Do we know what we need? Preference for feedback about accurate performances does not benefit sensorimotor learning.

Running Head: Feedback preferences affect learning.

Authors and Affiliations

Flavio Henrique Bastos[1*], Go Tani[1], Ricardo Drews[1], Stephan Riek[2], Welber Marinovic[2,3*]

1 School of Physical Education and Sport, University of São Paulo, Brazil

2 Centre for Sensorimotor Performance, School of Human and Nutrition Sciences, The University of Queensland, Australia

3 School of Psychology and Speech Pathology, Curtin University, Australia

*Corresponding author

E-mail: bastosfh@usp.br,welber.marinovic@curtin.edu.au

Abstract

Previous research on skill acquisition has shown that learners seem to prefer receiving knowledge of results (KR) about those trials in which they have performed more accurately. In the present study, we assessed whether this preference leads to an advantage in terms of skill acquisition, transfer, and retention of their capacity to extrapolate the motion of decelerating objects during periods of visual occlusion. Instead of questionnaires, we adopted a more direct approach to investigate learners' preferences for KR. Participants performed 90 trials of a motion extrapolation task (Acquisition phase) in which, every three trials, they could decide between receiving KR about their best or worst performance. Retention and Transfer tests were carried out 24 hours after the Acquisition phase, without KR, to examine the effects of the self-selected KR on sensorimotor learning. Consistent with the current literature, a preference for receiving KR about the most accurate performance was observed. However, participants' preferences were not consistent throughout the experiment as less than 10% (N= 40) selected the same type of KR in all their choices. Importantly, although preferred by most participants, KR about accurate performances had detrimental effects on skill acquisition, suggesting that learners may not always choose the KR that will maximise their learning experiences and skill retention.

Keywords: knowledge of results, motor learning, motion extrapolation, self-controlled practice

Significance statement

This study presents a new approach to understand the preference for feedback about successes, rather than about failures, when learning sensorimotor skills.

Our approach revealed that, although participants prefer receiving feedback about successes, this preference is not consistent over time, with learners deliberately requesting feedback about their worst trials during the learning process.

More importantly, the results clearly demonstrate that a preference for receiving feedback about successful trials can be detrimental to performance during skill acquisition and that a learning benefit associated with this preference is unlikely, which contradicts recent studies. Although learners' engagement can sometimes be beneficial (e.g. increasing motivation), additional knowledge about the skill acquisition process itself may be necessary to induce optimal choices about feedback during learning.

Introduction

Active learning has become very popular in contemporary educational contexts (Freeman et al., 2014). For active learning to succeed, students or learners are expected to engage in meaningful activities and, importantly, reflect on them (Bonwell & Eison, 1991). There is good evidence that student engagement is central to the success of active learning methods (Hake, 1998; Redish, Saul, & Steinberg, 1997). Although most of the literature on the topic focusses on academic performance, similar types of active learning methods have been used to investigate the acquisition of motor skills. For example, Huang, Shadmehr and Diedrichsen (2008) demonstrated that when learners were allowed to choose the motor actions they had to execute, they tended to repeat actions that had led to more errors in previous trials. Interestingly, learners who adopted this strategy had better performance on subsequent test trials than learners who did not.

The benefits of active learning methods in terms of retention and/or transfer of sensorimotor skills, hereafter referred to as self-controlled practice, have been shown to generalise across multiple experimental tasks and factors. Specifically, experiments using tasks with varying sensorimotor demands (e.g. anticipatory timing, throwing) and manipulating different factors, such as task difficulty (e.g. Andrieux, Boutin, & Thon, 2015), amount of practice (e.g. Post, Fairbrother, & Barros, 2011) and KR frequency (e.g. Carter, Carlsen, & Ste-Marie, 2014), have shown evidence of learning gains in self-controlled practice conditions.

Previous research on self-controlled KR – i.e. a condition in which participants are allowed to decide whether or not they receive KR – has shown that learners remembered requesting KR after trials in which they have performed better, compared to other trials (Chiviacowsky & Wulf, 2002, 2005; Chiviacowsky, Wulf, & Lewthwaite, 2012; McRae, Patterson, & Hansen, 2015; Patterson & Carter, 2010; Patterson, Carter, & Hansen, 2013). This remembered preference, in association with the learning gains observed in these conditions, contradicts the expected role of KR in sensorimotor learning. More precisely, studies with externally controlled KR conditions (i.e. in which learners have no choice over when to receive KR) have shown that KR improves sensorimotor skills when intrinsic information is not sufficient or precise enough (e.g. Moran, Murphy, & Marshall, 2012). In these conditions, KR has been considered to be more relevant to learning when informative about trials with poorer performance. Specifically, according to the Guidance Hypothesis (Salmoni, Schmidt, & Walter, 1984), KR would be expected to play a more important role when performance is poorer because it can guide learners to reduce their errors, while preventing maladaptive short-term corrections that can lead to the acquisition of unstable internal representations (Schmidt, 1991).

With respect to self-controlled KR conditions, the theoretical reason for requesting KR about accurate performances differs according to the perspective adopted to explain the learning advantages of self-controlled KR – referred to as *motivational-influences perspective* and *information-processing perspective* (Carter & Ste-Marie, 2017). In the former, KR about accurate performances would protect the learners' perceived competence, which would in turn lead to learning gains (e.g. Chiviacowsky et al., 2012). In the latter, KR about accurate performances could be used by learners to increase their confidence in response correctness, strengthening the association between planned and actual response (e.g. Patterson & Carter, 2010).

Nevertheless, the preference for receiving KR on trials perceived as ‘good’ is typically assessed using questionnaires applied after practice sessions and/or by comparing the mean performance obtained in trials with and without KR (Aiken, Fairbrother, & Post, 2012; Chiviacowsky & Wulf, 2002, 2005; McRae et al., 2015; Patterson & Carter, 2010; Patterson et al., 2013). Comparing trials with and without KR does not take into consideration the fact that, when learning a sensorimotor skill, the performance in the task changes with practice. Thus, for example, having more trials without KR at the beginning of the acquisition phase and more trials with KR at the end of this phase would result in larger error, on average, in trials without KR, since performance would be less accurate at the beginning of the acquisition phase. In turn, the use of a questionnaire after 30 (e.g Chiviacowsky, Wulf, & Lewthwaite, 2012), 60 (e.g Chiviacowsky & Wulf, 2002, 2005) or 90 practice trials (e.g. Paterson & Carter, 2010) does not allow assessing whether this preference differs among participants or, more importantly, whether this preference changes with practice.

Furthermore, the study carried out by Aiken et al. (2012) suggests that the results based on these questionnaires should be viewed with caution. In contrast to previous research, Aiken et al. (2012) employed a modified questionnaire using a Likert scale to assess the participants' preferences. Their results failed to show the typical preference for KR on perceived good trials, suggesting the need for a different approach to investigate what guides the decision for requesting KR in self-controlled conditions.

In the present study, we used an innovative approach to investigate how people request different types of KR ('good vs bad') about their performance when learning a motion extrapolation task. To achieve this, we allowed participants to choose between receiving KR about their most or least accurate performance after every three trials. This experimental design allowed us to answer a) whether or not there is a preference for receiving KR about most accurate performances, b) whether or not the same KR option is chosen throughout the acquisition process and c) if a specific preference could lead to an advantage during practice and/or skill retention and transfer.

Method

Participants

Forty volunteers (21 women, age range 18-35, average = 23.1) participated in this study. All participants reported having normal or corrected-to-normal vision and all gave written informed consent, which was in accordance with the Declaration of Helsinki and approved by the local Ethics Committee of the School of Physical Education and Sport – University of São Paulo (Brazil).

Task and procedures

The task goal consisted of synchronising a button press with the arrival of a moving target at a predetermined position on a monitor screen (see Figure 1). Button presses generated TTL pulses that were recorded using a data acquisition card (Labjack U3-HV). The target moved horizontally, from left to right, on a 22'' computer screen (Samsung 2233RZ, 120 Hz refresh rate, 1680x1050 resolution). A customized script – written in GNU Octave (Eaton et al., 2015), using the toolbox Psychtoolbox (Kleiner et al., 2007), on an Ubuntu Linux 12.04 operating system – controlled the experimental conditions, visual stimuli, and data collection. The target started its motion between 1.5 and 3 seconds (s) (pseudo randomly) after the beginning of the trial, and took 1.4 s to arrive at the predetermined position. After moving onset (initial velocity: 28.3 degrees of visual angle per second – dva/s), the target constantly decelerated in a ratio of 5.7 dva/s^2. Additionally, the moving target was occluded in the last

784 milliseconds (ms) of its displacement. The purpose of the deceleration during the occlusion was to make participants dependent upon the KR, as learning to estimate time of arrival, when the target moves with a constant speed and undergoes a fixed period of occlusion, occurs quickly (Marinovic, Reid, Plooy, Riek, & Tresilian, 2011; Marinovic, Tresilian, de Rugy, Sidhu, & Riek, 2014). In addition, time-of-arrival estimates depend greatly on the perceived speed of the moving target (Marinovic & Arnold, 2012; Smeets & Brenner, 1995). Thus, if participants relied exclusively on intrinsic feedback, they would systematically anticipate their responses, as deceleration of the moving target, during the occlusion period, would not be completely taken into consideration – due to our poor ability to perceive acceleration (Watamaniuk & Heinen, 2003). The experiment consisted of three phases: Acquisition (AQ), 24-hour Retention test (RT), and 24-hour Transfer test (TR). Note that our definition of transfer is that the acquired skill to extrapolate the motion of the target in one condition could be transferred to a condition requiring a larger extrapolation period. In the AQ, phase participants performed 93 trials of the task, receiving KR after every three trials. KR was provided in milliseconds, with the words ‘after’ or ‘before’, indicating the difference between the response (button press) and the arrival of the target to the contact line. Within a window of ±1 ms, participants would receive a ‘zero’ error KR. Except for the KR provided after the third trial – when participants received KR about all past three trials – participants were presented, after every three trials, with the choice between receiving KR about their most accurate performance or their least accurate performance on the past three trials.

The time interval between each trial was also self-controlled (determined by each participant). After trials with KR presentation, the duration KR remained on the computer screen was determined by each participant. Specifically, participants were instructed to press the response button when they were ready to start the next trial. After trials without KR presentation, participants were shown a message on the monitor screen instructing them to press the response button to start the next trial.

The RT test was carried out 24 hours after the AQ and consisted of 20 trials of the same task performed during the AQ, without KR. The TR test consisted of the same procedure used for the RT, but with an increased occlusion time of the moving target (Figure 1), to verify how the time estimation developed during the AQ would generalise to a context with increased uncertainty.

Figure 1 here

Data analysis

The data[1] were organised and analysed using R, a language and environment for statistical computing (R Core Team, 2016), and Jasp (JASP team, 2016).

Absolute Error (AE), defined as the absolute value of the difference between the participant's response time and the arrival of the moving target at the predetermined position (in milliseconds), Variable Error (VE), defined as the standard deviation of the temporal error and Constant Error (CE), defined as the average of the temporal error across three trials were the dependent measures of interest. The first three trials performed by the participants were used as indicative of their initial performance in the task (Baseline) – KR was provided only after the third trial, about each one of the past three trials. Additionally, KR time, defined as the duration (in seconds) KR remained on the computer screen, was considered an indicative of the time used by participants for KR processing.

[1] The data can be accessed here: https://data.mendeley.com/datasets/sg27fz5t27/draft?a=4707da39-8d60-4ab3-8877-a5bbf439f74f.

With regard to the AQ, trials were analysed in blocks of 3 trials (90 total – 30 blocks of 3 trials).

To determine whether learners prefer receiving KR about their most accurate performances, the amount of each type of KR requested per participant during the AQ was computed. Additionally, to verify whether participants changed their strategies of receiving KR about their best or worst performances from one request to another, the frequency they alternated the KR type (KR about most or least accurate performance) was calculated.

Instead of comparing trials with and without KR as in previous studies, we examined how KR requests are related to performance along the AQ by submitting AE, VE and CE to separate Bayesian linear regressions – JZS Bayes Factor Linear Model, with default prior scales (Rouder, Morey, Speckman, & Province, 2012), using the R package BayesFactor (Morey, Rouder, & Jamil, 2015). For this analysis, KR type, KR time and blocks of trials (as a repeated measure) were the predictor variables. One of the strengths of Bayesian statistics in relation to the frequentist approach is that it allows estimating the values of parameters (in this case, the contribution of a predictor in a regression model) and the uncertainty in this estimation (Kruschke & Liddell, 2017). Credible intervals (CI) (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2016) for the estimated parameters were computed sampling 10000 samples from the model using the *posterior* function provided by the BayesFactor package. Participants were considered as random effects, so that the null model included these effects.

Additionally, the time interval between trials, with (KR time) and without KR presentation, were compared with a Bayesian approach to t-test using the R package BayesFactor and the amount of each KR type was submitted to a Bayesian binomial test using Jasp.

With respect to the RT and TR tests, a Bayesian approach to correlation was used to estimate coefficients of correlation between the AE and the amount of KR about most accurate performances. This Bayesian approach to correlation was preferred to a Person's correlation because it allows to estimate the probability of a given correlation and the uncertainty in its estimation through CI calculations (M. D. Lee & Wagenmakers, 2014). For this analysis, we used the R package rjags (Plummer, Stukalov, & Denwood, 2016) as an interface with JAGS (Plummer, 2003), a program for analysis of Bayesian hierarchical models using Markov Chain Monte Carlo (MCMC) methods. To make the analysis less susceptible to outliers, we followed Lee and Wagenmakers' (2014) suggestion and used a multivariate t-distribution instead of the multivariate normal distribution. Based on Kruschke's (2013) suggestion, the prior distribution used was non-informative.

Results

Acquisition phase

As can be seen in Figure 2A, 75% of the participants chose to receive KR about their most accurate performance in more than 50% of their choices. A Bayesian binomial test, comparing the fit of the data under the alternative hypothesis – specifying that the proportion of KR requests about accurate performance is greater than .5 – and the null hypothesis, revealed that the data were 4.1e+32:1 in favour of the alternative hypothesis, or rather, 4.1e+32 times more likely to occur under a model in which KR requests about accurate performance is greater than .5 (median proportion: 0.68, CI: 0.65 to 0.70). This result is consistent with other studies using questionnaires (Chiviacowsky & Wulf, 2002, 2005; McRae et al., 2015; Patterson & Carter, 2010; Patterson et al., 2013) and indicates a preference for receiving KR about most accurate performances when learning a motion extrapolation task.

Figure 2B reveals that most of the participants did not use exclusively one type of KR, or both types in a blocked manner, during the AQ – i.e. they alternated requests of KR about their ‘good’ and ‘bad’ trials.

Figure 2 here

Figure 3 shows the average AE of all participants during AQ, RT and TR. A descriptive analysis suggests that the AE decreases across the blocks of trials during the AQ. In addition, the time between trials when participants received KR ($M = 3.06$, $SD = 1.19$) was longer than without KR ($M = 1.18$ $SD = 0.49$). A Bayesian t-test, comparing the fit of the data under the alternative and the null hypothesis, revealed that the data were 11e+11:1 in favour of the alternative hypothesis, or rather, 11e+11 more likely to occur under a model in which the time between trials is affected by receiving or not receiving KR, compared with a model without this effect.

Thus, blocks of trials, KR time and KR type were submitted to a JZS Bayes Factor Linear Model as predictors of the AE in the AQ. As can be seen in Figure 4, comparing the fit of the data under models with combinations of these predictors revealed that the data were 3.92 more likely to occur under a model with KR type and blocks of trials than under a model with blocks of trials only. Comparing the Bayes factor for these models also revealed that the data were 7.9 times more likely to occur under a model with KR type and blocks of trials than a model with KR time and these same predictors. This result indicates that choosing to receive KR about most accurate or least accurate trials leads to divergent effects on performance during the acquisition phase of our task.

To further examine this main effect of KR type and blocks, we used the *posterior* function (BayesFactor package) to sample from the model with the highest Bayes Factor (blocks of trials and KR type) so as to compute the estimate of the contribution of KR type to performance during the AQ. The estimated contribution of KR type to the grand mean of the AE, in the AQ, is error increment (median: 8 ms; CI: 2.5 to 13.5) associated with receiving KR about the 'best' performance and error reduction (median: -8 ms; CI: -2.5 to -13.5) associated with receiving KR about the 'worst' performance. The reason for the estimated errors to have the same distribution (magnitude and uncertainty), with only different signs, is a sum-to-zero constraint used by the BayesFactor package on fixed effects. This result indicates that KR about most accurate trials can hinder performance during the acquisition of a motion extrapolation task.

Considering that no instruction was provided concerning the constant deceleration of the moving target and that humans are poor at perceiving changes in speed (Watamaniuk & Heinen, 2003), participants were expected to undershoot the deceleration of the moving target during the occlusion and, consequently, respond earlier than necessary, especially in the early blocks of the AQ. The average CE of all participants (Figure 3) shows that the expected bias persisted until the 10th block of trials. The JZS Bayes Factor Linear Model, with the same predictors used for the AE, revealed that the best model was the one with only blocks of trials as a predictor, indicating that the data were 1.6+e16 times more likely to occur under a model in which the bias in performance changes with practice, than under a model without this effect. This result, therefore, is consistent with our prediction regarding participants anticipating their responses at the beginning of the AQ phase and improving their estimates with practice and KR.

The average VE of all participants did not vary markedly along the AQ phase (Figure 3), indicating that although participants became more accurate (AE) and less biased to anticipate their response (CE) along the AQ, their consistency did not statistically change with practice. The JZS Bayes Factor Linear Model, with the same predictors used for the AE, revealed that the data were more likely to occur under the null model than under a model with the effect of any combination of the predictors. Nevertheless, the data do not provide strong evidence against the null hypothesis, since the relative evidence of the null model, against the next best model (with only KR type), was 1.46:1, indicating that the data were only 1.46 more likely to occur under a model without the effect of any predictors on performance consistency than under a model with an effect of KR type on performance consistency.

Figure 3 here

Figure 4 here

Retention and Transfer tests

Compared to the VE and the CE, the AE was the most sensitive performance measure in the AQ phase with respect to the effects of the self-selected KR. For this reason, the Bayesian approach to a correlation analysis between performance and amount of KR about accurate trials, in the RT and TR tests, were limited to the AE.

With respect to the AE in the RT, the Credible Interval (CI) of correlation coefficients produced by the model shows values ranging from -0.11 to 0.54, having its peak value (median) at 0.24 (Figure 5). This result indicates that, although the CI reveals a small correlation between the AE and the amount of KR about most accurate performances, the values covering most of the distribution indicate only 9% probability of finding a negative correlation – i.e. that the higher the preference for KR about accurate performance, the lower the AE. Thus, this result is in clear contrast to the hypothesis that KR about most accurate performances would be associated with better retention.

The posterior distribution for the correlation coefficients in the TR followed the same pattern found for the RT, as can be seen in Figure 5. The CI for the correlation coefficients ranged from -0.14 to 0.47, with a peak value (median) of 0.18, which also does not support the hypothesis that KR about most accurate performances would be associated with better transfer. Overall, in contrast to the hypothesis that KR about accurate trials improves sensorimotor learning, the correlational analyses of both RT and TR tests indicate a trend for KR about accurate trials to impair the acquisition of a motion extrapolation task.

Small correlation coefficients were found between AE and KR time in the RT (median: 0.16; CI: -0.1972 to 0.4888) and in the TR (median: -0.13; CI: -0.4345 to 0.1902), suggesting no evidence of association between the amount of time participants remained with the requested KR on the monitor screen and the retention or transfer of the sensorimotor skill.

A descriptive analysis of the CE suggests that with the increased uncertainty in the TR test (augmented occlusion), participants overcompensated the deceleration of the moving target delaying the response, compared to the RT.

Figure 5 here

Discussion

Here, we sought to investigate how people request KR to learn time estimation in a motion extrapolation task, when given the choice of receiving KR about their most or least accurate performance. Previous reports employing questionnaires have shown a remembered preference for receiving KR about the most accurate trials (Chiviacowsky & Wulf, 2002, 2005; Chiviacowsky et al., 2012; McRae et al., 2015; Patterson & Carter, 2010; Patterson et al., 2013). Our results extend these findings using a new experimental approach, providing evidence for this preference in the acquisition of a motion extrapolation task using a more direct approach compared to the use of questionnaires. Our approach revealed that even learners demonstrating a high preference for one type of KR deliberately changed their options, with less than 10% of the participants choosing the same type in all their choices.

Because the task we employed did not allow participants to accurately predict the arrival of the moving target at the predetermined position without KR, one could argue that during the AQ phase KR about the most accurate performances could be used by participants to find the correct timing. Interestingly, our results show that, during the acquisition of a motion extrapolation task, choosing KR about the most accurate trials can be detrimental to performance. This negative effect is in line with the hypothesis that KR is more relevant when referring to poorer performances, since it would favour mechanisms related to error reduction by avoiding unnecessary corrections (Salmoni et al., 1984; Schmidt, 1991). Nevertheless, it is important to clarify that this expected negative effect of the KR about accurate performance was based on studies investigating conditions with externally controlled KR (i.e. when the decision to provide KR is made by an experimenter or coach, and not by the learner), which differs from what has been reported by recent studies investigating self-controlled KR (e.g. Chiviacowsky et al., 2012).

Furthermore, the observed negative effect on performance, combined with the preference for receiving KR about accurate trials, corroborates previous findings showing that humans do not always choose optimal learning strategies when given control over their learning contexts (Huang et al., 2008). Huang and colleagues (2008) suggest that an ‘artificial coach’ could be use to guide learners to boost motor skills, and we have shown that the same can be achieved by providing learners with prior knowledge of the testing context (Bastos et al., 2013). Nevertheless, whether prior knowledge of the testing context would lead to optimal KR selection strategies to learn the motion extrapolation task we used here is still an open question.

Given that the duration of the self-controlled inter-trial interval was longer between trials with KR presentation, relative to trials without KR, it was reasonable to suppose that the amount of time each participant spent with KR on the monitor would reflect time processing KR. Therefore, as increased (or additional) cognitive effort (T. D. Lee et al., 1994) has been considered a possible explanation for the effects observed in self-controlled conditions (Bastos et al., 2013), one could argue that more time taken to process or reflect upon the KR could be associated with learning gains. Nevertheless, our results show that the amount of time taken for KR processing was not a good predictor of performance during the acquisition process. Additionally, performance on retention and transfer tests have shown only small correlation coefficients with KR-time. These results suggest that the time taken to process KR does not lead to gains either in performance during the acquisition process, or for learning (retention or transfer) a motion extrapolation task. Future studies should investigate whether yoked groups, receiving KR and inter-trial interval according to a self-controlled group, can show enhanced performance during the transfer and retention tests. Since this restricted time to take advantage of KR could lead to increased cognitive effort, the yoked group should benefit more from this practice condition than the self-controlled group.

One of the main questions concerning learners' preference for KR about most accurate trials refers to the role KR plays on sensorimotor learning. Briefly, from an "information processing" point of view, one would not expect learning gains to be observed in a condition where KR is provided mostly about trials with more accurate performances, although this result would be expected from a "motivational" point of view (Sanli et al., 2013).

From a motivational perspective, one of the explanations for the benefits of self-controlled KR on sensorimotor learning is that KR about "good" trials (i.e. most accurate trials) would protect the learners' perceived competence, leading to learning gains (Chiviacowsky et al., 2012). In the referred study, participants were assigned to groups receiving self-controlled KR, varying the instruction about what should be considered a good performance on a timing task (4 ms, 30 ms or no instruction concerning a standard for performance). The poorer performance of the group with 4 ms performance standard, on transfer and retention tests, was interpreted as an effect of neglecting the learners' perception of competence. Although the authors argue that, "*from an information-processing perspective, no learning differences among groups would have been expected, as all groups experienced the same active engagement in the learning process and had the same opportunity to choose feedback*" (p. 6) providing high standards for precision in a timing task could lead learners to make maladaptive short-term corrections (Schmidt, 1991) during practice, which could be the underlying cause for the poorer transfer and retention observed in the group with 4 ms performance standard. In the present study, as no instruction was given concerning performance standards, one could conceive that higher perceived competence would be expected in learners that received KR mostly about their best performance. In this sense, although we do not have a measure of perceived competence, our results were expected to show that receiving KR about trials with more accurate performances would be associated with better learning. Nevertheless, the positive correlation coefficients, between the amount of KR about 'good' performances and the mean AE observed in RT and TR, points to a detrimental effect of this preference on sensorimotor learning, instead of a beneficial effect. It is important to clarify that the small median of the posterior distribution of the correlation coefficients indicates that KR about 'bad' performances is only weakly associated with better transfer and retention. Moreover, the credible intervals observed for both retention and transfer indicate that the opposite association is unlikely.

Our results do not corroborate previous studies manipulating KR in similar scenarios. For instance, comparing groups receiving exclusively KR about their three most or three least accurate trials (on every block of six trials), showed that young adults (Chiviacowsky & Wulf, 2007) and older adults (Chiviacowsky, Wulf, Wally, & Borges, 2009) benefited from receiving KR about most accurate performances. Crucially, however, the task used in these previous studies differed in their requirements of motion extrapolation mechanisms, unlike our work, which demanded the involvement of sensorimotor anticipatory mechanisms to trigger descending motor commands at the appropriate time of arrival of the occluded and decelerating target (see Bosco et al., 2015). Although generalisation to different tasks can be valuable when considering practical applications of self-controlled conditions, such as in physical education, sport and rehabilitation contexts, it is important to consider that different tasks weight differently the engagement of processes associated with sensorimotor learning (Krakauer & Mazzoni, 2011). Additionally, contrary to our study, neither of the studies conducted by Chiviacowsky and colleagues provided choice to the participants as they were assigned to groups with good or bad KR, which could explain the discrepancy between the results.

Generalising to physical education, sports training and rehabilitation contexts, our results suggest that, although giving control over KR has been shown to yield positive effects on sensorimotor learning, completely unrestricted practice conditions may lead to suboptimal learning strategies.

Conclusions

Our results corroborate evidence from previous studies, showing people prefer receiving KR about accurate trials during the acquisition of a motion extrapolation task. However, using a different approach, relative to questionnaires, we show that this preference is not absolute (i.e. it changes along the acquisition process), with less than 10% of the participants choosing the same type of KR in all their choices. Additionally, our study provides clear evidence that KR about accurate trials, although preferred by learners, can be detrimental to performance during practice. With respect to its effects on sensorimotor learning, our results indicate a negligible probability of association between improved retention, or transfer, and choosing to receive KR about more accurate performances.

Acknowledgements

Support was provided by the Brazilian Ministry of Education (Coordination for the Improvement of Higher Education Personnel – CAPES – grant 99999.007489/2015-03) to Flavio Henrique Bastos

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Figures

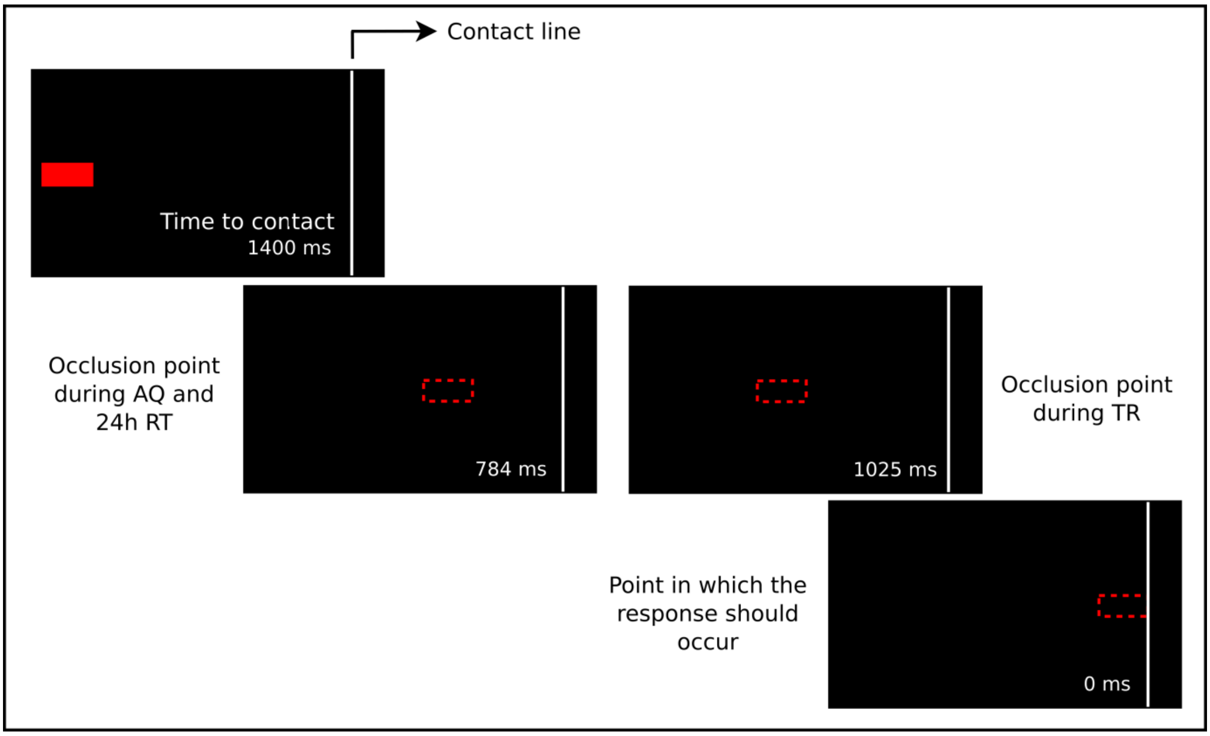


Figure 1

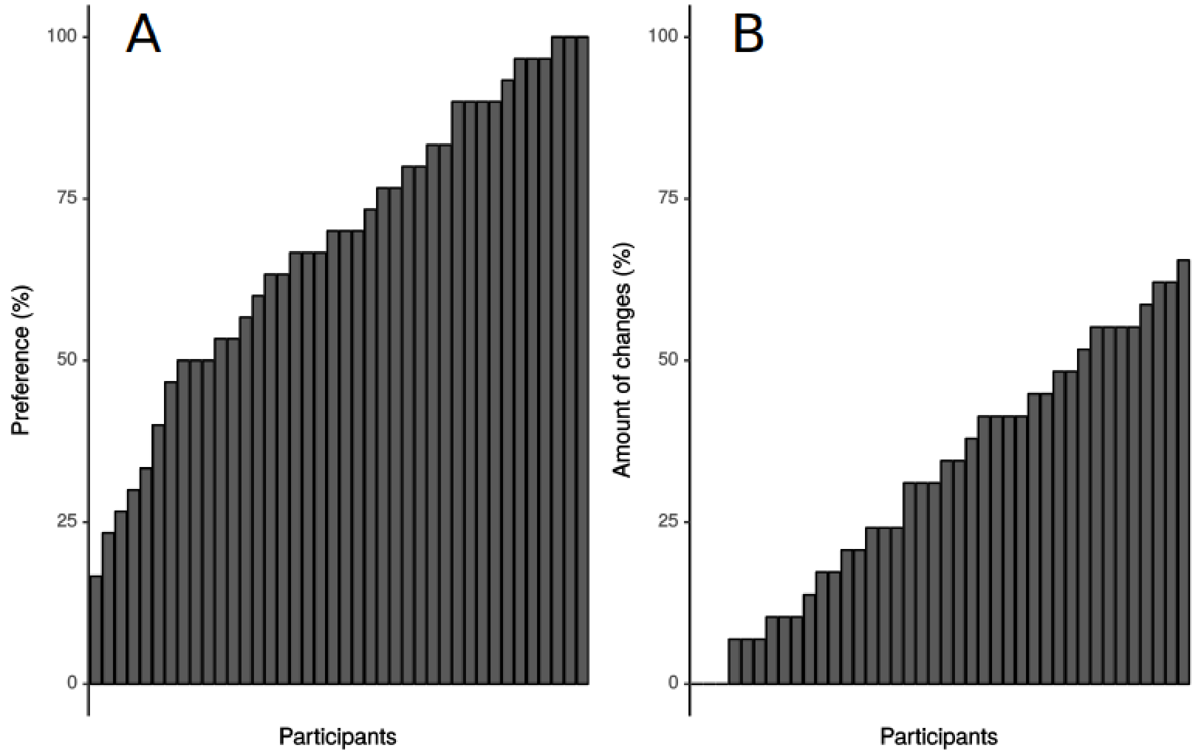

A
100
75
50
25
0
Preference (%)
Participants
B
100
75
50
25
0
Amount of changes (%)
Participants

Figure 2

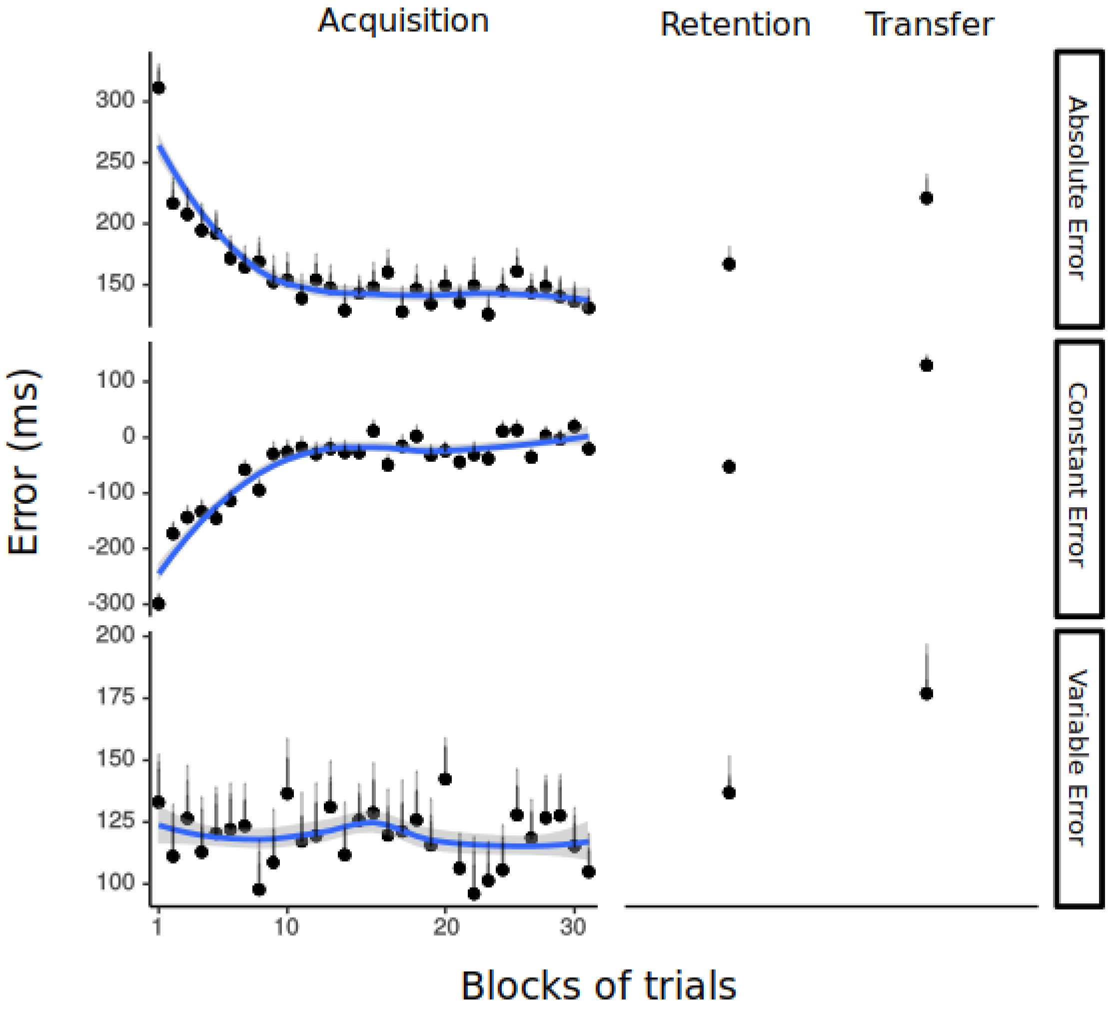


Figure 3

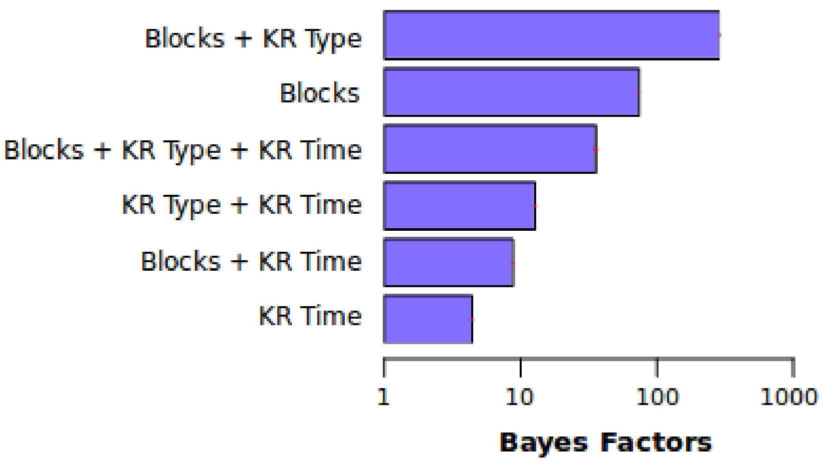
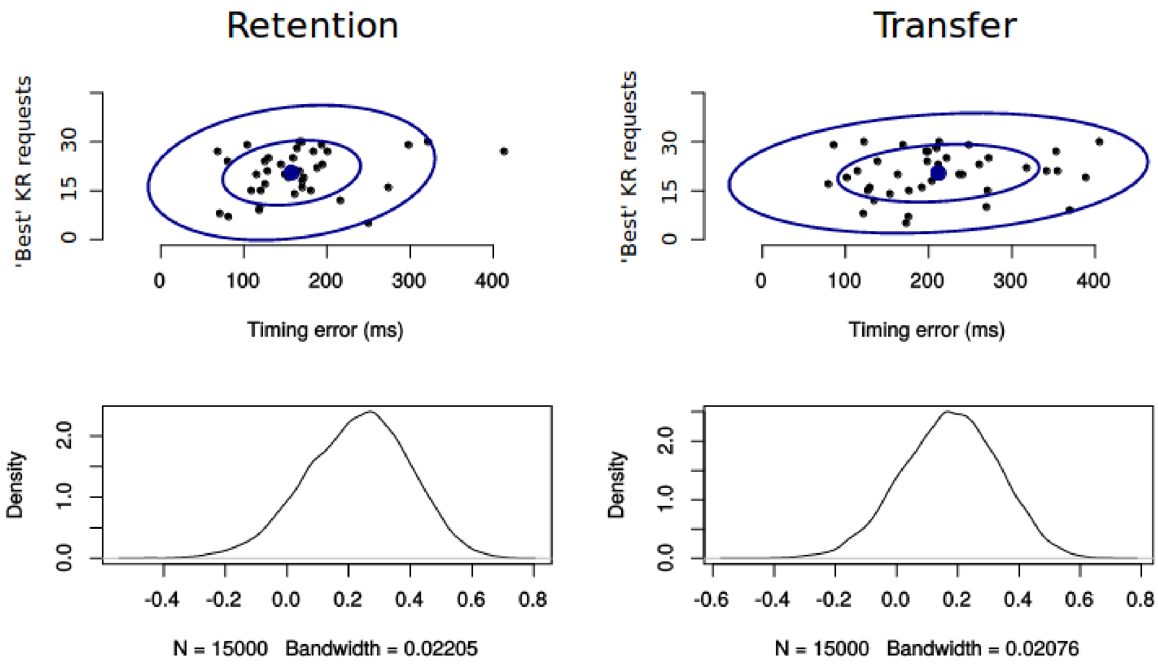


Figure 4



Retention
Transfer
'Best' KR requests
0
15
30
Timing error (ms)
0
100
200
300
400
Density
0.0
1.0
2.0
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
N = 15000 Bandwidth = 0.02205
N = 15000 Bandwidth = 0.02076

Figure 5

Captions

Figure 1: Schematic drawing of the visual stimuli (not to scale) during Acquisition (AQ), 24h-Retention test (RT) and 24h-Transfer test (TR).

Figure 2: Left panel: frequency of KR about the best performance requested by each participant. Right panel: Percentage of change from one choice to another, regarding the type of KR during the AQ.

Figure 3: Mean Absolute, Constant and Variable Errors of all participants (black dots), per block of trials, on Acquisition, Retention and Transfer. First block of the AQ indicates performance before any feedback was provided (Baseline). The blue line indicates a locally weighted smoothing of the data (loess) and the grey shading area the standard error of the mean for repeated measures.

Figure 4: Bayes factors for the six better models having the Absolute Error as the predicted variable and Blocks of trials, KR type and KR time as predictors. Each bar represents the relative evidence of a given model against the null model (i.e. how likely is the data under each model, relative to the null) with a Bayes factor of 1 indicating no evidence in favour of the alternative or the null hypothesis). Participants were considered as random effects.

Figure 5: Correlation between the amount of KR about most accurate performances and the Absolute Error in Retention (left plots) and Transfer (right plots) tests. Blue lines in the upper

plots show 50%CI and 95%CI derived from the posterior prediction. Actual data (black dots) do not appear to deviate systematically from the trend predicted by the model. Lower plots show the probability density of the posterior values for the correlations coefficients.