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Frontal Theta Band Oscillations Predict Error Correction and Post Error Slowing in Typing

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Performance errors are associated with robust behavioural and EEG effects. However, there is a debate about the nature of the relationship between these effects and implicit vs. explicit error awareness. Our aim was to study the relationship between error related electrophysiological effects, such as spectral perturbations in fronto-medial theta band oscillations (FMT), and error awareness in typing. Typing has an advantage as an experimental paradigm in that detected errors are quickly and habitually signalled by the participant using backspace, allowing separation of detected from undetected errors without interruption in behaviour. Typing is thought to be controlled hierarchically via inner and outer loops, which rely on different sources for error detection. Touch-typist participants were asked to copy-type 100 sentences as EEG was recorded in the absence of visual feedback. Continuous EEG data were analysed using independent component analysis (ICA). Time-frequency and ERP analyses were applied to emergent independent components. The results show that single-trial FMT parameters and Error Related Negativity (ERN) amplitude predict overt, adaptive post-error actions such as error correction via backspace; and, post-error slowing after errors, reflecting implicit error awareness. In addition, we found that those uncorrected errors which were slowed down the most were also the ones associated with a high level of FMT activity. Our results as a whole show that FMT are related to neural mechanism involved in explicit awareness of errors, and input from inner loop is sufficient for error correction in typing.

Public Significance

We investigated the patterns of brain activity which precede errors and error-correction during skilled typing. This is interesting because it tests how theories of action and error-monitoring apply in a domain where actions are made extremely rapidly (up to ten keys per second). Electroencephalography (EEG) allows us to identify signature changes which have previously been associated with error-related processes in the brain. We showed that two of these signature patterns, the "error related negativity" (ERN) and "fronto-medial theta band oscillations" (FMT), both predict whether a typist is likely to notice and correct an error they make, as well as predicting how much typing slows down after an uncorrected error. The results support the idea - which has been contested - that the ERN reflects our explicit recognition that we have made a mistake.

Introduction

Performance monitoring is crucial for keeping ongoing actions in-line with long term intentions. Errors lead to consistent behavioural and electrophysiological changes detectable by the electroencephalogram (EEG). These include post-error slowing (PES Rabbitt, 1966a) in addition to event related potential (ERP) components such as medio-frontal error related negativity (ERN) and centro-parietal error related positivity (Pe, Falkenstein, Hohnsbein, Hoormann, & Blanke, 1991; Gehring, Goss, Coles, Meyer, & Donchin, 1993) as well as medio-frontal oscillatory changes in theta frequency range (Luu & Tucker, 2001). The current investigation aims to study how changes in these parameters unfold

over time on an everyday task, and their implications for current theories of error awareness.

Error related negativity in particular is one of the most reliable error related ERP components (Gehring, Liu, Orr, & Carp, 2012). Even though ERN and Pe are strongly associated with error actions, they are independent of the motor effector used (Gehring & Fencsik, 2001; Holroyd, Dien, & Coles, 1998), and thus are viewed as indices of cortical activity associated with cognitive rather than motor control. In discrete trial tasks, ERN and Pe peaks appear 60-80ms and 180-300ms after the error response, respectively (Overbeek, Nieuwenhuis, & Ridderinkhof, 2005; van Veen & Carter, 2002). It is worth noting that timing of the peaks can be earlier in skilled actions. For example Herrojo-Ruiz, Jabusch, and Altenmuller (2009) and Maidhof, Rieger, Prinz, and Koelsch (2009) found that the ERN peak *precedes* the error key-press in piano playing.

A number of factors might be contributing to the earlier peak of ERN in such continuous tasks. Firstly, skilled actions such as typing and piano playing involve temporally overlapping responses (Soechting & Flanders, 1992), such that multiple key-presses are being prepared and executed at a given moment. This may in some cases increase the temporal gap between incorrect finger motion onset and its execution. Assuming that it is the onset of an error rather than its execution that leads to error detection (Rabbitt, 1978), this would lead to an earlier onset of error detection (and ERN) relative to error execution.

Another potential factor bringing the onset of ERN closer in time to the error action during continuous, skilled actions is error slowing (Rabbitt, 1978). In discrete trial tasks such as the flankers task (Eriksen & Eriksen, 1974), many errors are executed faster than correct responses, leading to a consistent difference in the average speed of errors and correct key-presses (e.g. Laming, 1979; Rabbitt, 1968). However, in continuous tasks like typing and piano playing, there is evidence showing that performance often starts to break-down before the error, and the error key-press itself is executed more slowly and with less force on average (Herrojo-Ruiz et al., 2009; Herrojo-Ruiz, Strubing, Jabusch, & Altenmuller, 2011; Kalfaoğlu & Stafford, 2014; Palmer, Mathias, & Anderson, 2012; Rabbitt, 1978; Shaffer, 1975). It is plausible that such error slowing is caused by a late and failed attempt to cancel the initiated error action (Rabbitt, 1978). Such an attempt, even if observed after a subset of errors, would be enough to slow the average speed of errors beyond that of correct key-presses. This would in turn push the average time of error execution later in time and bring it closer to the time of error detection and onset of ERN which are assumed to be triggered by the onset of the error.

While ERN is well established as an ERP component associated with errors, and is one of the most common ERP components used to study error detection, there is a relatively weak consensus in the literature about exactly what neural processes lead to ERN. While Pe is regarded as an index of conscious error awareness and post-error behavioural adjustment, there are different accounts linking ERN to different processes (Gehring et al., 2012). Three of the most popular perspectives are the mismatch theory (Falkenstein et al., 1991) which suggests ERN amplitude reflects the difference between the intended and executed actions; reinforcement learning theory (Holroyd & Coles, 2002), which proposes that ERN amplitude depends on the learning signal which is relayed from the subcortical structures (where the comparison of intended vs. executed actions is carried out) to the cortical structures; and conflict monitoring theory (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Yeung, Bogacz, Holroyd, Nieuwenhuis, & Cohen, 2004) which proposes that ERN amplitude reflects the amount of co-activation of the intended and executed actions at the time of action execution.

There are studies which report that ERN amplitude is related to error awareness (e.g. Gehring et al., 1993; Hewig, Coles, Trippe, Hecht, & Miltner, 2011; Scheffers & Coles, 2000; Shalgi & Deouell, 2012). However, many other studies show no relationship between ERN and error awareness (e.g. Endrass, Franke, & Kathmann, 2005; Endrass, Reuter, & Kathmann, 2007; Gehring & Fencsik, 2001; Nieuwenhuis, Ridderinkhof, Blom, Band, & Kok, 2001; O'Connell et al., 2007). Presence of a large number of studies failing to find a relationship between error awareness and ERN amplitude naturally leads to the conclusion that ERN is not strongly linked to conscious error awareness (e.g. conflict monitoring, Yeung, Botvinick, & Cohen, 2004). This lack of consistency in findings regarding the relationship between the ERN and error awareness is potentially due to the wide range of methodologies used. For example, many of the studies cited above use different motor responses including antisaccades, finger presses and force production in different behavioural paradigms such as flankers, go/no-go, digit entry, and time estimation tasks (see Wessel, 2012, for a review of results of studies using different methods).

The effect of methodological variability on inconsistent findings is further exacerbated in speeded reaction time tasks by the difficulty associated with distinguishing between subjectively detected from undetected errors (not only by the experimenter but also by the participant) in an objective manner. Using a non-habitual response to indicate error awareness in such designs can be problematic for a number of reasons: Even though error detection can take place very fast under natural circumstances and in well practised tasks such as typing (Logan, 1982; Rabbitt, 1978), remembering a briefly presented stimulus, responding to it within several hundred milliseconds, determining that the response was an error, and programming a novel action to signal the error can be heavy on working memory and attentional resources.

This means that trials in which errors are indicated are dis-

tinguished not only by the presence of errors (or the belief in error commission), but also by the evocation of a non-routine action and the commensurate cognitive load. Additionally, it is possible that this additional cognitive load of error signalling weakens the relationship with error-commission. For example, it is not implausible that cognitively onerous error signalling causes participants to raise the criterion against which they judge their confidence in having just made an error.

We reason that one parameter which can provide important insights into inconsistent findings is another frontal EEG measure: theta frequency band oscillations. Luu and Tucker (2001) showed that ERN could be a partial manifestation of an ongoing neural oscillation within the theta frequency band. A later study by Luu, Tucker, and Makeig (2004) showed quite convincingly that theta band oscillations (4Hz-7Hz) and ERN are strongly aligned in time, using single trial as well as grand average EEG traces: Phase of the theta oscillation was reset to more or less the same angle after each error, irrespective of its pre-error phase (i.e. *phase-locking,* Buzsaki, 2006). Even though it has been shown that ERN can be generated without phase-locking in theta band oscillations using simulated EEG data (Yeung, Bogacz, et al., 2004), a number of studies using empirical data and different analytical methods have since replicated the finding that increases in power of and partial phase-locking in theta band oscillations underlie the appearance of ERN (Trujillo & Allen, 2007), and predict post-error changes in performance (Cavanagh, Cohen, & Allen, 2009; Cavanagh & Shackman, 2014; Cohen & van Gaal, 2012; Cohen & van Gaal, 2014; Herrojo-Ruiz et al., 2011), a finding also supported by fMRI studies (Hoffmann, Labrenz, Themann, Wascher, & Beste, 2013). Fronto medial theta band (FMT) oscillations are strongly related to higher level cognitive functions such as conflict (or even anticipation of it, van Driel, Swart, Egner, Ridderinkhof, & Cohen, 2015), novelty detection and realisation of the need for increased control and thus are likely to underlie the associated ERP components such as the N2, correct related negativity (CRN, Vidal, Burle, Bonnet, Grapperon, & Hasbroucq, 2003; Yeung, Botvinick, & Cohen, 2004) as well as the ERN (Cavanagh & Frank, 2014).

Thus, the literature points to a strong link between ERN and theta oscillations; and between error related higher level cognitive processes and theta oscillations. From this perspective, it is possible that ERN (an ERP component driven by theta) is also related to error awareness. However, it is difficult to assert that ERN is an index of error awareness since it is observed after undetected as well as detected errors. We believe one of the more important reasons for this inconsistency in the literature is the difficulty in objectively separating subjectively detected errors from subjectively undetected errors (Wessel, 2012).

Typing. Typing has a number of benefits as an experimental paradigm for the study of psychological processes (Lashley, 1951; Wells, 1916). First, typing has become an integral part of many people's professional and social lives, making it highly ecologically valid. Further, results can be compared and contrasted with those from experimental tasks which involve essentially the same behaviour (i.e. button presses) but in discrete trials rather than in ongoing typing behaviour.

Second, and most importantly, error awareness is signalled by a highly-practised and objective response (i.e. the backspace) in typing. The number of hours of practice an ordinary person acquires over several years in typing is close to that expert athletes or musicians acquire in their fields (Ericsson & Krampe, 1993). Because the association between error awareness and pressing of backspace in typing is reinforced on a regular basis, error signalling response in typing requires minimal cognitive effort (Gentner, 1984; Ohlsson, 1996) and thus makes it more likely that an error will be signalled in time.

Hierarchical Control in Typing and Implicit vs. Explicit Error Detection. One model which provides insights regarding how error detection works in typing was developed by Logan and Crump (2011). According to this theory, typing is controlled hierarchically by two interacting loops. Briefly, the outer loop serves to read, comprehend and produce a word to be typed, which is then passed on to the inner loop. Inner loop decomposes the word into individual letters and prepares and executes the necessary key-strokes on the keyboard. In a series of experiments, Logan and colleagues have convincingly showed that these two loops use different sources to monitor the accuracy of typing and the outer loop has no direct access to the performance of the inner loop (e.g. Liu, Crump, & Logan, 2010; Logan & Crump, 2009, 2010). While the outer loop is sensitive to the ultimate outcome of the performance (i.e. feedback from the screen), inner loop relies on proprioceptive and kinesthetic feedback from the fingers (see Logan & Crump, 2011, for a review). Importantly, in this model slowing after errors (i.e. post-error slowing, PES) is an indicator of monitoring in the inner loop because it is observed even when false feedback to the outer loop suggests no error was committed (Logan & Crump, 2010).

One similar distinction in the neurophysiological error detection literature is made between implicit and explicit error detection (see Shalgi & Deouell, 2013, for a discussion). Implicit error detection is thought to be indexed by error related changes such as the ERN and PES in the absence of overt error reporting or signalling. On the other hand, explicit error detection is indexed by ERP components such as the Pe (Hajcak, McDonald, & Simons, 2003; Nieuwenhuis et al., 2001; Overbeek et al., 2005) and overt error signalling or reporting. Based on these findings, two hypotheses can be tested: A

significant relationship between ERN and PES without error correction would reinforce the idea that ERN is involved in implicit error detection. On the other hand, if ERN was found to be correlated to error correction this would suggest ERN is an index of overt error awareness (Hewig et al., 2011; Shalgi & Deouell, 2012). Both of these scenarios would indicate that inner loop constitutes an important input channel to the generic error detection mechanisms (Cohen, 2014; Miltner, Braun, & Coles, 1997) involved in monitoring responses. It also supports the idea that inner loop is not only capable of disrupting behaviour (i.e. PES) but also triggering adaptive post-error behaviours such as error correction in the absence of feedback to the outer loop.

In order to be able to test the above hypotheses, instructing the participants to use backspace to correct their typing errors was crucial. Using such a highly-practised error signalling response to separate explicitly detected errors from undetected or implicitly detected errors while electrophysiological data are concurrently recorded was a novel and necessary aspect of our methodology to test the above hypotheses.

Error Detection and Slowing in Discrete Trial vs. Continuous Tasks. One measure frequently used in studies of error detection is PES. Rabbitt (1966b) was one of the first authors to show that trials that follow error responses were associated with significant slowing compared to those following correct responses in discrete trial tasks. While it is plausible that PES reflects a conscious attempt to avoid further mistakes, or a shift in strategy to avoid errors by compromising speed for accuracy, Danielmeier and Ullsperger (2011) shows that there is no strong relationship between post error accuracy and PES in the literature (but also see Hajcak et al., 2003). Notebaert et al. (2009), Castellar, Kuhn, Fias, and Notebaert (2010) and Desmet et al. (2012) suggest alternatively that PES is more likely to reflect an orientation of attention triggered by low frequency events including but not limited to errors (but also see Forster & Cho, 2014).

In typing, Crump and Logan (2013) found that PES is associated with the inhibition of the urge to correct the error. In a series of experiments, Crump and Logan (2013) asked typists to type text under two sets of instructions. When the participants were asked to type without correcting their mistakes, significant PES was observed. However, when participants were instructed to correct their errors in another condition, no reliable PES was observed. In contrast, in an earlier analysis, we found reliable PES after uncorrected errors where participants were told to correct their mistakes (Kalfaoğlu & Stafford, 2014). Thus, an inhibition of backspacing can't explain the PES observed in our study. While there is no clear evidence about exactly what mental processes are indexed by PES, the observation that post-error behaviour often differs from post-correct behaviour suggests that some property of undetected errors (e.g. mismatch between intended and executed action, low vs. high frequency,

or the amount of conflict) can be distinguished from correct responses at some level.

Another behavioural parameter potentially associated with error awareness is error slowing. As mentioned earlier, errors in continuous tasks such as piano playing and typing are on average slower than correct actions (Herrojo-Ruiz et al., 2009; Kalfaoğlu & Stafford, 2014; Shaffer, 1975). It is possible that such error slowing (ES) is caused by a performance break down which foreshadows errors, or is caused by error awareness. We have shown previously that while performance breakdown is observable in uncorrected but not in corrected errors, both corrected and uncorrected error keypresses are slowed down in typing (Kalfaoğlu & Stafford, 2014). In fact, error slowing was found to be stronger in corrected errors than uncorrected errors. This suggests that even though ES might reflect both performance break down and error awareness, error awareness is a more potent contributor to ES than performance breakdown. If this claim is true, then we would expect the onset of error related EEG parameters to precede error execution. We would also expect the EEG parameters to be predictive of error slowing in corrected errors. Error slowing in corrected errors would be observed in cases where the error detection is not quick enough to stop the error key-press. In such cases, we would expect ES to be larger when error detection (i.e. the time of EEG signals) is closer to the time of error key-press, and smaller when error detection is too early or too late. Thus, the more timely and strong the EEG signals, the longer should ES be.

EEG Analysis in Typing. While typing is highly advantageous due to its high ecological validity, it can be potentially problematic due to diminished lack of control over the behaviour of the participant. Continuous copy typing involves multiple concurrent mental processes such as those associated with reading and eye movements, in addition to programming and executing temporally overlapping fingerpresses (c.f. discrete trial tasks). Thus, EEG recorded at the time of an error key-press will include such activations associated with temporally overlapping pre- and post-error actions in addition to processes specific to error detection. ERN is an ERP component typically recorded at the fronto-medial electrodes (Gehring et al., 2012), which are not directly above the hand area of the motor cortex (Boroojerdi et al., 1999). However, any non-error detection related activity associated with typing detectable at medio-frontal electrodes would add potential noise to the error related EEG signals beyond that present in discrete trial tasks. One of the main motivations behind our choice of independent component analysis (ICA) for our EEG analyses was this issue. ICA works by separating signals which are temporally maximally independent from each other into separate independent components (see Groppe, Makeig, & Kutas, 2008, for a discussion of ICA used in EEG analyses). ERN is shown to be specific to errors and independent of the body part (e.g. the eyes,

feet, fingers) involved in the error commission (Gehring et al., 2012). Therefore, whereas the ERN is expected to appear only after errors, the timing of non-error related activations (i.e. motor or other medio-frontal processes) would be non-specific with respect to the timing of the errors. Because of this lack of temporal correlation between error and non-error related signals, ICA would separate them into different independent components, even if they are recorded by the same electrode.

The aim of the current study is to use typing to investigate error awareness in skilled actions. In typing, performance speed can reach more than 10 finger presses every second. At such speeds, typists probably have little conscious awareness of where their fingers are in a given moment (e.g. Logan & Crump, 2009). Yet, error detection rates remain high, even in the absence of visual feedback (Kalfaoğlu & Stafford, 2014; Rabbitt, 1978; Snyder, Logan, & Yamaguchi, 2014). By separating detected from undetected errors using backspace and evaluating error related EEG parameters (ERN, FMT) and behavioural (ES, PES) measures, we aimed to gain a better understanding of how error awareness evolves in highly-practised actions and how this is manifested in terms of the parameters listed above. Specifically, we wanted to investigate the temporal relationship between error related EEG and behavioural effects in continuous tasks (Herrojo-Ruiz et al., 2009; Kalfaoğlu & Stafford, 2014) and to test predictions regarding EEG reflections of implicit and explicit error detection using behavioural data. For example, if ERN or FMT parameters are predictive of error correction, they are likely to reflect explicit error detection in typing. If they are related to implicit error detection, then they should be strong predictors of PES but not necessarily for error correction.

Methods

Participants

Twenty one participants (9 men), mean age 29 years (range: 18 to 45) were recruited using an institutional list of volunteers. Participants included students and administrative staff of the university. EEG data from two participants were discarded because EEG equipment stopped working. One participant was excluded from the analysis because she was unable to keep her hands in the home position on the keyboard in the absence of visual feedback, which made it impossible to extract meaningful data from her typing. Of the remaining 18 participants 5 were excluded due to excessive EEG artifacts (i.e. more than 25% of channels removed due to high noise) and one was removed because she had fewer than 15 epochs of uncorrected errors after artifact removal. One of the participants showed no error related activity (neither in EEG or ICA components, see offline data processing and analysis section below) and thus was not included in the EEG analyses. This left the number of participants in the

EEG analysis at 11 and the number of participants in the behavioural analysis at 19.

Typing Ability of the Participants. We only recruited participants who reported being a trained touch-typist. All participants included in the EEG analyses reported they were trained in an undergraduate keyboarding course, trained themselves with the help of typing software, or learned the skill as part of their professional training and thus were assumed to be able to type using 8-finger or 10 finger typing method (but see, Logan, Ulrich, & Lindsey, 2016). All our participants were able to locate the home row on the keyboard and type fluently in the absence of visual feedback. In order to familiarise them to the keyboard used and get baseline typing ability measures, we asked our participants to type a paragraph from the website http://www.typingtest.com/ for 2 minutes with full visual feedback. The average baseline typing speed of the 11 participants ranged from 60 to 94 words per minute (wpm) with an average of 73.00wpm (SD = 11.44). Typing accuracy ranged from 92% to 100% with a mean of 94.90% (SD = 2.17%). All participants had normal or corrected to normal vision.

After being verbally explained how the experiment is to be carried out step-by-step, each participant was asked to read the same information written on an informed consent form and sign it if she/he agreed to participate in the experiment. Department of Psychology Ethics Committee approved all procedures of this experiment including how the written informed consent was obtained prior to the start of the experiment, in line with university ethics regulations and British Psychological Society (BPS) guidelines.

Procedure

Participants were seated in front of the testing computer and asked to adjust their distance from the monitor and the keyboard such that they could type comfortably. Participants were asked to copy-type the first 100 sentences from the book *Cumulative Record* (Skinner, 1959). Sentences were presented one at a time, and the order of sentences was randomised for each participant. Presentation of the sentences was self-paced: When a participant finished typing one sentence, they had to press the right arrow button on the keyboard to see the next sentence. In each trial the participant was required to type the sentence from the beginning to the end, and to type as fast and accurately as possible. Participants were also told that it was crucial that they corrected any mistakes they made using backspace.

Participants received no visual feedback about their typing. Their hands were covered using a card-box and the monitor didn't present the letters typed by the participant. While the participants typed the sentences, the only information presented on the monitor was the sentence to be typed. One of the aims here was to replicate the results of a classic study of error detection by Rabbitt (1978) by using a method-

ology as similar to his as possible and extending it by EEG analyses. Further, elimination of visual feedback allowed us to study the control of typing without feedback of the outputs produced (the so called 'inner loop', Logan & Crump, 2010, 2011; Snyder et al., 2014). Another important motivation for the limitation of visual feedback in the current design was to discourage participants from looking back and forth from the monitor to their hands. Such muscular activity typically leads to large unwanted artifacts in the EEG data. One additional effect of lack of visual feedback recently shown in typing is a reduction in explicit error detection (Snyder et al., 2014) which is desirable since the high rate of error detection in typing (Crump & Logan, 2013; Kalfaoğlu & Stafford, 2014; Rabbitt, 1978) typically leads to uneven numbers of observations in corrected vs. uncorrected errors.

Behavioural Analysis

Typing-data were acquired using a high speed keyboard (DirectIN PCB v2010 from Empirisoft, `http://www.empirisoft.com/directinkb.aspx`) to ensure that the delay between a participant pressing down a key and the computer recording it is minimised. For each participant, we excluded key-presses which were slower than the 99% percentile or slower than 1000ms as outliers. A key parameter in our behavioural analyses was error slowing (ES). This was calculated for each error- and post-error letter in a word that was typed incorrectly.

Calculation of Error Slowing and Post-Error Slowing. To calculate ES and PES, we used as baseline the average inter-keystroke-interval (IKI) of correctly typed letters which are matched for word length and letter position. This is different from many of the cited studies, where PES is calculated by subtracting IKI of the letter immediately before the error from that of post-error key-presses (e.g. Crump & Logan, 2013; Logan & Crump, 2010). The latter approach is particularly useful when natural fluctuations in typing speed are considered. For example, if errors are more frequent during slower (or faster) than average speed typing, such a baseline would be more sensitive to 'local' changes in typing speed. When participants try to type faster than their usual typing speed (Yamaguchi, Crump, & Logan, 2013) or too slowly, their chances of making mistakes may increase.

However, Salthouse (1986) shows that IKIs of 3 key-presses before the error are no different from average IKIs. Similarly, we showed earlier that when participants are instructed to type as fast and accurately as possible, typing speed in 6 key-presses before the errors don't differ from that of key-presses matched for word length and letter position (Kalfaoğlu & Stafford, 2014). Another relevant finding from this study was that variability in IKIs preceding errors was significantly larger before uncorrected errors than before corrected errors. Thus, using pre-error IKI as the baseline for calculating PES could potentially increase the variability in PES and decrease the chances of finding subtle but reliable changes in typing performance following uncorrected errors.

It is also plausible that word structure, and letter position in a given word length might affect IKI and error likelihood. In order to control for such potential confounds we used a matching procedure where error and post-error slowing was calculated in the following way: Error slowing value was calculated by subtracting the IKI of the error key-press from the average IKI of letters matched for word length and letter position. For example, error slowing value for an error in the 4th letter of a 5 letter word is calculated by subtracting the IKI associated with that error key-press from the average IKI of all 4th letters in correctly typed 5 letter words. Same approach was used in calculation of slowing associated with post-error key-presses.

As the measure of post-error slowing in our single trial analysis, we used the average PES in the two keys following corrected and uncorrected errors (E+1 & E+2). We chose only 2 post-error key-presses because, "the [...] lengthier interval after an error is nearly always on the immediately following keystroke, and seldom occurs on keystrokes more than two removed from the error" (Salthouse, 1986, p.310). Crump and Logan (2013) showed that the proportion of post-error key-presses preceding backspace quickly fell below 10% after the second post-error key-press. Results of Kalfaoğlu and Stafford (2014) further show that after matching post-error key-presses to post-correct key-presses for word length and letter position (as is the case in the current study), the proportion of post-error key-presses preceding the backspace got even smaller (13.65% for E+1, 1.82% for E+2 and <1% for E+3). In light of the studies and observations summed above, we decided to use average slowing in E+1 and E+2 as the measure of PES in the current study.

If the error was corrected by the backspace, PES would be calculated using any correct post-error key-presses that preceded the backspace.

EEG Data Acquisition and Analyses

The recording computer was connected to the Biosemi USB Box (`http://www.biosemi.com/`), which received signals from the EEG amplifier as well as key-press information from testing computer. To make sure that the difference between latencies of key-presses as recorded by the testing and recording computers was minimal, we contrasted the IKIs as recorded by both. We found that this difference was 0.11ms (SD = 0.11ms). Since the median IKI for our typists was 155.81ms (SD = 19.43), the fastest typing at an average IKI of 124.49ms, the lag of less than 0.15ms for the transmission of signals was considered acceptable.

On-line Data Acquisition. EEG data were collected from 128 channels at a sampling rate of 2048Hz using a 128 channel Biosemi Actiview system (`http://www.biosemi.com/`). Data were analysed by custom Matlab scripts built

on the open source EEGLAB toolbox (`http://sccn.ucsd.edu/eeglab/`, Delorme and Makeig (2004)).

Independent Component Analysis. EEG recorded over the scalp at any moment in time is a linear mix of multiple co-existing neural processes (each of which will be activated to a different extent at different times), as well as other sources of electrical activity such as the muscular activity from the eyes or the scalp itself. In order to minimise the effects of these confounding variables (especially in such a dynamic task as typing), we used independent component analysis (ICA) which is a statistical blind source separation technique. Using ICA was also crucial in enabling us to study single trial correlations between EEG parameters and behavioural effects associated with error awareness. We conducted all our statistical analyses on error related IC activations returned by ICA (see offline data processing section below) for the reasons outlined above, and because channel C23, which corresponds to electrode FCz in the Biosemi EEG system we used, for one of the participants was removed due to bad connectivity with the scalp. To enable a visual comparison between error related independent component (ErIC) activity and its projection to medial frontal electrodes, we present data from these two sources during corrected errors in figures 1 and 2 respectively. Figure 3 shows the projection of the ErIC to all electrodes during the two significant peaks of the ErIC (i.e. the ERN and the following positivity). Figures 1, 2 and 3 are constructed using data from the 11 participants involved in the EEG analyses. See Groppe et al. (2008) for a review of the use of ICA in EEG analysis and Murphy, Robertson, Allen, Hester, and O'Connell (2012) and Beldzik, Domagalik, Froncisz, and Marek (2015) for similar uses of ICA in extracting EEG effects associated with errors.
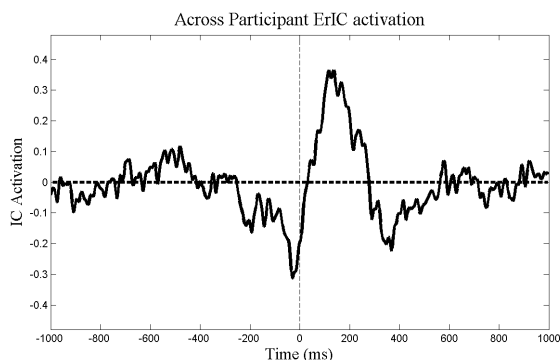

Figure 1. Figure showing the activity of the ErIC during corrected errors. The units of this activation are arbitrary but reflective of electrical potentials related with errors.

Off-line Data Processing and Analysis. EEG data were down-sampled from 2048Hz to 256Hz using Biosemi BDF Decimator software (`http://www.biosemi.com/`). Rest of EEG data analysis followed the below steps in the order
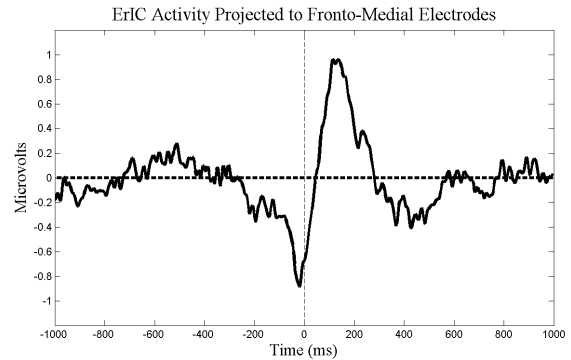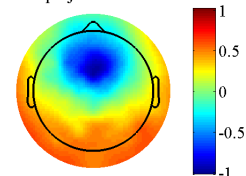

Figure 2. Figure showing the across participant average projection of ErIC activity during corrected errors onto the most medial frontal electrode available (closest to electrode FCz) for each participant. In all but one of the participants, this was electrode C23, location of which on the scalp corresponds to that of FCz, and in one participant where C23 was removed, it is C22. Electrode C22 is a medial electrode which is closest (more frontal) to C23 in the Biosemi EEG system used.
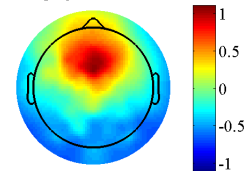

Figure 3. Scalp maps showing the across participant average projection of the ErIC to all electrodes at the time of ERN peak (20ms before the error) and at the peak of the following positivity (113ms after the error) in microvolts during corrected errors.

they appear here: Data were digitally filtered to remove frequencies above 60Hz and below 1Hz using a finite impulse response filter, as implemented in EEGLAB. Correct key-presses were matched to error key-presses in terms of IKI and letter. A staircase procedure was applied to find the closest IKI with a step size of 0.5ms to match the IKIs of the correct key-presses to errors.

Key-press events in the EEG were labelled as corrected error (CE), uncorrected error (UE), correct matched to corrected error (CMC), and correct matched to uncorrected error

(CMU). Continuous EEG data were cleaned of artefacts and noisy channels by visual inspection. Artefacts were defined as sudden and substantial (> 3 standard deviations) changes of amplitude in multiple electrodes at the same time. Blinks, swallows and head movements are among the typical generators of such artefacts. If these substantial changes appeared only in one electrode with no similar activations in spatially adjacent electrodes, the electrode was identified as a noisy channel. After removing noisy channels, an average of 109 channels (SD = 13.44, range = 80 - 124) were retained for each participant. The data were re-referenced to the average electrode. Continuous data were submitted to extended infomax ICA Lee, Girolami, and Sejnowski (1999) using runica function Makeig, Jung, Bell, Ghahremani, and Sejnowski (1997) of the EEGLAB toolbox. The average number of data points decomposed for each participant was 533,985 (34 min, 46 sec) (range = 451,739 - 644,737). Independent component source locations were estimated by creating an equivalent current dipole model for each component using dipfit function from EEGLAB. This function estimates dipole location by applying inverse source modelling methods to a standard boundary element head model (Oostendorp & van Oosterom, 1989). The ICs whose dipoles had a residual variance of more than 20%, or were outside the brain were removed. Any remaining components that were considered to reflect muscle activity, electrocardiogram, or eye movements, on the basis of their dipole location, spectra and scalp maps were considered artefacts and excluded from further analysis. In total, 251 ICs were included in the analysis, each participant contributing 23 (SD = 16) ICs on average (range = 4 - 53). EEG data were then separated into epochs of CE, UE, CMC, and CMU. Epoch length was 2 seconds (-1000 to 1000ms after the key-press) for ERP analyses; and 6 seconds long for the time-frequency analyses (-5000 to 1000ms after the key-press). ERSP and ITC values were computed for all remaining ICs from all the participants using wavelet analysis using Morlet wavelets (Herrmann, Grigutsch, & Busch, 2005) as implemented by the *newtimef* function in EEGLAB toolbox.

For the time-frequency analyses, ERSP and ITC were extracted from 10 linearly spaced frequencies from 3Hz to 6Hz. We selected the lower half of the FMT oscillations because the theta effect was found to be the strongest at these frequencies in our earlier investigations (Kalfaoğlu (2012), see also figure 4d). Baseline period used for ERSP and ITC calculations was from 5000ms to 200ms before the key-press. The number of cycles in the wavelet used in the time-frequency transformations was 3 for extracting ERSP and ITC values at 3Hz and increased linearly to 6 for extracting ERSP and ITC values at 6Hz (with a sliding window length of 1113.28ms).

Once the ERP, FMT ERSP and ITC were extracted from the ICs, we used k-means clustering algorithm of EEGLAB to identify the ICs which represented error related activity.

It is already established that errors are closely associated with ACC activity (Carter et al., 1998; Reinhart & Woodman, 2014), and are strongly associated with theta power bursts and phase-locking (Luu & Tucker, 2001; Luu et al., 2004). Thus, in the clustering algorithm, we defined important parameters as the dipole location, and ERSP and ITC in the 3-6Hz oscillations during corrected errors. The weightings given to these parameters for clustering purposes were not uniform (i.e. 1:1:1) but rather 2:2:1 for dipole location, theta ERSP and theta ITC, respectively. The theta ERSP and dipole location were given twice the weight compared to theta ITC parameter because we expected i) the variability in the location of error related neural activity to be smaller than that in phase of theta oscillations (on which the ITC measure relies) at the time of the error key-press, and ii) the variability in the theta ERSP to be less than that in phase of the theta oscillations at the time of error key-press.

Of the 8 clusters returned by the clustering algorithm one was easily identifiable as an error related cluster based on the activity of the ICs at the time of the error key-press. Figure 4 shows the average scalp map, dipole locations, ERSP, ERP, and ITC measures of the error related cluster. This cluster had ICs from 11 out of 12 participants. All of the EEG analyses reported here are conducted on this cluster of 11 participants. The participant who contributed no ICs to the error related cluster showed no ERN in the EEG record (neither before nor after the ICA).

Note on Number of Epochs

On average, participants contributed 71 CE (range 45-108), 36 UE (range 20-55), 115 CMC (range 66-193), and 65 CMU (range 37-152) epochs to across participant ERP analyses; and 59 CE (range 35 - 110), 32 UE, (range 17 - 73), 93 CMC (range 47 - 169), and 51 CMU (range 32 - 116) epochs to across participant time-frequency analyses. The reason for the smaller number of epochs in time-frequency analysis was because we used a longer epoch length for these analyses. The longer the epoch length, the larger the probability of a temporal overlap with artefacts and other epochs. Such overlapping epochs are automatically discarded.

As shown above, there were considerable differences between the numbers of epochs of different key-press types. In order to avoid the possibility that the observed effects are driven by unequal sample sizes, the number of epochs in all analyses reported below were matched using a bootstrap based procedure: For each participant, first the key-press type with the smallest number of epochs (denoted "n_s" for smallest n) was identified. Then, for each participant, only n_s randomly selected epochs were used in the between-key-press comparisons of ERP and theta oscillatory measures. When calculating the ERP of a participant for a given key-press type, 1000 bootstrapped samples of size "n_s" were taken and the average of these samples represented the ERPs
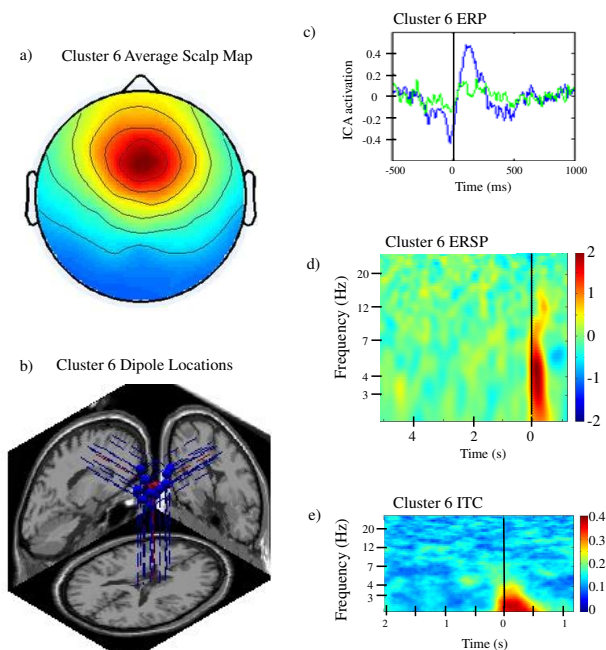
Figure 4. a) The average scalp map of the error related cluster (i.e. cluster 6). b) Dipole locations (average dipole in red) of the error related cluster. c) A comparison of ERP activations of the independent components (ICs) during corrected error key-presses (blue line) to matched correct key-presses (green line). d) and e) show the average event related spectral perturbation (ERSP) and Inter-trial coherence (ITC) values of the Error related ICs in the error related cluster at the time of corrected error key-presses, respectively. For d) and e) the magnitude of ERSP and ITC are represented by the colour scale.

of interest for that participant and key-press type. We followed the same procedure for the time frequency analyses.

Correction for Multiple Comparisons

Event related potential and FMT differences between corrected and uncorrected errors and matched correct key-presses were tested using t-tests at each time point. A t-score adjustment (t_{max}) based on permutations was used as described by Groppe (2010); Groppe, Urbach, and Kutas (2011a, 2011b). Briefly in this method, data points from two conditions to be compared are randomly re-allocated to one of two conditions (as in the null hypothesis) and a t-score is calculated. This is repeated for each time point (i.e. each one of n comparisons), and the maximum t-score (i.e. the t_{max}) from these n comparisons is recorded. This is repeated 1000 (in our analyses) times, resulting in 1000 t_{max} values. Then, the 95% confidence intervals of the distribution of the t_{max} values are determined, and used as new critical t-scores.

For the theory driven predictions that ERN will peak be-

tween -100 to 100ms of key-press, (see Herrojo-Ruiz et al., 2011; Maidhof et al., 2009, for timing of ERN in continuous actions), FMT power burst (i.e. ERSP) and coherence (ITC) will appear between -100 to 100ms after the key-press (Herrojo-Ruiz et al., 2011; Luu & Tucker, 2001), we used a critical t-score at an alpha of 0.05, such that any difference with a t-score of larger than this critical value would be considered statistically reliable. For differences which are not predicted by previous literature, we applied a critical t-score adjusted for the number of multiple comparisons. Both of these cut-off t-scores are presented in all figures presenting EEG comparisons.

Results

Behavioural Results

The average IKI of the 11 participants included in the EEG analysis was 161.19ms (SD = 22.91ms, range: 124.49ms - 193.27ms). Average error detection rate across participants was relatively low (M= 63.99%, SD= 16.67), possibly due to lack of visual feedback on the screen (Snyder et al., 2014). Corrected error key-presses for these participants were significantly slower than matched correct key-presses by 35.86ms (SD = 12.28, t(10) = 9.68, p < 0.001). Similarly, uncorrected errors were found to be significantly slower than matched correct key-presses by 18.14ms (SD = 14.86, t(10) = 4.05, p = 0.0023). Average PES for the 2 key-presses following corrected errors failed to reach statistical significance (19.08ms, SD = 40.36, t(10) = 1.57, p = 0.15). Average PES for the 2 key-presses following uncorrected errors was statistically reliable (39.06ms, SD = 23.18, t(10) = 5.59, p < 0.001). In summary, both corrected and uncorrected error key-presses were significantly slower than matched correct key-presses. Correct post-error key-presses following uncorrected errors were also reliably slower than matched correct key-presses. For a whole analysis of the behavioural data from all 19 participants, please see Kalfaoğlu and Stafford (2014).

Across-trial ERP Results

Figure 5 shows the ERPs and difference waves associated with corrected and uncorrected errors in relation to each other and matched correct key-presses. Corrected errors were associated with a significant negativity compared to matched correct key-presses between -152ms and 4ms after the key-press. Corrected errors were also associated with a significant positivity peaking at 113ms after the key-press. This post-ERN positivity is considered to be the early Pe (Endrass et al., 2007; O'Connell et al., 2007; van Veen & Carter, 2002) based on its tight temporal coupling to ERN, topography, onset and dipole location, rather than the late Pe which is a centro-parietal ERP component shown to be functionally

dissociable from the ERN (see Endrass, Klawohn, Preuss, & Kathmann, 2012; Endrass et al., 2007).
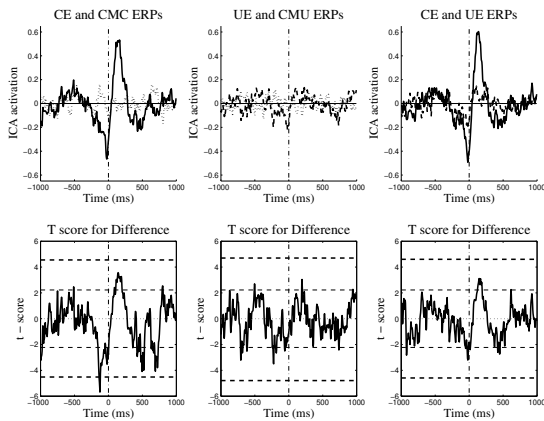

Figure 5. The plots above show ERPs associated with corrected errors (CE, solid line), correct key-presses matched to them (CMC, grey line); uncorrected error key-presses (UE, dashed line) and correct key-presses matched to them (CMU, grey line). The plots below show the t-values associated with the comparison at each time point. Critical t-value adjusted for multiple comparisons are marked by the bold dashed line; and the critical t value at p = 0.05 (t(10)= ±2.228) is shown by the thin dashed line.

Uncorrected errors were associated with a brief but significant negativity compared to matched correct key-presses between 63ms and 55ms before the error.

Importantly, the negativity associated with corrected errors were significantly larger than those associated with uncorrected errors. As figure 5 shows, this difference in magnitude was significant between -51ms and 20ms after the error.

Across-trial FMT Results

Error Related Spectral Perturbations. Figure 6 shows FMT ERSPs associated with corrected and uncorrected errors in relation to each other and matched correct key-presses. Corrected errors were associated with a reliably stronger FMT ERSP compared to both matched correct key-presses (between -106ms and 426ms after the key-press) and uncorrected error key-presses (between -4ms and 340ms after the key-press). Uncorrected error key-presses were also associated with reliably stronger FMT ERSP than matched correct key-presses between -121ms and 425ms after the key-press.

Inter-trial Coherence. Figure 7 shows the FMT ITC associated with corrected and uncorrected errors in relation to each other and matched correct key-presses. Corrected errors were associated with significantly higher ITC than both matched correct key-presses (between -51ms and 379ms after the key-press) and uncorrected error key-presses (between
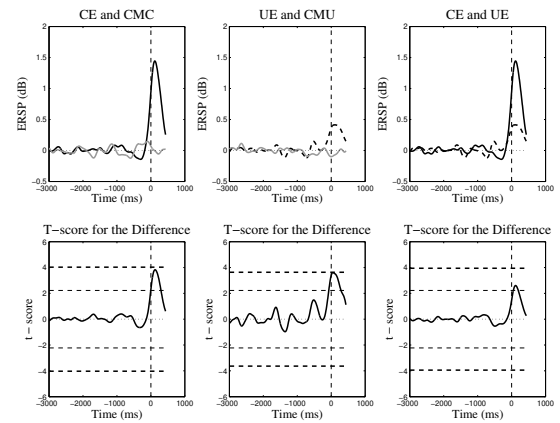

Figure 6. The plots above show theta band ERSP during corrected errors (CE, solid line), correct key-presses matched to them (CMC, grey line); uncorrected error key-presses (UE, dashed line) and correct key-presses matched to them (CMU, grey line). The plots below show the t-value associated with the comparison at each time point.

-59ms and 277ms after the key-press). Uncorrected error key-presses however, were associated with no higher ITC than matched correct key-presses.
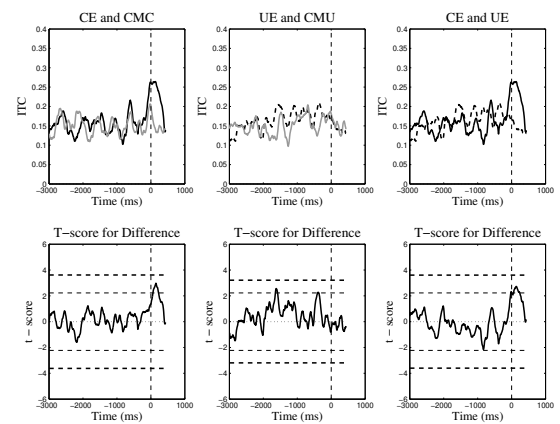
Figure 7. The plots above show theta ITC during corrected errors (CE, solid line), correct key-presses matched to them (CMC, grey line); uncorrected error key-presses (UE, dashed line) and correct key-presses matched to them (CMU, grey line). The plots below show the t-value associated with the comparison at each time point.

Table 1 shows the effect sizes and associated statistical power for the sample size used (11) for comparisons reported.

Table 1

Table showing the effect sizes and associated statistical power for the reported statistical comparisons for Error Related Negativity and Positivity (ERN and Pe, respectively), Event Related Spectral Perturbation (ERSP), and Inter Trial Coherence (ITC). The effect sizes were calculated at the time points at which t-values reached the peak for the comparison (Peak Time). Comparisons included corrected errors (CE), uncorrected errors (UE) and matched correct key-presses to corrected (CMC) and to uncorrected errors (CMU)

	Comparison	Peak Time	Effect Size	Power
ERN				
	CE vs. CMC	-19.53	1.48	0.99
	CE vs. UE	-19.53	1.33	0.97
	UE vs. CMU	-58.59	1.06	0.89
ERSP				
	CE vs. CMC	125.0	1.53	1.00
	CE vs. UE	117.2	1.17	0.94
	UE vs. CMU	50.78	0.86	0.87
ITC				
	CE vs. CMC	158.4	1.53	0.99
	CE vs. UE	136.7	1.47	0.99
	UE vs. CMU	148.4	0.15	0.07

Table 2

Summary table for regression results assessing the relationship between ERN and behavioural variables.

Criterion	Peak ERN Amplitude (b)	t-value	R^2
Error Correction	-0.31	-3.37***	0.19
PES_{All}	-0.07	-1.08	0.11
$PES_{Uncorrected}$	-0.18	-2.19*	0.09
ES_{All}	0.02	0.51	0.001
$ES_{Uncorrected}$	0.07	0.92	0.01
$ES_{Corrected}$	0.01	0.19	0.03

$* - p < 0.05$; $** - p < 0.01$; $*** - p < 0.001$

Single-trial ERN Results

The relationship between ERN amplitude and behavioural variables were tested using regression analyses. In these analyses, the predictor variables included were i) participant number and ii) single trial standardised peak ERN amplitude between -152 and 4ms after the error (this time window corresponds to the time points at which ERN amplitude was significantly different than matched correct key-press). Separate regression analyses were conducted for each dependent variable: i) error correction ii) PES in all errors iii) PES in uncorrected errors iv) ES in all errors v) ES in uncorrected errors and vi) ES in corrected errors. PES in corrected errors could not be analysed because most corrected errors were followed immediately by the backspace (only 109 data points were available for this analysis). Results of all ERN regression analyses are summarised in table 2.

ERN and Error Correction. This analysis showed that standardised single trial peak ERN amplitude predicted error correction better than chance ($R^2 = 0.19$, F(12,995)= 20.85, p < 0.001). The more negative the peak ERN, the more likely the error correction (beta= -0.31, t(11)= -3.38, p < 0.001).

ERN and PES. Standardised single trial peak ERP amplitudes as sorted by ES and PES in corrected and uncorrected errors is shown in figure 8.[1]

We found that standardised single trial ERN amplitude reliably accounted for a small amount of variability in PES fol-

lowing uncorrected errors ($R^2 = 0.09$, F(12,196) = 1.95, p = 0.041). The more negative the ERN amplitude within -152 and 4ms of the key-press, the longer was the PES (beta = -0.18, t(11) = -2.19, p = 0.030) in uncorrected errors (see figure 8).

ERN and ES. Single trial amplitude of ERN was not predictive of ES in corrected, uncorrected, or all errors combined (p for all beta values > 0.35).

Single-trial FMT Results

Single trial FMT ERSP as sorted by ES and PES in corrected and uncorrected errors is shown in figure 9. Because our across trial analyses showed that significant differences between errors and matched correct key-presses start no earlier than 106ms before the error, we conducted our single trial analyses using shorter epochs. Epochs started 1000ms (instead of 5000ms) before and ending 1000ms after the error key-press). This enabled us to include more epochs and thus data points in the regression analyses as shorter epochs are less likely to be discarded due to overlap with other epochs and artefacts.

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[1]Most corrected errors were immediately followed by a backspace and many were followed by subsequent errors (i.e. no correct post-error key-press and thus no PES value). Some errors were letters incorrectly inserted to the ends of the words and hence could not be matched to a correct key-press for letter position (no ES value). This is the primary reason for the smaller number of post-error than error trials in figures 8 and 9, and the differences in degrees of freedom in different regression analyses.
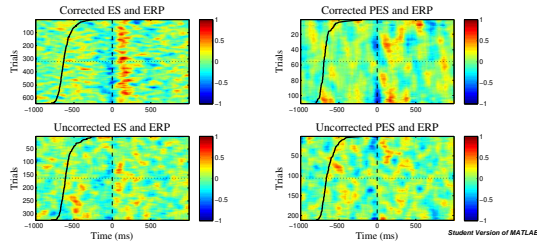
Figure 8. Figure showing single trial ERPs sorted by ES (plots on the left) and PES (plots on the right) for corrected (plots on top) and uncorrected errors (plots on bottom) across all participants. Colour bar shows the within trial standard deviation in ERP (red - above average amplitude, blue below average amplitude). Dashed vertical line shows the time of error key-press. The S shaped solid line shows error (ES - plots on the left) and PES (plots on the right) associated with each error trial. This line is not referenced to the x-axis in order to improve visualisation of ERP values at the time of key-press (i.e. slowing values are not all negative). The top-right tail of this line shows the largest amount of ES and lower-left tail shows the least amount of ES. The dotted horizontal lines mark the error response with the median value of error or PES marked by the s-shaped line.
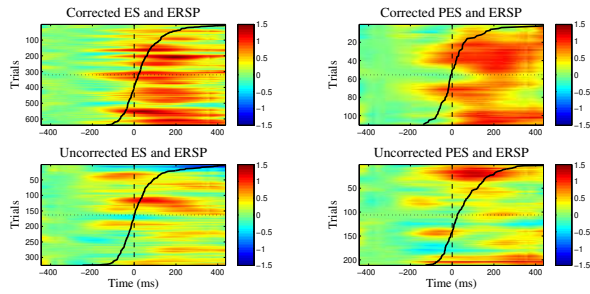

Figure 9. Plots showing standardized single trial FMT ERSP values sorted by ES (left) and PES (right) in corrected (above) and uncorrected error key-presses (below). Colour bar shows the within trial standard deviation in ERSP. Dashed vertical line shows the time of error key-press and the dotted horizontal lines mark the error response with the median value of error or PES. The S shaped solid line shows ES and PES associated with each error trial.

Table 3

*Summary table showing the beta (*b*) values for regression results assessing the relationship between FMT ERSP peak time, FMT ERSP peak magnitude, their interaction predicting the behavioural variables and the R^2 value associated with the regression model.*

Criterion	Peak Time (b)	Peak Magnitude (b)	Interaction (b)	R^2
Error Correction	-0.05	0.58***	0.01	0.22
PES_{All}	-0.13*	0.06	-0.03	0.13
$PES_{Uncorrected}$	-0.25***	0.12	-0.01	0.14
ES_{All}	-0.03	-0.07*	-0.07*	0.03
$ES_{Uncorrected}$	-0.001	-0.09	-0.07	0.02
$ES_{Corrected}$	-0.04	-0.07	-0.09*	0.05

* − p < 0.05; ** − p < 0.01; *** − p < 0.001

To test if single trial amplitude and timing of the FMT ERSP peak are predictive of error correction probability, we conducted logistic regression analyses with the following predictor variables: i) Standardised single trial peak FMT ERSP (dB) within -106 and 426ms of the key-press (i.e. the period when theta ERSP was significant, see figure 6); ii) standardised squared difference between the time of the peak theta band ERSP and the error key-press (ms); and iii) their interaction. The temporal difference between error key-press and theta ERSP peak was squared before standardising the values in order to remove the sign of the difference value.

FMT Parameters and Error Correction. This regression analysis showed that ERSP parameters could predict error correction better than chance (R^2 = 0.22, F(14,993) = 22.01, p < 0.001). The stronger the FMT ERSP, the more likely the error correction (beta = 0.58, t(13) = 7.20, p < 0.0001, see table 3 for beta weights of ERSP predictors).

FMT Parameters and PES. Similarly, these FMT ERSP predictors were found to predict PES in all errors better than chance (R^2 = 0.13, F(14,302) = 3.34, p < 0.001). It was found that the smaller the temporal difference between the error key-press and peak of FMT ERSP, the greater the PES (beta=-0.13, t(13) = -2.25, p= 0.026, see figure 10).

A multiple regression analysis showed PES after uncorrected errors can be predicted by peak FMT ERSP and its time (R^2 = 0.14, F(14,194) = 2.63, p = 0.003). Time of FMT ERSP peak amplitude relative to the key-press was found to be predictive of PES in uncorrected errors (b= -0.25, t(13)=
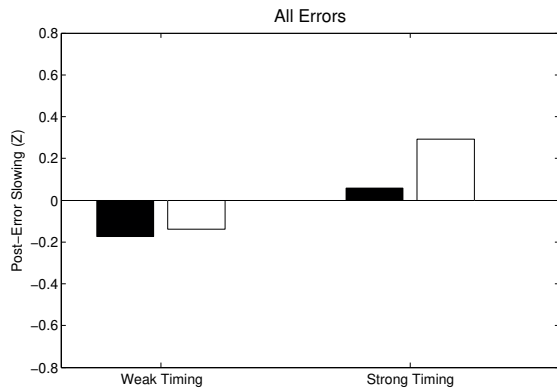
Figure 10. Figure showing the amount of PES following all errors associated with above average FMT ERSP peak magnitude (white bars) and below average FMT ERSP peaks magnitude. Errors with longer than average temporal lag between FMT ERSP onset and error key-press onset are shown on the left, and those with shorter than average lag are shown on the right. PES values are standardized for each participant.
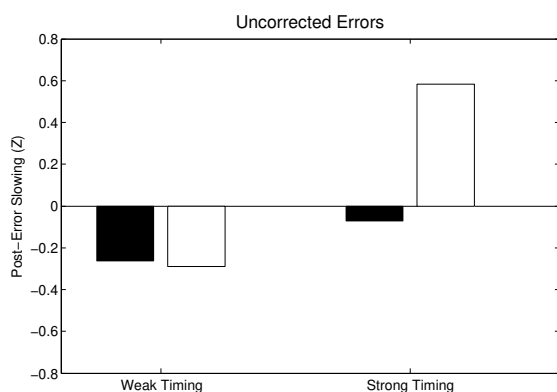
-3.43, p < 0.001).

Figure 11. Figure showing the amount of PES following uncorrected errors associated with above average FMT ERSP peak magnitude (white bars) and below average FMT ERSP peak magnitude. Errors with longer than average temporal lag between FMT ERSP onset and error key-press onset are shown on the left, and those with shorter than average lag are shown on the right. PES values are standardized for each participant.

FMT Parameters and ES. It was found that a small amount of variance in ES could be reliably predicted by FMT ERSP variables (R^2 = 0.03, $F(14,950)$ = 2.67, p = 0.002). The time of FMT ERSP peak (beta= -0.06, t(13)= -2.04, p= 0.042) and interaction between the peak amplitude of FMT ERSP and its time had a reliable effect on ES across all errors (beta= -0.07, t(13)= -2.21, p= 0.027). This suggests that

whether the peak theta power burst will affect ES depends on when this peak happens in relation to the key-press.

While FMT ERSP parameters were not found to predict ES in uncorrected errors (R^2= 0.02, p = 0.90), the model with ERSP parameters could account for variability in ES in corrected errors (R^2= 0.05, F(14,625)= 2.29, p = 0.006). Interaction between peak amplitude of FMT ERSP and its time was predictive of ES in corrected errors (beta= -0.089, t(13) = -2.29, p = 0.023).

Discussion

The primary aim of our study was to test the relationship between error awareness and error related behavioural and EEG effects.

ERN. We found using 2 different analytical approaches that ERN amplitude was related to overt error detection. First, our ERP analyses showed that ERN amplitude during corrected errors was greater than that during uncorrected errors. Second, single trial peak ERN amplitude was found predictive of error correction probability. In addition, magnitude of ERN could reliably predict the amount of PES following uncorrected errors.

In the introduction we suggested that if ERN is predictive of PES in uncorrected errors, this would support the claim that ERN is associated with implicit error detection, but if ERN was found to be correlated with explicit error correction (i.e. pressing backspace after errors) probability, it would support the claim that ERN is involved in overt error awareness. Our results provide support for both of these hypotheses, and neither can be unequivocally rejected based on the current findings. One possible interpretation is that ERN amplitude reflects a process involved in implicit error detection (PES following uncorrected errors) which is also necessary for explicit error detection (backspacing). It is also possible that error awareness is one continuous variable where very few errors are detected with absolute certainty and very few escape error detection all together, and most errors lie at some level between these two ends. We found that when there is overt error correction, ERN amplitude is large; when errors are undetected, ERN is significantly smaller but predictive of disruption in the performance following the error. One claim that can be rejected based on our results is that ERN is not related to overt error detection. The observation that single trial ERN magnitude on its own is predictive of explicit error correction in an every day task in particular has important implications for the ERN - error awareness literature.

While the view that ERN is predictive of overt error awareness is in line with many relatively recent reports (e.g. Hewig et al., 2011; Navarro-Cebrian & Kayser, 2013; Roger, Benar, Vidal, Hasbroucq, & Burle, 2010; Scheffers & Coles, 2000; Shalgi & Deouell, 2012; Wessel, Danielmeier, Morton, & Ullsperger, 2012), it contradicts the traditional view

that ERN is related to implicit but not to explicit error awareness (e.g. Ehlis, Herrmann, Bernhard, & Fallgatter, 2005; Endrass et al., 2005, 2007; Hester, Foxe, Molholm, Shpaner, & Garavana, 2005; Hughes & Yeung, 2011; Nieuwenhuis et al., 2001; O'Connell et al., 2007; Overbeek et al., 2005; Steinhauser & Yeung, 2010).

In a review, Wessel (2012) concluded that there are no systematic differences between the methods used by the studies which found a significant relationship between ERN amplitude and error awareness and those with a null result. Wessel (2012) notes however that error signalling response used (e.g. an awareness button vs. a forced choice rating of awareness) can introduce a response bias towards reporting awareness of an error. This in turn can lead to classification of certain unsure errors as unaware errors, inflating the negativity associated with unaware errors. Similarly, in a review report Shalgi and Deouell (2013) emphasise that the method of assessing the participants subjective confidence in the accuracy of their responses is a crucial factor in studying the relationship between ERN and conscious error awareness.

From this perspective, primary strength of our study lies in its methodology. Not only is typing highly ecological, correction of errors is beyond a simple error signalling response in this task. The goal in typing is to produce a desired text without error. Pressing of backspace after an error in this respect is a crucial and integral part of the task and is required for realisation of this goal. In almost all studies reviewed, error signalling serves as a secondary task in addition to the primary task where the participant should 'respond as fast and accurately as possible'. One exception to this is a study conducted by Shalgi and Deouell (2012) where participants were asked to bet on their accuracy and actually earned money. Shalgi and Deouell (2012) showed that under these circumstances, ERN amplitude was strongly related to subjective error awareness. Our results are in line with this conclusion that ERN amplitude is related to awareness of performance accuracy.

Another hypothesis we proposed in the introduction was regarding the relationship between ERN and ES. In an earlier report error slowing was found to be associated with error detection (Kalfaoğlu & Stafford, 2014). Supporting our behavioural proposition that error slowing is related to error detection, ERN onset was found to precede corrected error execution by 156ms. The average IKI of participants was 161ms, which suggests that participant became aware of their errors around the time previous key-press was executed. In contrast, a related prediction of this hypothesis was not supported by our data. Peak amplitude of ERN was not predictive of ES in corrected error key-presses. It was another fronto-medial EEG signal, fronto-medial theta band oscillations, that was predictive of ES in corrected errors.

Fronto-Medial Theta Band Oscillations. Fronto-medial theta oscillations were also found to be closely

related to error awareness in our study. As with ERN, FMT ERSP was found to be stronger in corrected and uncorrected errors than matched correct key-presses. Corrected errors were associated with stronger FMT ERSP and ITC than uncorrected errors. Further, the magnitude of FMT ERSP was found to be predictive of error correction using single trial analyses. These results reinforce the idea the FMT activity reflects processes involved in explicit error awareness. However, FMT parameters were also found to predict the amount of PES in uncorrected errors, which is typically assumed to be an index of implicit error detection. Our interpretation of these findings is that activity in FMT oscillations reflect processes involved in error awareness, and further suggest that the distinction between implicit and explicit error awareness might not be as clear cut (Shalgi & Deouell, 2012, 2013) in typing as other tasks involving non-habitual error signalling responses.

The interaction between the magnitude and timing of the FMT peak relative to key-press was found to predict how much errors are slowed compared to matched correct key-presses in corrected errors. If ES was caused purely by performance breakdown, we would expect no relationship between FMT parameters and ES. Although a very small amount of variability can be explained by FMT parameters, this finding supports the hypothesis that error slowing is at least partly driven by error awareness (Kalfaoğlu & Stafford, 2014). Cavanagh, Zambrano-Vazquez, and Allen (2012) showed previously that theta band oscillations may underlie many frontal ERP components such as the N2, ERN, and FRN (feedback related negativity), which are associated with frontal lobe functions such as novelty, conflict, punishment and error. Our results support this view of theta as the common thread to ERPs associated with many frontal functions, and extend it to show that the theta band ERSP and phase-locking are strong predictors of error awareness as well as *adaptive behavioural consequences* of these neural processes in continuous and skilled actions such as typing in addition to discrete trial tasks. Time-frequency results showed that phase-locking (ITC) in FMT oscillations was the variable most specific to error correction that we measured (more so than the magnitude of ERN or FMT ERSP). While both ERN and FMT ERSP were found to be more pronounced during uncorrected errors compared to matched correct key-presses, phase-locking in FMT during uncorrected errors was not significantly different than that during matched correct key-presses. In other words, uncorrected errors were associated with no increase in phase-locking but significant increases in FMT ERSP (see uncorrected errors in figure 6 vs. figure 7). On the other hand, increases in ERSP were found to be reliably associated with slowed typing performance.

The observation that FMT ERSP is not as specific to error correction as FMT phase-locking suggests that they might be indexing similar (and highly overlapping) but not identi-

cal neural processes (Cohen & Donner, 2013). For instance, FMT ERSP is associated with response conflict and PES in discrete trial tasks (Cavanagh et al., 2009; Cohen, 2014). While response conflict might lead to slowing, it doesn't necessarily lead to error correction in typing[2]. Our results suggest the timing of the theta response in relation to the error response were essential for the spectral perturbations to have an effect on the behaviour: phase-locking mediates its effect on error correction, while timing of its peak mediates its effect on PES (figures 11, 10 and table 3).

Another implication of the finding that FMT phase-locking is more specific to error correction than FMT ERSP is that it underscores the proposition that theta band phase-locking and phase-synchronization are plausible mechanisms for synchronising the activities of multiple cortical and sub-cortical areas involved in frontal functions when the need for higher level control is needed (Cavanagh & Frank, 2014). Error correction in typing requires the typist to disengage from the execution of externally guided actions (letters presented on the screen), and execute an internally generated action (i.e. the backspace), and after the performance is "cleared" of the error (or "cured" using the terminology of Crump & Logan, 2013), to reinstate external guidance of actions. This would require coordinated activity of lots of neurons in multiple cortical and sub-cortical areas which would be difficult without synchronisation (i.e. phase-locking) at the local level in the beginning. The idea that phase-synchronisation in theta band oscillations is a likely mechanism serving as the 'lingua franca' among involved structures has been proposed earlier by Cavanagh et al. (2012).

Comment on timing of EEG effects. Our results suggest that error related EEG changes could take place just before or as the error action was completed in typing. A look at figures 6 and 5 shows that on average, the *onset* of EEG effects shortly preceded the execution of error key-press. A similar observation has been reported by Herrojo-Ruiz et al. (2009), who showed that in piano-players ERN could precede the error action, by up to 3 key-presses. These authors concluded error detection could be based on internal forward models which serve to predict the outcome of an action before the motor command is received by the effector muscles (Wolpert & Miall, 1996).

Our interpretation of the early error related EEG effects is different for a number of reasons. First, the EEG effects reported here are not as early as those reported by Herrojo-Ruiz et al. (2009). Second, we found that the pressing down of the uncorrected (as well as corrected) error key-presses was also slowed down, suggesting that slowing down is not necessarily caused by the prediction of an upcoming error. One possible explanation of our results then becomes: The accuracy of an action can be detected as soon as it is *initiated*. If it is an error, the action can be slowed down in an attempt to cancel it. This attempted cancellation may lead to suc-

cessful cancellation of an error, or, if failed, to a delay (observed as ES), an idea we borrow from Rabbitt (1978). In our response-locked ERP analysis, time 0 was the time at which the error key was physically pressed down. Pressing down of the key takes place after the initiation of the action, which can be further delayed due to ES. As mentioned before, if it is the initiation of an action (or the proprioceptive feedback from it) which leads to error awareness, error-related EEG effects can indeed precede the time of error key-press. This would be observed in the ERP analyses as a pre-error EEG effect. Thus a simpler explanation for the observed pre-error EEG effects is that error related EEG effects are caused by the initiation and not the prediction of the error action. As emphasized before, on average, onset of none of the error related EEG effects observed preceded error key-press was earlier than the average onset of the pre-error key-press. See Kalfaoğlu and Stafford (2014) for a more detailed methodological comparison of our study to that of Herrojo-Ruiz et al. (2009).

Comment on PES. Another point worth discussing is our post-uncorrected-error slowing in relation to the findings of Crump and Logan (2013). These authors suggest that PES is caused by the inhibition of a well learned response to "cure" errors (i.e. the backspace). They show that when this inhibition is released, PES also disappears. In fact, corrected errors in their study were associated with post-error speeding where post-error key-presses were found to be faster than pre-error key-presses. Our findings partially support their interpretation in that PES following uncorrected errors in the absence of inhibition of backspace was much smaller than those reported in studies where participants are not allowed to correct their errors (usually several hundred ms in Crump & Logan, 2013; Logan & Crump, 2010; Snyder et al., 2014; Wilbert & Haider, 2012; Yamaguchi et al., 2013, as opposed to the current PES of 39ms). However, we did find that PES was statistically significant even though our participants were free, and in fact encouraged, to use the backspace to correct their errors. Further, we observed significant ES and error related EEG effects in errors which were in fact corrected (i.e. no inhibition of backspace), suggesting that inhibition of the backspace on its own can't explain PES. PES was found to be correlated with EEG effects predictive of error correction, such as theta band power bursts in many uncorrected errors, suggesting that PES is at least partly associated with error detection processes. However, since only a small amount of variance in uncorrected errors was accounted for by theta parameters and PES reported in the current study is much

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[2]Quantification of the amount of response conflict in continuous tasks such as typing is not as straightforward as it is in discrete trial tasks. This is because multiple key-presses are being carried out at any given moment and thus temporally overlap (Flanders & Soechting, 1992). Our study was not designed to manipulate or assess the amount of response conflict.

smaller than those where error correction via backspace was not allowed, it is plausible that PES is also affected by other factors including inhibition of error correction.

It is possible that the way we calculated PES affected its magnitude and thus relationship with error detection. As the baseline for calculating PES, we used the average IKI of correct key-presses matched to length of the error word and its position in the error word. In contrast, Crump and Logan (2013) used the pre-error key-press (E-1) as their baseline. Although Kalfaoğlu and Stafford (2014); Salthouse (1986); Wilbert and Haider (2012) report that pre-error typing speed before errors is not different than that before errors, if, for example the key-presses preceding errors were systematically faster than the average speed of matched correct key-presses, this would lead to a smaller PES when the average value is used as a baseline. To check if using E-1 as a baseline would affect our conclusions regarding the association between PES and error detection, we re-conducted our analysis using E-1 as a baseline. We found that calculating slowing this way resulted in significant error slowing in corrected errors (30.20ms, p<0.05). Further, our regression model including FMT ERSP peak amplitude and time still predicted the amount of PES in all errors combined [3], and uncorrected errors [4]. This suggests slowing after errors is related to error detection, even if PES is calculated using the IKI of E-1 as a baseline.

Another observation that supports Crump and Logan (2013) conclusion that PES is caused by an inhibition of error correction via backspace is post error speeding, which we didn't observe neither using the average of matched correct key-presses or E-1 as a baseline. The contrast between our PES results and those of Crump and Logan (2013) might be caused by a difference in post-error key-presses included in analysis. One possible reason also acknowledged by Crump and Logan (2013) is the self-selection of fast post-error key-presses in post-corrected-error slowing calculations. Majority of corrected errors are followed immediately by backspace presses (Crump & Logan, 2013; Snyder et al., 2014), suggesting that error correction is quite fast. Thus it is likely that only the key-presses which are fast enough to be pressed before the backspace is pressed are executed in the time window between the error key-press and error-correction key-press (i.e. backspace). Further, these post-error key-presses could have been quick *error* key-strokes themselves. This would prevent the inclusion of average and slower than average key-presses in post-corrected-error slowing calculations, reducing average post-corrected-error slowing. The same problem is present in our analyses too and is a likely contributor to the very small number of post-corrected error key-presses (also see Kalfaoğlu & Stafford, 2014, figure 2, which shows the large variability in PES in post-corrected-error key-presses). Nevertheless, our observation of reliable ES in corrected errors, and use of

matched *correct* key-presses as a baseline alleviates the concerns about self-selection leading to diminished PES (unless one would argue that the processes driving ES and PES are distinct).

Other potential methodological differences (other than the baseline used and lack of error correction inhibition) that might explain why PES in the current study is smaller than those reported in the literature include lack of visual feedback and our use of sentences as opposed to single words (continuous vs. discrete typing of words). Snyder et al. (2014) directly compared the effect of visual feedback on PES in two typing experiments. Their within participants analyses showed that the magnitude of PES was not affected by visual feedback in typing single words. The amount PES reported by these authors were also larger ($\sim$ 150ms and $\sim$ 400ms in experiments 1 and 2 respectively) than reported in the current study (43ms). Similarly Wilbert and Haider (2012) also showed that in the absence of visual feedback from the screen PES magnitude was $\sim$ 400ms. It is important to note that participants were not able to correct their mistakes using backspace in these experiments. Based on these reports, we believe lack of visual feedback cannot explain the small PES on its own.

In many studies that report large PES values participants were required to type single words in each trial. A look at recent literature suggests that both when participants typed single words (Logan & Crump, 2010; Snyder et al., 2014; Wilbert & Haider, 2012; Yamaguchi et al., 2013, experiments 1, 2) or paragraphs (Crump & Logan, 2013; Yamaguchi et al., 2013, experiments 3, 4), PES was considerably larger than reported in the current study. In studies where single words were used, PES ranged from 150 to 400ms, and in those where paragraphs were used, the range was 120 to 337ms. Thus, it doesn't seem plausible that our use of sentences as opposed to words or paragraphs is an important factor in the diminished PES. Again, in all of experiments cited above, participants were not allowed to press the backspace. In light of the arguments above, we propose that PES reflects a number of processes including error detection as well as an inhibition of the natural tendency to press backspace.

Explicit vs. Implicit Error Detection. Whether a participant will correct her typing error depends on whether she is aware of that error. According to the hierarchical control model of typing Logan and Crump (2011), a participant's awareness of typing errors depends on contributions from both inner and outer loops. Since the outer loop has access to no feedback about the performance, it can't contribute to error awareness in the current study. Assuming that error

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[3](R^2 = 0.10, p < 0.01), *beta* for FMT ERSP timing = -0.22, p < 0.05)

[4](R^2 = 0.13, p < 0.01, *beta* for FMT ERSP timing = -0.21, p < 0.01, *beta* for FMT ERSP magnitude = 0.15, p < 0.05)

correction responses in the current study rely on inner loop monitoring only, our results show that inner loop can trigger error correction (supporting those of Snyder et al., 2014).

However, many uncorrected errors were also associated with PES. PES is typically associated with error monitoring in inner loop and was shown to correlate significantly with EEG indices of error detection in our study. This suggests that inner loop error detection is not sufficient to cause error correction in all cases. One plausible explanation for this observation is that error awareness relies on input from multiple channels and its output is not binary (action was correct or incorrect), but continuous. For example, when feedback from different channels (e.g. inner and outer loops) regarding the accuracy of an action are congruent, the output of the error monitoring processes (possibly indexed by theta band oscillations in the medial frontal areas which receive input from multiple cortical and subcortical structures Cohen, 2014) would be strong and lead to swift and adaptive changes in observed behaviour such as pressing of the backspace in case of errors or undisturbed execution of following key-presses in case of correct actions. In such cases, the outcome would be binary (hit or correct rejection).

However, input from the inner loop can often be noisy, especially in tasks like copy-typing where multiple key-presses are executed and monitored every second. Similarly, typists may prefer to look at the text they are copying from instead of the echo of their key-strokes on the screen, so that input from the screen is not continuously available at the outer loop level. When input from one channel is noisy, absent or incongruent with others, the output is likely to be slower and weaker, leading to disruptions in behaviour which may not be adaptive such as PES following uncorrected errors and higher rates of misses and false alarms regarding error detection. When Logan and Crump (2010) provided false feedback to outer loop contradicting that from inner loop, many participants incorrectly classified their errors as correct (misses) and many correct key-presses as errors (false alarms). Similarly, when Snyder et al. (2014) removed visual feedback from the screen, error detection rates dropped from 89% to 63%. In the current study where there was no feedback, error detection rates were also similarly low (64%). Crump and Logan (2010) did the opposite by degrading the tactile feedback from the keyboard to the inner loop while participants could see the outcome of their typing. These authors found that both typing speed and error rate were worsened under these conditions.

Thus a view where FMT ERSP reflects the outcome of processes involved in error detection fits well with our data. When input from multiple channels indicate presence of an error, 'explicit' error detection takes place (error correction via backspace). When the available input is suboptimal due to incongruent or lack of sensory information, the strength is weakened, behaviour appears disrupted (i.e. slowed) and the

probability of false alarms and misses increases.

One potential limitation of our study was the number of participants included in the study (11). To provide a comparison with other studies assessing the relationship between error awareness and EEG parameters we looked at the review paper of Wessel (2012). A total of 15 studies of error awareness are reported in this review and the participant numbers range from 7 to 20 with a mean participant number of 14.27 and standard deviation of 3.94. We believe the sample size of 11 in our study is not a major limitation. First a comparison with the studies reviewed in Wessel (2012) suggest that it is possible to get reliable results with even a smaller sample size. Second, the effect sizes for our across trial comparisons were high, increasing the observed statistical power of our analyses beyond the acceptable range (see table 1). Third, even though the number of participants was relatively small, the data points contributed by each participant was high (see methods for the details - our participants had to type 100 sentences which required 1580 key-presses).

Another problem we endured was the uneven number of sample sizes in corrected and uncorrected errors. Comparing the average values coming from samples of unequal sizes has a number of potential undesired effects. To minimize such undesired effects, we used a bootstrap based method to match the sample sizes before making comparisons (see section *Note on Number of Epochs* for details).

Conclusions

We present evidence to reinforce the proposition that error awareness is not necessarily a binary variable (see Wessel, 2012, for a discussion) but there exists a continuum between being maximally aware and absolutely unaware of ones errors, with most errors lying somewhere in between. We show using a number of statistical methods that some errors are associated with very robust ERP and theta band oscillatory EEG effects (strong ERN, phase-locking and ERSP in FMT), and these are very likely to be the corrected ones; as well as some errors which are associated with less prominent EEG effects (no phase locking but reliable ERSP, weak ERN) and these tend to be uncorrected errors. Among the uncorrected errors, some are associated with some residual awareness effects such as PES and these again are much more likely to be the ones with weak but timely theta effects. These findings add more weight to the hypothesis that ERN is an index of processes involved in explicit error awareness (Shalgi & Deouell, 2012) and suggest that the type of responses used to signal the errors of performance are crucial factors to consider when interpreting the relationship between the ERN and error awareness.

To our knowledge, this is the first time fronto medial theta oscillatory dynamics have been studied in relation to error awareness using a well-learned error signalling response in an ecologically valid task. Using this methodology, we show

that timing of the FMT changes are important factors mediating their effect on post-error (PES) adjustments in performance. The fact that these observations are made during the performance of an everyday task gives us confidence that the neuro-physiological changes that we report here are representative of those taking place in the fronto-medial areas of thousands of typists' brains every time they press (or fail to press) the backspace in response to their errors.

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