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Electroencephalographic evidence for a reinforcement learning advantage during motor skill acquisition

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ABSTRACT

The feedback that we receive shapes how we learn. Previous research has demonstrated that quantitative feedback results in better performance than qualitative feedback. However, the data supporting a quantitative feedback advantage are not conclusive and further little work has been done to examine the mechanistic neural differences that underlie the relative benefits of quantitative and qualitative feedback. To address these issues, participants learned a simple motor task in quantitative and qualitative feedback conditions while electroencephalographic (EEG) data were recorded. We found that participants were more accurate and had a larger neural response – the feedback related negativity - when qualitative feedback was provided. Our data suggest that qualitative feedback is more advantageous than quantitative feedback during the early stages of skill acquisition. Additionally, our findings support previous work suggesting that a reinforcement learning system within the human medial-frontal cortex plays a key role in motor skill acquisition.

1. Introduction

Feedback about a performance outcome is critical during the early stages of motor learning (Newell, 1977) and it has been shown that extrinsic feedback facilitates the efficiency and effectiveness of skill acquisition (Trowbridge & Cason, 1932; Bilodeau & Bilodeau, 1958; Bennett & Simmons, 1984; Magill & Wood, 1986; Reeve, Dornier, & Weeks, 1990; Salmoni, Ross, Dill, & Zoeller, 1983; Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2018; Sherwood, 1988; Winstein & Schmidt, 1990). In the motor learning literature, extrinsic feedback has been dichotomized based on the information conveyed within the feedback signal – knowledge of results (KR) and knowledge of performance (KP) (Salmoni, Schmidt, & Walter, 1984). KR is the provision of information about a movement outcome (e.g., response accuracy), whereas KP is the provision of information about the quality and precision of a movement pattern independent of the outcome.

An interesting but relatively unexplored issue relating to the provision KR is whether or not performance feedback should be qualitative (e.g., "you missed the target") or quantitative (e.g., "you undershot the target by 5 cm") in nature. In seminal work, Magill and Wood (1986) had performers learn to move their limb through a series of wooden barriers to produce a specific six-segment movement pattern within a movement time criterion. Magill and Wood observed that performance during the early stages of skill acquisition (i.e., the first 60 trials) was comparable for qualitative and quantitative KR conditions; however, in the later stages of acquisition (the last 60 trials) quantitative KR resulted in more accurate performance in terms of meeting the movement time criterion. Interestingly, Magill and Wood's findings are frequently interpreted not only to evince the importance of quantitative KR during later skill acquisition, but also in terms of the comparable benefit of qualitative and quantitative KR during early skill acquisition (see also Smoll, 1972; Reeve & Magill, 1981).

From a theoretical perspective, the provision of qualitative or quantitative KR defines whether reinforcement or supervised learning is occurring (Sutton & Barto, 1998). During reinforcement learning feedback only indicates the outcome of an action (i.e., qualitative feedback), whereas during supervised learning feedback indicates the direction and magnitude of an error (quantitative feedback). In other words, an important distinction between reinforcement or supervised learning relates to the amount of information present in the learning signal as the inclusion of magnitude of error associated with a supervised learning signal carries more information than a reinforcement learning signal. The supposition that there is an amount of information carried within a feedback signal is also referred to as the level of feedback precision – an idea also put forward by Magill and Wood (1986). More recently, research has also begun to differentiate the role of reinforcement learning signals (i.e., task performance errors) and sensory learning signals in motor learning (i.e., sensory prediction errors; Morehead, Taylor, Parvin, & Ivry, 2017).

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Event-related brain potentials (ERPs) have been used to probe the role of reinforcement learning in motor skill acquisition. For example, in a series of experiments Krigolson and Holroyd (2006), 2007a, 2007b, Krigolson, Holroyd, Van Gyn, & Heath, 2008) demonstrated that a specific neural response – the feedback related negativity (FRN) - was elicited when participants failed to achieve movement goals during the performance of simple motor tasks. Notably, a well cited theoretical account posits that the FRN reflects a dopaminergic dependent reinforcement learning signal within the medial-frontal cortex (Holroyd & Coles, 2002). Specifically, Holroyd and Coles proposed that the FRN reflects a reinforcement learning prediction error computed within the basal ganglia that is conveyed to the anterior cingulate cortex via the midbrain dopamine system. Thus, the FRN is evoked when a movement goal is not met and has been proposed to represent an underlying mechanism for subsequent behavioural modification. Recent evidence also suggests that the FRN is sensitive to the extent of an error – in other words – the degree of difference between the movement goal and the outcome (Frömer, Stürmer, & Sommer, 2016; Luft, Takase, & Bhattacharya, 2014; Meadows, Gable, Lohse, & Miller, 2016; Ulrich & Hewig, 2014).

With this in mind, recent evidence is counter to Magill and Wood (1986) original finding that the provision of quantitative feedback results in more accurate performance than the provision of qualitative feedback. Cockburn and Holroyd (2018) recorded ERP data while participants learned to guess the duration of one second. In a key manipulation, the authors provided participants with qualitative feedback indicating the valence of the outcome (e.g., correct or incorrect) or quantitative feedback that conveyed the outcome and also corrective information (e.g., you responded 100 ms too early). Cockburn and Holroyd's study showed that FRN amplitude was inversely related to the amount of feedback information provided to participants. Put another way, the neural response associated with feedback evaluation was larger when qualitative as opposed to quantitative feedback was provided. Somewhat problematically however, Cockburn and Holroyd did not observe a performance difference between the qualitative and quantitative feedback conditions thus making it impossible to gauge the relationship between the amount of feedback information provided and performance.

Here we present the results from two studies to examine the impact of qualitative and quantitative feedback on the acquisition of a simple pointing task during the early stage of motor skill acquisition. In the first study, participants manipulated a stylus to move a cursor to a target location without vision while ERP data were recorded. At the end of their responses participants were either provided with qualitative (i.e., "hit" or a "miss") or quantitative (i.e., a visual display indicating their movement relative to the target) feedback. Given this manipulation, we sought to clarify an apparent division in the literature. In line with the classic motor learning literature (e.g., Magill & Wood, 1986), we hypothesized that participants would be more accurate and the amplitude of the FRN would be larger in the quantitative as opposed to in the qualitative feedback condition. In turn, and based on the work of Cockburn and Holroyd (2018; and also Magill, 2001), we acknowledged the possibility that participants would be more accurate and elicit a larger FRN in the qualitative than quantitative feedback condition. As we had to manipulate target size in our first experiment to get clean ERP data and avoid N200 contamination (see Krigolson, 2018), we ran a follow up behavioural study that was identical to the first without the target size manipulation to replicate our behavioural findings. Importantly, we predicted that our results would highlight whether the provision of qualitative or quantitative feedback differentially influences early motor skill acquisition.

2. Experiment one

2.1. Methods

2.1.1. Participants

Fifteen undergraduate students (8 female, age: 21 years [19 25]) participated in this study for course credit. All participants were right handed and had normal or correct-to-normal vision, and none reported any neurological or psychological impairments. Written consent was obtained via a project approved by the Office of Research Services at the University of Victoria, and this work was conducted according to the ethical standards prescribed in the 1964 Declaration of Helsinki.

2.1.2. Task and apparatus

Participants were seated in a sound dampened room in front of midline centred 19" LCD computer monitor (1280 × 1024, 75 Hz response rate) located 700 mm from the front edge of the table. Participants held a stylus (160 mm in length, 17.9 g) in their right hand and slid it across a graphics tablet (197 Hz: WACOM Intuos 4, model PTK-1240, Kazo, Japan) to manipulate the position of a cursor (5 mm diameter, RGB value [0, 150, 0]) appearing on the computer monitor. Movement of the stylus corresponded to unitary (i.e., 1:1) movement of the cursor appearing on the monitor. The task was custom-coded using MATLAB (Version 8.6, Mathworks, Natick, USA) and the Psychophysics Toolbox extensions (Brainard, 1997). For all trials, visual stimuli were presented on a dark grey screen (RGB value [100, 100, 100]).

At the start of a trial, participants moved the cursor via the stylus onto a home position (i.e., a 25 mm^2 open square, RGB value [0, 0, 0]) located on the left side of the display at the monitor's midline 113 mm from the screen's lower edge. Once the cursor was placed on the home position a black square target (13 mm^2; RGB value [0, 0, 0]) located either 250, 275, 300, or 325 mm (target displacement depended on experimental block; see below) in the sagittal plane from the home position was presented for a 800–1200 ms preview after which time a tone (50 ms duration, 3000 Hz) cued participants to initiate their response. At movement onset (see details below) the cursor and the target were extinguished and thus participants had to move the stylus to the target location without vision of the cursor or the target (i.e., open-loop reaching; for an extensive review see Heath, Neely, Krigolson, & Binsted, 2010). Following a delay of 400–600 ms after movement completion, participants were shown a feedback screen indicating the outcome of the reaching trial (see below).

Reaching responses were completed in two knowledge of results (KR) conditions. In the qualitative KR condition participants were provided with a feedback screen for 1000 ms indicating whether their endpoint was within the target region ("HIT") or off the target region ("MISS"). In the quantitative KR condition participants were shown the end location of their cursor relative to the target for 1000 ms; that is, participants were provided feedback related to the magnitude and direction of their reaching error (see Supplementary Fig. 1). For purposes of experimental analyses, comparison between conditions (qualitative versus quantitative), on- and off-target trials are referred to as hits and misses, respectively. In a manipulation of task difficulty, if participants were on target (i.e., their cursor was completely within the target), the size of the target was reduced 1.5 mm on a subsequent trial. In contrast, if participants missed the target, (i.e., their cursor did not touch the target at all) target size was increased by 1.5 mm. The manipulation of task difficulty was included to help avoid frequency contamination of the FRN (see Krigolson & Holroyd, 2007b, 2007b) and ensure overall accuracy was approximately 50 %. Note, the task was still "learnable" as we expected to see a difference in radial error between experimental conditions. Participants were also required to complete their response with a movement time MT bandwidth between 600 and 1000 ms relative to movement start. Reaching responses outside of the bandwidth were provided a screen message i.e., "TOO FAST" or "TOO SLOW" and those trials were repeated less than 5 % of trials).

Qualitative and quantitative KR trials were performed in 8 blocks (4 qualitative, 4 quantitative) of 30 trials for a total of 240 experimental trials. The order of the qualitative and quantitative feedback blocks was randomized, but all 4 blocks in each condition were completed sequentially. In other words, participants either completed 4 blocks with qualitative feedback and then 4 blocks with quantitative feedback or vice versa. Two of the target locations were assigned to each of the experimental conditions to avoid carry over effects and within each condition the target location was varied between the two locations for that condition between trials. Target size was reset to the original target size at the start of each experimental condition (13 mm^2). At the start of the experiment participants completed 20 practice trials from a novel start location to a novel target location to gain experience with the experimental apparatus.

2.1.3. Behavioural data acquisition

For the behavioural data, position of the stylus was filtered via a dual-pass Butterworth filter with a low-pass cutoff frequency of 30 Hz. Position data were differentiated via a five-point central finite difference algorithm to compute instantaneous velocities. Movement onset and offset were determined via a velocity criterion that exceeded or fell below, respectively, 30 mm/s for 30 consecutive frames. Dependent variables included reaction time (RT: time from auditory tone to movement onset), movement time (MT: time from movement onset to offset), radial error (RE: the vector displacement from the centre of the movement target) and the 95 % confidence ellipses related to the variability of endpoints in the primary and secondary movement directions (i.e., area of the confidence ellipse) (see Heath et al., 2010 for more detail on this dependent measure). Note, we also examined overall effects on RE and also examined practice effects on RE by collapsing the RE scores for each of the 120 trials into 10 equally sized bins for each of the experimental conditions.

2.1.4. EEG data acquisition

Electroencephalographic data (EEG) was recorded using BrainVision Recorder software (Version 1.21, BrainProducts, GmbH, Munich, Germany) from 41 electrodes that were mounted in a fitted cap with a standard 10–20 layout. EEG data were recorded from Fp1, Fp2, Fpz, F3, F4, F7, F8, Fz, FC1, FC2, FC5, FC6, FT9, FT10, C3, C4, Cz, T7, T8, CP1, CP2, CP5, CP6, TP9, TP10, P3, P4, P7, P8, Pz, PO7, PO8, POz, Oz, along with mastoid electrodes at TP9 and TP10. Three facial electrodes were also placed for eye blink detection: one placed on the outer canthi of the right and left eyes and one placed under the right eye. Electrodes were originally referenced to a common reference and electrode impedances were kept below 20 kΩ at all times. The EEG data were sampled at 250 Hz, amplified (ActiChamp, BrainProducts, GmbH, Münich, Germany), and filtered through an antialiasing low-pass filter of 8 kHz. Experimental event markers were delivered to the EEG acquisition computer via 8-bit parallel port delivering integers between 1 and 255.

2.1.5. EEG data processing

EEG data were processed offline using BrainVision Analyzer 2 software (Version 2.11, BrainProducts, GmbH, Münich, Germany) using methods we have previously used in our laboratory (see http://www.neuroeconlab.com/data-analysis.html). Processing began with removing any faulty or excessively noisy channels and remaining channels were re-referenced to the average mastoid channels. Next, data were filtered using a dual-pass Butterworth filter with a pass band of 0.1 Hz–30 Hz and a 60 Hz notch filter. Subsequently, data segments surrounding events of interest (i.e., 1000 ms before to 2000 ms after feedback stimulus onset) were extracted from the continuous EEG. These segments were then submitted to independent component analysis (ICA) to correct eye movement artifacts (Delorme & Makeig, 2004; Luck, 2005). Following ICA, data were reconstructed without the ocular ICA components and any removed channels were interpolated using the method of spherical splines. Shorter data segments were then constructed (from 200 ms to 600 ms after feedback stimulus onset) and a baseline correction was applied to all segments using a 200 ms window preceding event onset. Finally, all segments underwent an artifact rejection algorithm that marked and removed segments that had voltage gradients greater than 10 μV/ms and/or a 100 μV absolute within segment voltage difference. The artifact rejection procedure resulted in a loss of less than 10 % of the overall data.

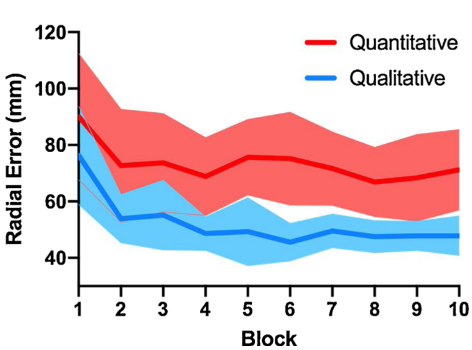
For each participant and experimental condition (qualitative hit, qualitative miss, quantitative hit, quantitative miss), event-related potential (ERP) waveforms were calculated by averaging the preprocessed segmented EEG. Next, difference waveforms were calculated by subtracting the average hit trial waveforms from average miss trial waveforms for both experimental conditions (qualitative, quantitative). Grand average waveforms were created from each participant's conditional and difference waveforms by averaging corresponding ERPs across all participants. To assist with ERP component identification, a spatial-temporal principal component analysis (Spencer, Dien, & Donchin, 2001) was conducted on the grand average ERP data to identify a principal component with a spatial topography and timing consistent with the FRN. Based on the PCA analysis (see Results), we conducted a mean peak analysis on the difference waveforms for each condition (qualitative, quantitative) at channel FCz (maximal spatial PCA loadings) at 300 ms (+/- 25 ms mean window) and quantified the FRN in this manner for statistical analysis.

2.1.6. Statistical analyses

Behavioural measures and the FRN amplitude were contrasted between qualitative and quantitative KR conditions using paired samples t-tests ($p < .05$). 95 % confidence intervals are reported for all data (Cumming, 2013; Masson & Loftus, 2003).

3. Results

RT and MT values did not differ between qualitative and quantitative conditions (RT: 345 ms [306 383] versus 347 ms [311 382]; $t(14) = 0.21$, $p = 0.83$; MT: 886 ms [865 908] versus 894 ms [874 915]; $t(14) = 0.83$, $p = 0.41$). The analysis of RE demonstrated that overall, participants were more accurate in the qualitative (50.3 mm [45.4 55.63]) than quantitative (71.9 mm [54.8 88.9]) condition, $t(14) = 3.47$, $p = 0.003$ (see Fig. 1 left panel). Furthermore, visual inspection of Fig. 1 (left panel) and a simple effects comparison of the first and last blocks within each condition (Qualitative: $t(14) = 2.46$, $p = 0.024$; Quantitative: $t(14) = 3.91$, $p < 0.001$) demonstrated that RE diminished as a function of practice. To examine the impact of errors on performance in the two feedback conditions we compared the



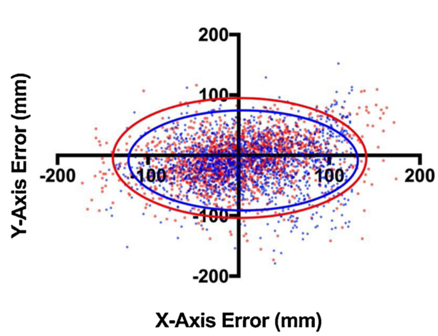


Fig. 1. Left Panel. Radial error as a function of block for both the qualitative and quantitative feedback conditions showing greater movement accuracy in the qualitative feedback condition (the shaded error region reflects the 95 % confidence interval). Right Panel. Endpoint 95 % confidence ellipses highlighting reduced endpoint variability in the qualitative as opposed to the quantitative feedback condition.

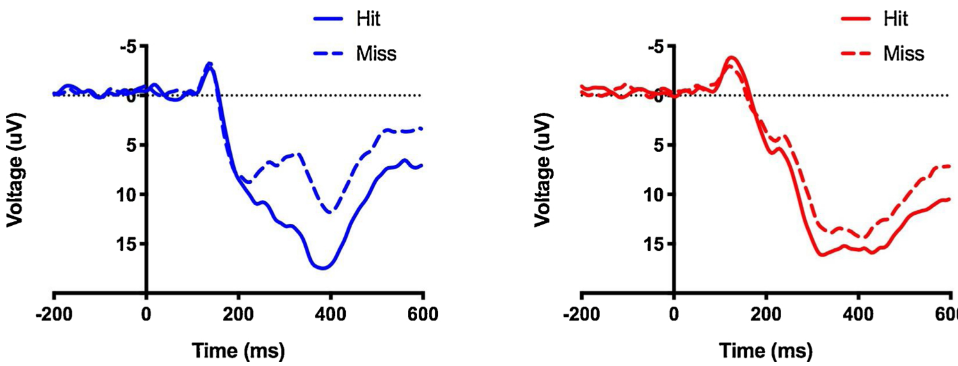


Fig. 2. Grand average ERP waveforms for the qualitative (left) and quantitative (right) feedback conditions.

change in RE on the trial after miss trials and found that participants made larger post error adjustments in the qualitative feedback condition (9.0 mm [6.4 11.5]) than in the quantitative feedback condition (5.8 mm [4.3 7.3])($t(14) = 3.43$, $p = 0.004$). Finally, we also found that the confidence ellipses for the qualitative condition were smaller than for the quantitative condition $t(14) = 2.33$, $p < 0.05$ (see Fig. 1 right panel).

As noted above, a spatial-temporal analysis of the ERP data revealed that the first spatial component accounted for 87 % and had maximal loadings at channel FCz. The temporal PCA on this spatial factor revealed a component with maximal loadings at 300 ms that accounted for 24 % of the variance. Based on the spatial temporal PCA results, and previous literature examining the FRN and its role in motor learning (see Krigolson & Holroyd, 2006, 2007a), we conducted an ERP peak detection analysis on the FRN. This analysis revealed that the amplitude of the FRN was more negative for the qualitative (-7.3 u V [-9.2–5.3]) than quantitative (-2.3 u V [-4.0 -0.5]) feedback condition ($t(14) = 3.1$, $p = 0.009$) (see Figs. 2 and 3). Finally, we examined whether or not the mean FRN amplitude per participant was related to subsequent mean behavioural performance and found a relationship between mean post error adjustments (change in RE following error trials) and mean FRN amplitude, $r = -0.33$, $p = 0.05$.

4. Experiment two

One potential confound with Experiment One was that the trial to trial change in target size might have biased reaching strategies and/or our results[1] . As such, we ran a second behavioural study to affirm that the aforementioned target size confound did not bias our findings.

5. Methods

5.1. Participants

Thirty-five undergraduate students (19 female, age: 21 years [19 24]) participated in this study for course credit. All participants were right-handed and had normal or correct-to-normal vision, and none reported any neurological or psychological impairments. Written consent was obtained via a project approved by the Office of Research Services at the University of Victoria, and this work was conducted according to the ethical standards prescribed in the 1964 Declaration of Helsinki.

5.2. Task and apparatus

The task and apparatus were identical to Experiment One in all regards with the following exceptions. Target size did not change on a trial to trial basis. Instead, in both feedback conditions, participants completed aiming movements to a small target "+" presented at one of the two target locations used in Experiment One (250 mm, 300 mm). In the qualitative feedback condition, a hit was considered to be +/−50 mm in both movement axes and hit/miss feedback was provided accordingly. In the quantitative feedback condition, participants were shown their final endpoint location relative to the movement target and the target "hit" zone (i.e., +/− 50 mm). It is important to note that participants were instructed that their goal was to be as accurate as possible each block and try and hit the target location exactly (i.e., the "+"). As in Experiment One, vision of the participants cursor and target location were extinguished at movement onset and participants completed 8 blocks (4 qualitative, 4 quantitative) of 30 trials for a total of 240 experimental trials. The order of the qualitative and quantitative feedback blocks were randomized, but all 4 blocks in each condition were completed sequentially. Note, the target locations were also randomly counterbalanced between the two experimental conditions between participants. At the start of the experiment participants completed 20 practice trials from a novel start location to a novel target location to gain experience with the experimental apparatus. No electroencephalographic data were recorded in Experiment Two. Behavioural data acquisition, measures, and statistical analyses were identical to Experiment One.

6. Results

As in Experiment One, RT and MT values did not differ between qualitative and quantitative conditions (RT: 326 ms [314 338] versus 325 ms [314 326]; $t(34) = 0.09$, $p = 0.93$; MT: 718 ms [651 785] versus 713 ms [650 776]; $t(34) = 0.51$, $p = 0.62$). Our analysis of RE indicated participants were more accurate in the qualitative (53.4 mm [47.8 59.0]) than quantitative (74.4 mm [60.2 88.4]) condition, $t(34) = 2.79$, $p = 0.008$ (see Fig. 4 left panel). Again, a comparison of the first and last blocks within each condition (Qualitative: $t(34) = 3.76$, $p = < 0.001$; Quantitative: $t(34) = 3.34$, $p < 0.001$) demonstrated that RE diminished as a function of practice. Interestingly, we did not find a difference in the magnitude of post error adjustments between the qualitative (12.4 mm [8.4 16.5]) and quantitative feedback conditions (15.7 mm [11.6 20.3]; $t(34) = 1.41$, $p = 0.17$) as we did in Experiment One. Finally, as in Experiment One, we found that the confidence ellipses for the qualitative condition were smaller than for the quantitative condition $t(34) = 2.10$, $p < 0.05$ (see Fig. 4 right panel).

7. Discussion

We examined how the provision of quantitative and qualitative feedback impacts early motor skill acquisition. In two experiments, our behavioural data demonstrated that participants were more accurate when provided with qualitative as opposed to quantitative feedback. Further, our behavioural results from both experiments demonstrated an

[1] It is important to recall that the change in target size was deliberate to ensure an equal number of trials between hit and miss trials to avoid frequency modulation of the FRN.

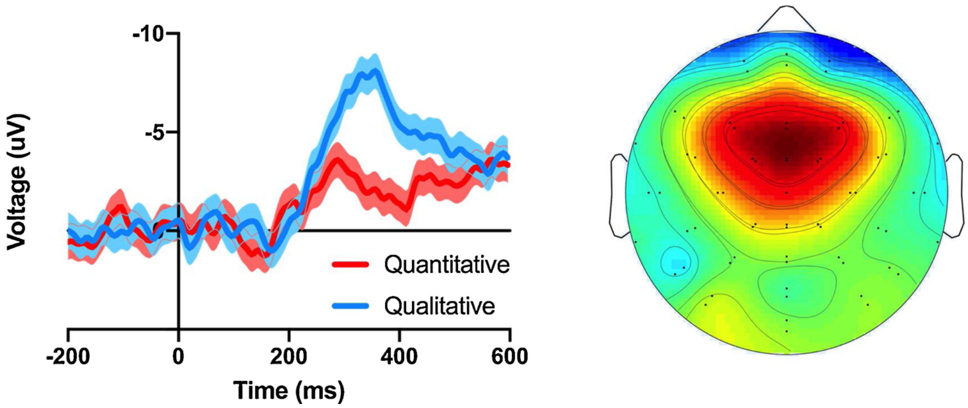


Fig. 3. Grand average ERP difference waveforms for the qualitative and quantitative feedback conditions with 95 % within subject confidence intervals (left) and topographical map of the FRN derived from spatio-temporal principal component analysis.

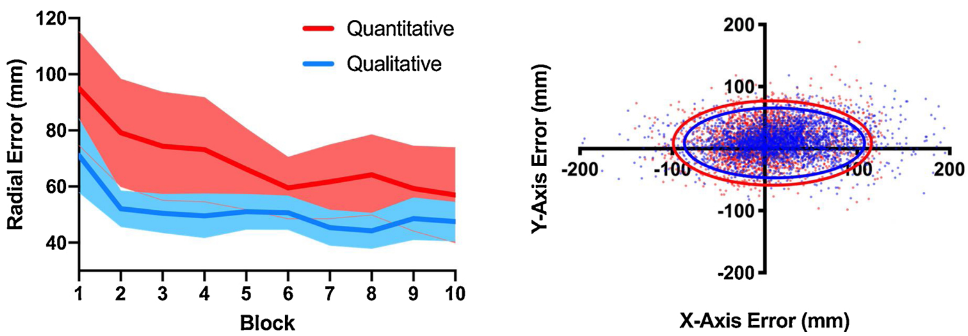


Fig. 4. Left Panel. Radial error as a function of block for both the qualitative and quantitative feedback conditions (the shaded error region reflects the 95 % confidence interval). Right Panel. Endpoint 95 % confidence ellipses.

overall improvement in reaching performance over the course of the experiment. An analysis of our ERP data from Experiment One revealed that the amplitude of the feedback-related negativity (FRN) was greater for qualitative as opposed to for quantitative feedback. The results in the present experiment are in line with previous work demonstrating that tracking (Krigolson & Holroyd, 2006, 2007b), aiming (Anguera et al., 2009; Krigolson & Holroyd, 2007b), and postural (Colino et al., 2017; Hassall, Maclean, & Krigolson, 2014) errors evoke a FRN. Our findings are also in line with a prominent theory proposing that the FRN is the electroencephalographic correlate of a dopaminergic reinforcement learning signal within the medial-frontal cortex used to reinforce behaviour (Holroyd & Coles, 2002). It is worth noting that within the domain of motor tasks such as the one employed here, we propose that the FRN is not reinforcing a specific stimulus – response coupling per se but is instead reinforcing an underlying movement structure (Luft et al., 2014).

The increased movement accuracy and larger FRN amplitude that we observed in the qualitative feedback condition in Experiment One and the increased movement accuracy that we observed in the qualitative feedback condition in Experiment Two may appear to be at odds with the extant motor learning literature reporting a performance advantage when quantitative feedback is provided during motor skill acquisition (e.g., Magill & Wood, 1986; Reeve & Magill, 1981; Smoll, 1972). However, recall that Magill and Wood (1986) found that the provision of qualitative and quantitative feedback resulted in comparable performance during the initial stage of skill acquisition – a result that has been taken as evidence that qualitative feedback may be as effective as quantitative feedback in the initial phase of motor skill acquisition (Magill, 2001). It is important to clarify that the provision of qualitative and quantitative feedback being discussed here actually differentiates two different types of learning – reinforcement and supervised. Indeed, what we have labeled as qualitative feedback reflects reinforcement learning – the provided feedback is solely about the outcome of a given action. Conversely, what we have labelled as quantitative feedback reflects supervised learning – the provided feedback indicates the outcome of a given action but also provides corrective / guiding information to improve future performance (see Sutton & Barto, 1998)[2] . With this in mind, Cockburn and Holroyd (2018) recently found that FRN amplitude was greater during reinforcement learning than during supervised learning when participants performed a modified time-estimation task (see also Baker & Holroyd, 2011). Thus, the data presented here can be reconciled with previous literature if one frames the feedback conditions in the present experiment as reinforcement (qualitative feedback) and supervised learning (quantitative feedback). As such, if human motor learning is governed at least in part by reinforcement learning principles then our results suggest that the provision of outcome feedback results in enhanced performance and larger neural signatures during the early stages of skill acquisition. One can only speculate at this point in time however as to whether or not the qualitative feedback advantage (i.e., reinforcement learning advantage) that we observed in the present experiment is specific to certain task structures or is generalizable to all learning environments.

It is important to note that a converse argument for our findings could also be true. Our results could be interpreted as a reduction in FRN amplitude in the quantitative feedback condition as opposed to an enhanced FRN amplitude in the qualitative feedback condition. Indeed, differences in feedback modality between the qualitative condition (visual-verbal) and the quantitative condition (visual-spatial) might have caused the differences in FRN amplitude that we observed here.

[2] During reinforcement learning feedback can be quantitative and during supervised learning feedback can be qualitative. What distinguishes the two feedback conditions (and the two types of learning) is whether or not the feedback only contains information about the outcome (reinforcement learning) or if the feedback also provides corrective information (supervised learning).

Specifically, the reduction in FRN amplitude in the quantitative condition could be attributed to increased variability in feedback processing time which would have “smeared” the amplitude of the FRN thereby reducing it (c.f., Baker & Holroyd, 2011). Alternatively, the blunting of the FRN in the quantitative condition could also be related to the acquisition of knowledge about task structure (i.e., an internal model; McDougle et al., 2019). Indeed, with an internal model of the task in the quantitative feedback condition participants might have been able to accurately predict the outcome and the FRN was blunted (Frömer, Nassar, Stuermer, Sommer, & Yeung, 2018).

Another explanation for a relative blunting of the FRN in the quantitative feedback condition relates to learning the underlying structure of a task. Specifically, Collins (2017) has proposed that learning an underlying task structure has an initial cost that results in performance decrements. Thus, another explanation for the behavioural and electroencephalographic deficits that we observed in the quantitative condition is that the availability of feedback about the magnitude of movement errors in this experimental condition provided information about the underlying task structure. And, as proposed by Collins (2017), acquiring this underlying task structure resulted in a performance deficit relative to the qualitative feedback condition where the type of feedback that was available did not lend itself to learning the underlying task structure.

In terms of previous studies that highlight an advantage for performers receiving quantitative as opposed to qualitative feedback, we can only speculate. It is quite possible that task differences or stage of skill acquisition impact the relative benefits of qualitative versus quantitative feedback. Here, we used an open-loop reaching paradigm and it is therefore possible that the differences seen here between the qualitative and quantitative conditions were related to the fact that vision of the limb and target was not available during aiming movements (see Heath, 2005). Alternatively, it is possible that in the early stages of acquisition qualitative feedback is more beneficial than quantitative feedback – a possibility suggested by Magill (2001) and supported by Cockburn and Holroyd (2018). Supporting this view, Fitts and Posner’s (1967) proposed the initial stage of motor learning is cognitive in nature and therefore during this stage of learning the motor system may be better suited at integrating relative (i.e., qualitative) than absolute (i.e., quantitative) feedback.

8. Conclusions

Here we demonstrate that the provision of qualitative feedback resulted in improved accuracy and a larger neural signal associated with feedback evaluation. Based on these results we propose that qualitative feedback serves as a viable resource in the early stage of motor skills acquisition and that such feedback serves a reinforcement learning system within the human medial-frontal cortex.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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