error = (S_{error}/S_{total}) * 100 \qquad [1]$$

In addition, to allow a better comparison between groups the total distance of the traced path per trial was calculated as an accuracy measure that was independent of the bandwidth manipulation.

Statistical analyses

All data were analysed with IBM SPSS Statistics version 23. Data were first checked for normality using the Shapiro-Wilk test. If the data was not normally distributed, a log transformation was performed. Missing values were replaced with mean substitution. On average, missing values constituted 3.9% of the data. To check if the difficulty manipulation was successful,separate repeated-measures ANOVAs were done for error percentage, movement time and total distance as dependent variables on baseline scores with all participants grouped across difficulty levels as the within-subjects factor. . To check hypothesis 1, i.e., task difficulty affects motor learning and retention, separate Group (P-LD, P-MD, P-HD) by Time (pre-, post and retention) ANOVAs were used with repeated measures on Time for error percentage, total distance and movement time as dependent variables. To examine the impact of individual differences in initial skill level on motor learning and retention, i.e. hypothesis 2, Pearson correlations were calculated between the scores on the pre-test and the improvement on the post- and retention-tests for all dependent variables. We tested hypothesis 3, i.e., task difficulty affects transfer to unpractised tasks, by a Group (P-LD, P-HD) by Time (immediate, delayed) ANOVA with repeated measures on Time for error percentage, total distance and movement time on the unpractised MD-test as dependent variables. Only the P-LD and P-HD groups are taken into account here to allow a direct comparison in performance on an unpractised task between two different directions of transfer. For all ANOVA's, a Greenhouse Geisser correction was performed when the assumption of sphericity was violated. Post-hoc tests were performed using Tukey's HSD. To check for any differences between the NASA-TLX scores for the different groups, an one-way ANOVA was performed on the raw ratings of all the subscales and the total workload score. For all analyses, the significance level was set at $\alpha = 0.05$.

Results

Motor performance

At baseline, there was a significant main effect of difficulty for both error percentage ($F(2,70) = 323.9$, $p < .001$) and movement time ($F(2,70) = 9.4$, $p < .001$), confirming that the width of the wall of the star created a task difficulty effect in terms of performance (Fig. 2). Post hoc comparisons revealed that error percentage during the execution of the HD task was 20.3 % higher than during the MD task and 32.9 % higher than during the LD task and that the error percentage in the MD vs. the LD task was 12.7% higher (Fig. 2A). During the HD task, movement time was 14.7 % longer than during the MD task and 22.0 % higher than during the LD task (Fig. 2B). Task difficulty did not affect the total distance of the path (Fig. 2C, $F(2,70) = 0.8$, $p > .05$). There was no task difficulty effect in terms of mental workload, measured as global outcome or on the six subscales of the NASA-TLX (see table, Supplemental Digital Content 1).

Motor learning

Practice improved motor performance in all groups (Time main effect) as measured by total distance ($F(1,52) = 9.6$, $p = 0.001$) and movement time ($F(1,33) = 5.2$, $p = 0.029$) (Figs. 3B-C), but no improvement was seen in error percentages ($F(2,66) = 30.6$, $p = 0.241$) (Fig. 3A). There were no group by time interactions for either outcome. Movement time at pre-test correlated with improvements at both post- and retention tests (Table 1). For total distance, performance at pre-test did not correlate with improvements at post- and retention tests when the difficulty was low (Table 1), although 10 out of 12 subjects improved their performance (Fig. 4A). Performance at pre-test did correlate with improvements at post-test when the difficulty was medium or high (Table 1) but the distribution of the scores underlying the correlations was the opposite: at medium difficulty, 4 of 12 subjects improved whereas at high difficulty 9 of 12 subjects improved (Fig. 4B-C). There was only a correlation between total distance at the pre-test and improvement at the retention-test when the difficulty was medium (Table 1).

Transfer

To examine the direction effects of transfer to untrained levels, scores for immediate (directly after practice) and delayed (24 h after practice) transfer from the P-LD and P-HD groups to the MD-task were compared. The groups did not differ in their performance on the MD-task for error percentage ($F(1,22) = 0.4$, $p = 0.554$), total distance ($F(1,22) = 0.3$, $p = 0.569$) and movement time ($F(1,22) = 1.1$, $p = 0.304$).

Discussion

We determined the effects of task difficulty on motor skill acquisition, retention, and transfer. Practicing a mirror star-tracing motor task at three levels of difficulty affected motor performance in terms of error percentage and movement time, but task difficulty did not affect motor skill acquisition, retention and transfer to untrained difficulty levels. Task difficulty also did not affect the perceived mental workload as measured by the NASA-TLX. Unexpectedly, initial skill level only influenced skill acquisition and retention when practicing with a medium or hard difficulty level. We discuss these findings with a perspective on the optimal challenge point framework for motor skill learning.

The data did not support hypothesis 1: task difficulty did not affect performance immediately and 24 h after motor practice (Fig. 3). Based on the challenge point framework, we expected that practicing the star-tracing task at a medium or high compared with low difficulty level would have afforded learning benefits. Despite a clear effect of task difficulty on motor performance at pre-test (Figs. 2A-B), the magnitude of skill acquisition and retention were both independent of task difficulty. Previous studies suggested a putative role for mental effort in the effects of task difficulty on motor learning by reporting correlated increases in mental workload and motor learning (12,15). Clearly, this was not the case in the present study, as perceived mental demand did not differ between difficulty levels (Supplemental Digital Content 1). Although we gave feedback to participants about the time and accuracy for the trial they just completed, seeing the star during tracing gave participants the possibility to rely on a more objective feedback by simply aiming at the middle of the star wall (26). Regardless of difficulty level, aiming at the middle of the star wall is always an effective strategy. Therefore, this objective feedback, which we suspect subjects themselves discovered, may have dominated over the more subjective feedback created by the difficulty manipulation, i.e., higher error percentages. A lack in improvement in those error percentages further support the possibility that participants ignored those percentages and instead aimed for the middle of the star wall (Fig. 3A). These same effects were seen in a dart-throwing task, where task difficulty was manipulated by manipulating target sizes. In this task, visual feedback also provided participants with the possibility to aim for the middle of the target and task difficulty did not affect motor learning (14). Because of the availability of this concurrent knowledge of performance during tracing, movement slowing with increasing difficulty in the current task may be a mechanism to minimize mental workload (Fig. 2B). Movement slowing is probably related to an increase in the time needed to generate more detailed motor plans and process afferent feedback with an increase in demand for accuracy. Movement slowing can provide participants with extra time to interpret the increasing amount of task-relevant information when the bandwidth is narrow and more errors are made, which can reduce the perception of task difficulty in terms of information flow (4).

The optimal challenge point framework suggests that in addition to nominal task difficulty, individual characteristics can also affect motor learning. One important individual factor is the ability to process information, which varies widely between individuals (15–17). In a reaching task with two levels of nominal difficulty, a cluster analysis revealed that more pronounced individual variations in mental workload and performance occurred with increasing nominal task difficulty (15). The current results also show high variability within groups as well as in the magnitude of learning. These results highlight the mediating role of mental workload in the effects of task difficulty on motor learning, which could be confirmed by measuring brain activity. Correlating changes in brain activity and changes in motor performance could disentangle the relationship between individual information processing capacities, mental workload and motor learning.

Another important individual factor influencing functional task difficulty is initial skill level. High correlations between performance on the pre-test and the amount of improvement in the P-MD and P-HD groups underscore the influence of functional task difficulty on motor learning (Figs. 4A-B). In these two groups, participants with the lowest initial skill levels improved the most, which is in line with the optimal challenge point framework. Because participants in these groups made a lot of corrections during tracing, indicated by a high total distance, the potential was high to extract learning-relevant information. By using the strategy of movement slowing described above, participants benefited from these errors without overloading their information processing capacity. The interaction between initial skill level and nominal task difficulty is seen in the different distributions of the individual scores forming the correlations in the two groups. The P-MD compared with the P-HD group produced fewer errors and therefore a longer total distance in the beginning - corresponding to a lower initial skill level - was necessary in order to improve, so that only 4 of 12 participants in this group improved motor performance (Fig. 4B). In contrast, in the P-HD group almost all, 9 of 12, participants improved, suggesting that participants with a higher initial skill level still benefited from practicing at the most difficult level (Fig. 4C). This analysis tentatively suggests that practicing an unfamiliar motor task at high vs. lower difficulty levels could produce greater magnitudes of motor learning and supports the challenge point framework.

When performing the easy (LD) task, participants made few errors (Fig. 2A). As reasoned by the challenge point framework, only participants with a very low initial skill level would make enough errors to benefit from practice with the easy task. However, unexpectedly the initial skill level in the P-LD group was unrelated to improvement at the post-test, while still almost all, 10 of 12, participants in this condition improved their performance (Fig. 4A). Therefore, improvement in this group must be mediated by some other approach than error detection. Recently, studies that minimized error during motor practice showed that errorless learning could also benefit motor learning (errorless learning) (28–30). In errorless learning participants rely on feedback minimally, resulting in the evolution of implicit learning. This learning is robust because the memory traces are more resistant to interference and stress in particular.

A comparison between the present and past data raise the hypothesis that mental instead of motor effort mediate the previously reported effects of task difficulty on motor learning (12,14,15,27). Results from the current study suggest that not nominal task difficulty, but the effect of task difficulty on mental workload has an impact on motor learning and that the optimal challenge point framework is only applicable if a certain amount of error is present. If participants make enough errors, they put effort into processing the information arising from those errors and use this information to improve. However, against the framework, when theavailable information from a task is insufficient, participants are still able to improve by adopting a more implicit type of learning. In addition, if a manipulation of difficulty is used where it is possible to minimize the effect of difficulty on mental workload, for example by moving slowing or generating more objective feedback, effects of task difficulty on motor learning seems to be minimal (13,14). Future work is needed to confirm this hypothesis and determine the relationship between mental workload, errors and the difficulty level used in practicing a motor skill.

Assuming that the improvement in the P-LD and P-HD groups are indeed mediated by different underlying approaches, comparing their performance on an unpractised difficulty level would allow us to compare directly between learning from errors (error-prone learning) and errorless learning . However, when tested on the unpractised medium level MD-task, learning using an easy and a hard task produced similar magnitudes of transfer. The transfer and the practice tasks were rather similar, a phenomenon defined as ‘near transfer’ (31). The relationship between difficulty of the motor task and transfer seems to depend on the distality of the transfer test: similarity of the transfer and practice task reduces the effects of task difficulty on transfer (10,31). However, it is not clear how error-prone vs. errorless learning influence this relationship. Therefore, further research should increase the dissimilarity between practice and transfer task and compare learning with errors vs errorless learning.

This study has several limitations. First, by having participants trace the star as rapidly and as accurately as possible, we increased variation in motor performance as participants could practice at any point along the speed-accuracy trade-off continuum (32). Therefore, future studies should develop a composite outcome, comprising both speed and accuracy. Second, we only considered performance of participants before and after learning, while ignoring the rate of learning during practice. Although absolute improvements between groups did not differ, there is a possibility that there is a difference in learning rates, which could give further insights into differences between error-prone vs. errorless learning. Had we increased practice time in tandem with task difficulty, it is possible that each group would have reached its learning asymptote at a different time, producing a hierarchical learning pattern according to task difficulty. While keeping a broad perspective, a further limitation is that we did not apply the current experimental conditions to athletes needing to learn a new skill or to individuals undergoing rehabilitation who need to re-learn a skill impaired by an injury. Our data imply that highly capable athletes may benefit by practicing a new skill at high difficulty and patients re-learning a ‘lost’ skill would progress more effectively if practicing under conditions with a lower difficulty level.

In conclusion, the current results suggest that the optimal challenge point framework does not fully capture the complex relationship between task difficulty and motor learning. It seems likely that the effects of task difficulty on motor learning as predicted by the framework are mediated by mental workload and that the framework is only applicable when a certain amount of errors is present. While applicable to explain the variations in the P-MD and P-HD groups, the framework fails to explain the results of the P-LD group. Contrary to the framework, we found that magnitude of motor learning in an easy task is independent of the available information. For motor skill acquisition, retention and near transfer the current results suggest that both learning with and without errors is equally effective. Task difficulty affected the approach used to learn with, but did not affect the magnitude of skill acquisition, retention or transfer.

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All authors state that there are no financial and personal relationships with third parties that could have inappropriately influenced the present work. The results of the current study do not constitute endorsement by the American College of Sports Medicine and are presented clearly, honestly and without fabrication, falsification or inappropriate data manipulation.

References

1. Guadagnoli MA, Lee TD. Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning. J Mot Behav. 2004 Jul 1;36(2):212–24.
2. Miller GA, Galanter E, Pribram KH. Plans and the structure of behavior. [Internet]. New York: Henry Holt and Co; 1960 [cited 2017 Dec 17]. 222 p. Available from: http://gateway.ovid.com/ovidweb.cgi?T=JS&NEWS=N&PAGE=toc&SEARCH=2004-16335.dd&LINKTYPE=asBody&D=psbk
3. Adams JA. A closed-loop theory of motor learning. J Mot Behav [Internet]. 1971 Jun 1 [cited 2017 Dec 19];3(2):111–50. Available from: http://www.tandfonline.com/doi/abs/10.1080/00222895.1971.10734898
4. Fitts PM. The information capacity of the human motor system in controlling the amplitude of movement. J Exp Psychol. 1954 Jun;47(6):381–91.
5. Meister D. Behavioral foundations of system development [Internet]. New York: Wiley; 1976 [cited 2017 Dec 14]. 373 p. Available from: https://books.google.nl/books/about/Behavioral_foundations_of_system_develop.html?id=AXBbAAAAMAAJ&redir_esc=y
6. Wulf G, Shea CH. Principles derived from the study of simple skills do not generalize to complex skill learning. Psychon Bull Rev [Internet]. 2002 Jun 1 [cited 2016 Nov 16];9(2):185–211. Available from: http://www.springerlink.com/index/10.3758/BF03196276
7. Newell KM. Motor skill acquisition. Annu Rev Psychol [Internet]. 1991 Feb 1 [cited 2017 Sep 26];42(1):213–37. Available from: http://www.annualreviews.org/doi/pdf/10.1146/annurev.ps.42.020191.001241
8. Akizuki K, Ohashi Y. Changes in practice schedule and functional task difficulty: a

study using the probe reaction time technique. J Phys Ther Sci [Internet]. 2013 Jul 1 [cited 2017 Dec 12];25(7):827–31. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3820397/pdf/jpts-25-827.pdf

9. Abbas ZA, North JS. Good-vs. poor-trial feedback in motor learning: The role of self-efficacy and intrinsic motivation across levels of task difficulty. Learn Instr [Internet]. 2017 [cited 2017 Nov 14];1–8. Available from: http://linkinghub.elsevier.com/retrieve/pii/S0959475216300950

10. Sanli EA, Lee TD. Nominal and functional task difficulty in skill acquisition: Effects on performance in two tests of transfer. Hum Mov Sci [Internet]. 2015 Jun 30 [cited 2017 Mar 29];41:218–29. Available from: http://dx.doi.org/10.1016/j.humov.2015.03.006

11. Stevens D, Anderson DI, O'Dwyer NJ, Williams AM. Does self-efficacy mediate transfer effects in the learning of easy and difficult motor skills? Conscious Cogn. 2012 Sep 30;21(3):1122–8.

12. Akizuki K, Ohashi Y. Measurement of functional task difficulty during motor learning: What level of difficulty corresponds to the optimal challenge point? Hum Mov Sci [Internet]. 2015 Oct 31 [cited 2016 Nov 16];43:107–17. Available from: http://dx.doi.org/10.1016/j.humov.2015.07.007

13. Joseph ME, King AC, Newell KM. Task difficulty and the time scales of warm-up and motor learning. J Mot Behav [Internet]. 2013 May 1 [cited 2016 Nov 29];45(3):231–8. Available from: http://www.ncbi.nlm.nih.gov/pubmed/23611248

14. Ong NT, Lohse KR, Hodges NJ. Manipulating target size influences perceptions of success when learning a dart-throwing skill but does not impact retention. Front Psychol [Internet]. 2015 Sep 14 [cited 2016 Nov 25];6:1378. Available from: http://journal.frontiersin.org/Article/10.3389/fpsyg.2015.01378/abstract

15. Shuggi IM, Oh H, Shewokis PA, Gentili RJ. Mental workload and motor performance dynamics during practice of reaching movements under various levels of task difficulty. Neuroscience [Internet]. 2017 Sep 30 [cited 2017 Sep 3];360:166–79. Available from: http://ac.els-cdn.com.proxy-ub.rug.nl/S0306452217305250/1-s2.0-S0306452217305250-main.pdf?_tid=9f5000d2-90d7-11e7-87da-00000aacb35f&acdnat=1504464323_8e6b40520481e5e12728d9255c7c72ff

16. Seidler RD, Bo J, Anguera JA. Neurocognitive contributions to motor skill learning: The role of working memory. J Mot Behav [Internet]. 2012 Nov 1 [cited 2017 Dec 21];44(6):445–53. Available from: http://www.tandfonline.com/doi/pdf/10.1080/00222895.2012.672348?needAccess=true

17. Parasuraman R, Jiang Y. Individual differences in cognition, affect, and performance: Behavioral, neuroimaging, and molecular genetic approaches. Neuroimage [Internet]. 2012 Jan 2 [cited 2017 Dec 21];59(1):70–82. Available from: http://www.sciencedirect.com/science/article/pii/S1053811911004393?via%3Dihub

18. Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Adv Psychol. 1988 Dec 31;52:139–83.

19. Hart SG. Nasa-Task Load Index (NASA-TLX); 20 years later. Proc Hum Factors Ergon Soc Annu Meet [Internet]. 2006 Oct [cited 2017 Oct 31];50(9):904–8. Available from: http://journals.sagepub.com/doi/10.1177/154193120605000909

20. Holding DH. Transfer between difficult and easy tasks. Br J Psychol [Internet]. 1962 Nov 1 [cited 2017 Dec 20];53(4):397–407. Available from: http://doi.wiley.com/10.1111/j.2044-8295.1962.tb00845.x

21. Oldfield RC. The assessment and analysis of handedness: The Edinburgh inventory. Neuropsychologia [Internet]. 1971 Mar 1 [cited 2017 Oct 24];9(1):97–113. Available from:

http://www.sciencedirect.com/science/article/pii/0028393271900674?_rdoc=1&_fmt=high&_origin=gateway&_docanchor=&md5=b8429449ccfc9c30159a5f9aeaa92ffb

22. Stratton SM, Liu Y-T, Hong SL, Mayer-Kress G, Newell KM. Snoddy (1926) revisited: Time scales of motor learning. J Mot Behav [Internet]. 2007 Nov 1 [cited 2016 Dec 17];39(6):503–15. Available from: http://www.tandfonline.com/doi/abs/10.3200/JMBR.39.6.503-516
23. Snoddy GS. Learning and stability: A psychophysiological analysis of a case of motor learning with clinical applications. J Appl Psychol. 1926 Mar;10(1):1–36.
24. Martenuik RG. Information processing in motor skills [Internet]. Waterloo: Holt, Rinehart and Winston; 1976 [cited 2017 Jun 7]. 244 p. Available from: https://books.google.nl/books/about/Information_Processing_in_Motor_Skills.html?id=FGWpQgAACAAJ&redir_esc=y
25. Wulf G, Shea C, Lewthwaite R. Motor skill learning and performance: A review of influential factors. Med Educ [Internet]. 2010 Jan 1 [cited 2017 Oct 31];44(1):75–84. Available from: http://doi.wiley.com/10.1111/j.1365-2923.2009.03421.x
26. Ong NT, Hodges NJ. Balancing our perceptions of the efficacy of success-based feedback manipulations on motor learning. J Mot Behav [Internet]. 2017 [cited 2017 Nov 14];2895(November):1–17. Available from: https://www.tandfonline.com/doi/full/10.1080/00222895.2017.1383227
27. Trempe M, Sabourin M, Proteau L. Success modulates consolidation of a visuomotor adaptation task. J Exp Psychol Learn Mem Cogn [Internet]. 2012 Jan [cited 2016 Dec 30];38(1):52–60. Available from: http://doi.apa.org/getdoi.cfm?doi=10.1037/a0024883
28. Maxwell JP, Masters RS, Kerr E, Weedon E. The implicit benefit of learning without errors. Q J Exp Psychol Sect A Hum Exp Psychol. 2001 Nov 1;54(4):1049–68.
29. Poolton JM, Masters RSW, Maxwell JP. Passing thoughts on the evolutionary stability

of implicit motor behaviour: Performance retention under physiological fatigue. Conscious Cogn. 2007;16(2):456–68.

30. Masters RSW, Poolton JM, Maxwell JP. Stable implicit motor processes despite aerobic locomotor fatigue. Conscious Cogn. 2008;17(1):335–8.

31. Ollis S, Button C, Fairweather M. The influence of professional expertise and task complexity upon the potency of the contextual interference effect. Acta Psychol (Amst) [Internet]. 2005 Mar 1 [cited 2017 Dec 21];118(3):229–44. Available from: http://www.sciencedirect.com/science/article/pii/S0001691804000873?via%3Dihub

32. King AC, Ranganathan R, Newell KM. Individual differences in the exploration of a redundant space-time motor task. Neurosci Lett. 2012 Nov 7;529(2):144–9.

Figure Captions

Table 1

Pearson correlations between scores on the pre-test and improvements immediately (post-test) and 24h (retention-test) after learning.

Fig. 1

Experimental set-up of the mirror star-tracing task. Partcipants had to trace the star as fast and accurate as possible with a stylus, while staying within the bandwidth. The sheet of cardboard prevented parcipants from directly seeing their hands, so they could only look at their moving hand through a mirror.

Fig 2.

Baseline differences between tasks for all participants grouped together (N = 36) for error percentage (A), movement time (B) and the total distance of the path (C). Error bars represent standard error. ** $p < .01$, *** $p < .001$.

Fig 3.

Improvement in motor performance of the three groups relative to the pre-test, quantified by error percentage (A), movement time (B) and total distance (C). Errors bars represent standard error.

Fig 4.

Correlation between scores on the pre-test and improvement at the post-test for the total distance of the path for the three groups separate

Supplemental Digital Content

Supplemental Digital Content 1. Table that provide the NASA-TLX scores. doc