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John de Grosbois, Kimberley Jovanov, and
Luc Tremblay

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1 RUNNING HEAD: Accuracy instructions and online control

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6 Accuracy instructions differently modulate visual and non-visual contributions to ongoing reaches

7 John de Grosbois^{1,2}, Kimberley Jovanov^{1,2}, Luc Tremblay^{1,2}

8 ¹Faculty of Kinesiology and Physical Education, University of Toronto, Toronto, Ontario, Canada

9 ²Centre for Motor Control, University of Toronto, Toronto, Ontario, Canada

10 Canada

11

12

13 Correspondence:

14 Dr. Luc Tremblay

15 University of Toronto

16 55 Harbord St.

17 Toronto, Ontario, M5S 2W6, Canada.

18 luc.tremblay@utoronto.ca.

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Abstract

The control of ongoing goal-directed reaches is influenced by both visual and non-visual sensorimotor processes. Notably, intentions to produce accurate movements also influence reaching performance. However, it is not known whether these improvements associated with accuracy-based intentions can be attributed to changes in movement planning and / or online control. Notably, such improvements may come about via both visual and non-visual online control processes. Using frequency domain analyses, the relative online contributions of visual and non-visual sub-processes to reaching performance have been previously identified (e.g., de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). Thus, the current study tested if the relative contributions of these online control sub-processes are influenced by instructions to be accurate. Reaching movements were completed in the presence of three experimental manipulations. First, vision during voluntary reaches was either provided or occluded. Second, high- and low-accuracy instruction sets were provided. And third, the predictability of visual information was manipulated through blocked and randomized feedback scheduling. The results indicated that the contribution of online visuomotor processes (i.e., visual sub-process) was increased by the availability of online vision and instructions to be accurate. In contrast, the non-visual sub-process was promoted in the absence of online vision, but suppressed when a randomized feedback schedule was implemented with instructions to be accurate. Ultimately, instructions to be accurate increase the relative contribution of vision-based online sensorimotor processes and can decrease the contributions of non-visual online sensorimotor processes.

Keywords: online control; accuracy instructions; intentions; vision; proprioception

44 Public Significance Statement:

45 The current study examined the use of sensory information during simple reaching movements.

46 More specifically, how efforts to produce accurate movements influence visual and non-visual

47 contributions to performance. Instructions to be accurate facilitated visual processing but

48 inhibited non-visual processing associated with reaches.

Accuracy instructions differently modulate visual and non-visual contributions to ongoing reaches

As shown in the seminal contributions of Woodworth (1899), movements completed with vision available (i.e., full-vision) are typically performed with greater levels of accuracy than movements completed without the availability of online vision (i.e., no-vision). Equally unsurprising was the additional finding that providing instructions to produce accurate movements led to improvements in endpoint accuracy. Inherently, these performance changes could stem from changes in movement planning and / or online feedback utilization (i.e., online control). Thus, the current study sought to evaluate the influence of instructions to be accurate on the contributions of online control processes.

Theories of online control (e.g., Crossman & Goodeve, 1983; Howarth, Beggs, & Bowden, 1971; Meyer, Abrams, Kornblum, Wright, & Smith, 1988; see Elliott, Helsen, & Chua, 2001 for a review) have developed hand-in-hand with advancements in the techniques associated with the quantification of movement performance. For example, earlier work (e.g., Fitts, 1954; Keele & Posner, 1968) quantified movement accuracy solely based on target hits and misses. A presumption was that feedback acted as a servomechanism (e.g., Craik, 1947) and that the utilization of feedback would result in relatively more target hits. The invention of motion tracking systems led to the quantification of movement accuracy in terms of the spatial variability of the movement endpoints (e.g., Zelaznik, Hawkins, & Kisselburgh, 1983). The evaluation of movement variability has since garnered insights into the complexities of online

control as a multi-faceted construct (e.g., Tremblay, Hansen, Kennedy, & Cheng, 2013).

In addition to the association between online feedback utilization and changes in endpoint performance, Woodworth (1899) also noted that movements completed with vision available exhibited more quantifiable discontinuities. Consequently, greater contributions of online feedback utilization came to be associated with the presence of movement discontinuities and researchers developed techniques for both their quantification (e.g., jerk score: see Tresilian, Stelmach, & Adler, 1997) and their utility (e.g., index of error-correction effectiveness: see Khan, Franks, & Goodman, 1998). However, it has since been demonstrated that a simple reliance on the incidence of discontinuities is unwarranted, given that neither the presence (e.g., Elliot, Carson, Goodman, & Chua, 1991; Jeannerod, 1986; Poston et al., 2013), nor the absence (e.g., For example, Pélisson, Prablanc, Goodale, & Jeannerod, 1986) of discontinuities can be strongly associated with changes in online feedback utilization.

Subsequently, Elliott et al. (1991) formalized the idea of feedback utilization in the absence of observable discrete corrections in what became known as the pseudocontinuous model of online control. In the pseudocontinuous model, corrective processes are completed in an iterative, overlapping fashion, which often results in a relatively smooth kinematic profile. Accordingly, methodologies based on movement variability across trials have been developed (i.e., multiple-trial measures). These methodologies have focused on either the magnitude of the variability at different points across the movements (i.e., Khan & Franks, 2003; Khan et al., 2006; Hansen, Elliott, & Khan, 2008) or correlations between position-based kinematic markers

across multiple movements (i.e., Bernier, Chua, Franks, & Khan, 2006; Elliott, Binsted, & Heath, 1999; Heath, Westwood, & Binsted, 2004; Messier, & Kalaska, 1999). In general, significant decreases in variability across the movement and lower correlations have been associated with a relatively greater contribution of online control process. However, given the necessity of multiple trials within these types of measures, they are likely more sensitive to the contributions of offline, planning-related processes than within trial measures (e.g., de Grosbois & Tremblay, 2018).

A novel, within-trial approach for quantifying iterative, pseudocontinuous corrective processes was developed by de Grosbois and Tremblay (2016). This approach utilized analyses in the frequency domain (i.e., pPower analysis). de Grosbois and Tremblay (2016) reasoned that a relatively stable visuomotor feedback time could be expected due to the convergence of two lines of research. First, the relative stability of corrective reaction times across a range of movement parameters (e.g., Cressman, Cameron, Lam, Franks, & Chua, 2010; Saunders & Knill, 2003; Veyrat-Masson, Brière, & Proteau, 2010). And second, the overlap of these corrective reaction times with the minimum time with vision that is required to observe a change in reaching endpoint performance (e.g., Zelaznik et al., 1983). The contribution of this relatively stable visuomotor influence on reaching performance was isolated by fitting a smooth, 5th order polynomial to the acceleration profile (i.e., a minimum jerk trajectory: see Flash & Hogan, 1985) and evaluating the relative frequency power in the residuals¹. It was asserted that these residuals

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1 A 5th order polynomial was chosen because of the four natural bends found within the

would better contain information regarding the influences of online corrective processes (see also Noy et al., 2015). Notably the frequencies at which differences between conditions were observed could provide evidence for the underlying rates of the associated processes responsible for the performance differences (see de Grosbois and Tremblay, 2016 for a more detailed discussion). Using this methodology, increased relative power has been observed in the presence relative to the absence of online vision at frequencies between 4 and 10 Hz (e.g., de Grosbois & Tremblay, 2016; de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). Additionally, a second frequency peak that differentiated performance across the same vision conditions has also been observed between approximately 17 and 20 Hz (e.g., de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). This second peak was proposed to represent a non-visual process because its relative contribution to performance was found to increase in the absence, rather than in the presence of online vision. Although there is ample evidence that proprioception can mediate online control processes (e.g., Goodman et al., 2018; Gosselin-Kessiby, Messier, & Kalaska, 2008), de Grosbois and Tremblay (2018) proposed that this second peak may reflect a strategic change in the manner in which the reaching movements were planned and controlled. Indeed, strategic changes in movement planning have been shown to alter the contributions of online control processes (e.g., Roberts, Burkitt, Elliott, & Lyons, 2016). Such a multifaceted organization of online reaching performance is consistent with contemporary models of online control (e.g., Elliott et al., 2010; Elliott et al., 2017). However, a direct association between the

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acceleration profile of a discrete aiming movement.

higher, secondary peak and non-visual online control processes has only been implied. Additionally, the association of the lower frequency peak and visuomotor online control processes have been based solely on manipulations of the availability of vision. One possible avenue to address both of these potential issues is the combining of vision availability with accuracy-based instruction sets.

Because reaching performance can be significantly influenced by instruction sets (e.g., Adam, 1992; Elliott et al., 1991; Zhai, Kong, & Ren, 2004), the influence of strategic instruction sets could be used to further evaluate the nature of the frequency peaks observed in de Grosbois and Tremblay (2017). Accordingly, the primary purpose of the current study was to further investigate the nature of the visual and non-visual control mechanisms attributed to the lower and higher frequency peaks reported in de Grosbois and Tremblay (2017; see also de Grosbois & Tremblay, 2018). To this end, two experiments were completed wherein manipulations of the availability of online vision (i.e., full-vision; FV and no-vision; NV) were paired with two different instruction sets (i.e., low and high accuracy instructions). Further, the scheduling of the availability of vision was presented in either a blocked (i.e., Experiment 1) or randomized fashion (i.e., Experiment 2). Participants were instructed to either focus on being as accurate as possible (i.e., high-accuracy instruction) or to simply land in the general vicinity of the target (i.e., low-accuracy instruction). Although blocked and randomized trial scheduling likely influence both the planning and the online control of reaches (e.g., Khan, Chua, Elliott, Coull, & Lyons, 2002), it was presumed that under a randomized trial scheduling that differences between

vision conditions could be more directly attributable to the contributions of online control (i.e., plan consistently for the worst-case scenario; e.g., Elliott, Hansen, Mendoza, & Tremblay, 2004).

The primary analysis was completed using the aforementioned pPower frequency-domain analyses. However, to validate both the primary manipulations and the pPower measure, additional performance variables were also assessed. These additional measures included average movement endpoint, variable error, time after peak limb velocity, and Z^2 correlations. Notably, the latter three have been directly associated with online control. Overall, it was first hypothesized that endpoint accuracy (i.e., endpoint position / constant-error) would improve both with vision available and with accuracy-focused instruction sets. Likewise, it was hypothesized that all the dependent measures previously associated with online control would indicate a greater contribution of online control when online vision was available, and with instructions to be accurate. That is, under both full-vision conditions and high accuracy instruction sets, endpoint variability and Z^2 correlations were hypothesized to be smaller, whereas, the time spent after peak-limb velocity was expected to increase (e.g., Elliott et al., 1991). Lastly, and most relevant to the primary purpose of the current study, it was hypothesized that if the relative magnitudes of the lower and higher frequency peaks in the pPower spectra represent the relative contribution of visual and non-visual control processes to reaching performance, then the visual process was expected to be facilitated in the full-vision condition, and the non-visual process was expected to be facilitated in the no-vision condition. Notably, instructions to produce accurate movements were expected to enhance these effects.

Methods

Power Analysis

An *a-priori* power analysis was conducted to determine the expected minimum required sample size for the current study. The analysis was undertaken using the G*power software (see: Faul, Erdfelder, Lang, & Buchner, 2007; version 3.1.9.2) and was based on the results reported by de Grosbois and Tremblay (2017). Partial eta squared effect sizes for the main effect of vision condition at the lower and higher frequency peaks were computed using the reported *F* statistics (e.g., Bakeman, 2005). Alpha (i.e., α) was set to .05 and power (i.e., β) was set to .95. The analysis indicated that the minimum required participants was 7 for the analysis of the lower frequency peak and 5 for the analysis of the higher frequency peak. Given that this analysis was computed based on the results of a single published study, it was anticipated that the effect sizes reported could have been overestimates, and as such, additional participants were collected in both experiments.

Participants

Twelve participants were recruited for Experiment 1 (5 males; 7 females; age range 18 to 31), and 12 new participants were recruited for Experiment 2 (5 males; 7 females; age range 18 to 36). All were right-handed as determined by a modified version of a handedness questionnaire (Oldfield, 1971). Informed written consent was obtained prior to the beginning of the experimental trials. Monetary compensation was provided in the amount of \$5 CAD upon completion the protocol, which lasted approximately 30 minutes. All procedures were approved

187 by the local research ethics board.

188 **Materials and apparatus**

189   The experimental procedures were completed in a dimly lit room wherein participants sat
190 at a desk in front of a custom aiming console (i.e., console dimensions: length = 51 cm; width =
191 28 cm; height = 9 cm). The console was oriented such that its long axis extended in the
192 participant's medial-lateral plane (see *Figure 1*). Participants also positioned their head in a chin-
193 rest, extending approximately 29 cm above the surface of the aiming console. The shorter edge
194 of the aiming console was aligned with the centre of the chin-rest. A 1 by 1 cm of Velcro™ patch
195 served as the home position and was positioned approximately 40 cm to the right of the chin rest.
196 A small (i.e., approximately 0.5 by 0.5 cm) green light emitting diode (LED) served as the target,
197 and was located 30 cm to the left of the home position and below the surface of the aiming
198 console. Notably, the LED became visible to participants only when illuminated. Also, a piezo-
199 electric buzzer (Mallory Sonalert Products, Inc., Indianapolis, IN, USA) was utilized to provide
200 an auditory go-signal during the experiment.

201   The availability of visual information of the environment was manipulated via liquid-
202 crystal goggles (i.e., PLATO, Translucent Technologies Inc., Toronto, ON, CA: Milgram, 1987).
203 The goggles could take two states: 1) transparent / open whereby they permitted vision of the
204 environment; or 2) translucent / closed whereby they withheld vision of the environment.

205   Both position and acceleration data were collected during movements at a concurrent
206 sampling rate of 250 Hz. The position data were acquired using an optoelectric motion tracking

system (i.e., Optotrak Certus, Northern Digital Inc., Waterloo, ON, Canada), which tracked the position of the participant's right index finger via an infrared light emitting diode (IRED). The acceleration data were acquired via a triple-axis accelerometer (i.e., MMA7361L; NXP Semiconductors, Eindhoven, Netherlands) embedded in an orthotic wrist-brace worn by the participant on their right hand (i.e., model 225ZZ; Life Brand, Toronto, ON, Canada). One of the three axes of the accelerometer was oriented with the primary direction of movement (i.e., the medial-lateral axis). Data from the accelerometer was sampled with a multi-function data acquisition card (i.e., model PCI-6042E, National Instruments Inc., Austin, TX, USA). Custom MATLAB scripts (The Mathworks Inc., Natick, MA, USA) controlled the experimental procedures and devices.

Design and procedures

Each trial commenced with the participant resting their right-index finger at the home position. The target LED was illuminated and the goggles were open (i.e., transparent) for a variable foreperiod of 1 to 1.5 s, after which an auditory go-signal was sounded (i.e., 50 ms, 2900 Hz). Movement start was defined as the first occurrence of limb velocity greater than 30 mm/s that was maintained for at least 12 ms following the go-signal. In the full-vision condition, the goggles remained open until movement end. Movement end was calculated as the first occurrence of a limb velocity less than 30 mm/s that lasted for at least 20 ms (i.e., five samples) following movement start. The no-vision condition progressed in a similar manner as the full-vision condition up to the moment of movement start, at which the goggles closed and remained

closed for the remaining duration of the trial. The goggles remained in the closed state until the start of the next trial (i.e., the participant returned to the home position without vision and received no explicit visual terminal feedback). In addition to the manipulation of the availability of vision, two instruction sets were employed.

In the high-accuracy instruction set, participants were told to try to be as accurate as possible, within a 400 to 500 ms movement time bandwidth. Note that the 500 ms duration was critical for the frequency analyses (see below) and that reaches taking more than 512 ms (or less than 400 ms) were re-run. In the low-accuracy instruction set, participants were told to land in the general vicinity of the target, while maintaining the same movement time bandwidth (i.e., 400 to 500 ms). This latter condition was conceptually comparable to the “automatic” condition employed by Woodworth (1899) in that online vision was available, but participants were instructed not to focus on completing accurate movements. In Experiment 1, the two vision conditions and the two instruction sets were arranged in four blocks of 30 trials, and scheduled in a blocked organization. Four block orders were utilized and counter-balanced across participants. Each participant completed either two blocks of full-vision followed by two blocks of no-vision, or the reverse. Within the two blocks of each vision condition, the instruction sets were also counter-balanced. In Experiment 2, the vision conditions were presented in a randomized trial schedule, while the instruction sets remained in separate blocks of trials. Thus, two blocks of 60 trials were completed, which were counterbalanced across participants. To prevent carry-over effects across trials (e.g., Cheng, Luis, & Tremblay, 2008), the vision condition scheduling was

pseudo-randomized in that the same vision condition could not be repeated on more than two consecutive trials. In both experiments, participants completed a minimum of 10 familiarization trials in the condition associated with the first block to get comfortable with the required movement time bandwidth. Both experiments included a total of 120 experimental trials, and lasted approximately half an hour.

Data processing and analysis

Based on previous work (i.e., de Grosbois & Tremblay, 2017; de Grosbois & Tremblay 2018) four dependent measures of online control were chosen and calculated to evaluate performance. Variable error (i.e., VE) was computed as the within-condition standard deviation of the movement endpoints in the primary movement axis. Smaller VE values have been associated with an increased contribution of online control processes (e.g., Tremblay, et al., 2013).

Time after peak velocity (i.e., TAPV) was computed as the number of milliseconds elapsed between the sample at which peak limb velocity was reached and the sample at movement end. Longer TAPV values have been associated with a greater contribution of online control processes (e.g., Binsted, Brownell, Vorontsova, Heath, & Saucier, 2007; Elliott et al., 1991; Hansen, Glazebrook, Anson, Weeks, & Elliott, 2006; Soechting, 1984).

Third, a correlational measure of online control was computed as within-condition correlations across trials between the position attained at 75 % of movement time, and the position achieved at movement end. These correlations were then converted into Z-scores using a

fisher-transform and squared (i.e., Z^2 ; e.g., Bernier et al., 2006; de Grosbois & Tremblay, 2016; de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). Smaller correlational values have been interpreted as evidence of a greater contribution of online control (e.g., de Grosbois & Tremblay, 2016; Heath, 2005; Heath, Westwood, Binsted, 2004).

Lastly, proportional power spectra were computed from the acceleration profiles of each trial (i.e., pPower; see de Grosbois & Tremblay, 2016; de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). These spectra were attained via a multi-step process. First, using the MATLAB polyfit() and polyval() functions, the best fitting 5th order polynomial was determined and computed for each acceleration trace. This best fitting polynomial was then subtracted from the acceleration trace yielding residuals. Second, a Hanning truncation window of the same duration as the movement was generated via the MATLAB hanning() function, and was multiplied by the residuals to reduce edge effects and spectral leakage (e.g., Randall, 2008; Warner, 1998). Third, the data were converted into a frequency domain representation via a fast-fourier-transform (i.e., FFT; MATLAB fft() function) with a transform length of 128 samples (i.e., movement times up to 512 ms). The output of the FFT was converted into a power spectrum by multiplying the Fourier coefficients by their complex conjugate (i.e., via the MATLAB conj() function) and dividing by the transform length. These spectra were then normalized by the total power up to the Nyquist frequency (i.e., 125 Hz), and expressed as a relative percent contribution of resolvable frequencies to the residual variance (i.e., the pPower spectrum)². The pPower

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² See the appendix of de Grosbois (2017) for a MATLAB script outlining the main analysis.

spectra were subsequently evaluated qualitatively for apparent peaks on a trial-by-trial basis. Both the frequency and the relative magnitude of such peaks were separately subjected to further analyses. Greater relative magnitudes of observed peaks in pPower spectra at 10 Hz and below have been associated with a greater relative contribution online visuomotor control (e.g., the α peak; see de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018), and greater relative magnitudes of observed peaks in pPower spectra between approximately 17 and 20 Hz have been associated with the contribution of a non-visual process (e.g., the β peak; see de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). Thus, to ensure the capture of both peaks, frequency spectra were evaluated up to 30 Hz.

The main analyses were computed separately for each experiment for all dependent variables as a 2 Vision Condition (full-vision, no-vision) x 2 Instruction Set (high-accuracy, low-accuracy) repeated-measures ANOVA. In the event of a significant interaction between Vision Condition and Instruction Set, pairwise comparisons were completed across the two levels of each factor. In this case, a Bonferroni correction was applied to p -values based on the number of t -tests completed (i.e., 4). The corrected p -values have been reported in the results section as p_{b4} where the 'b' indicated that a Bonferroni correction has been applied, and the '4' indicated the number of comparisons corrected for. Statistical significance was determined at $p < .05$ for all analyses. The effect size reported for each ANOVA was generalized eta squared (η_G^2 ; see Bakeman, 2005; Olejnik & Algina, 2003). The ANOVAs were computed using the EZ package (Lawrence, 2013) in the R statistics program (version 3.1.2; R-core Team, 2014). All error bars

depicted in figures represent within-subject 95 % confidence intervals (see Loftus & Masson, 1994).

Results

A summary of all condition's means and standard deviations for all dependent variables can be found in *Table 1*.

Experiment 1: Blocked vision conditions

The analysis of average movement endpoint in the primary movement axis yielded no significant effects or interactions, $F_s(1,11) < 2.16$, $p_s > .160$, $\eta_G^2s < .060$. The grand mean endpoint position was 307.8 mm ($SD = 5.8$).

The analysis of variable error in the primary movement axis (i.e., VE) yielded a significant main effect of Vision Condition, $F(1,11) = 97.93$, $p < .001$, $\eta_G^2 = .529$. Performance in the full-vision conditions yielded significantly smaller VE values (i.e., $M = 4.68$ mm, $SD = 0.92$) relative to the no-vision conditions (i.e., $M = 8.59$ mm, $SD = 1.66$). No significant main effect or interaction involving Instruction Set was observed, $F_s(1,11) < 3.13$, $p_s > .104$, $\eta_G^2s < .085$.

The analysis of the time spent following peak limb velocity (i.e., TAPV) resulted in no significant effects or interactions, $F_s(1,11) < 1.78$, $p_s > .110$, $\eta_G^2s < .013$. The grand mean TAPV was 288 ms ($SD = 20$).

The analysis of the Z^2 correlations yielded a significant main effect of Vision Condition,

$F(1,11) = 34.12, p < .001, \eta_G^2 = .454$. Performance in the full-vision conditions yielded significantly smaller Z^2 values (i.e., $M = 0.29, SD = 0.15$) relative to the no-vision conditions (i.e., $M = 1.15, SD = 0.48$). No significant main effect or interaction involving Instruction Set was observed, $F_s(1,11) < 0.34, ps > .570, \eta_G^2s < .007$.

Prior to the analysis of the pPower data, the spectra were qualitatively examined for observable peaks (see *Figure 2*, panel a). As in de Grosbois and Tremblay (2017; see also de Grosbois & Tremblay, 2018), two peaks were evident: 1) one in the relatively lower frequencies, denoted as the alpha peak (α_{Peak}); and 2) one in the relatively higher frequencies, denoted as the beta peak (β_{Peak}). Analysis of the frequency of the α_{Peak} resulted in no significant effects or interactions, $F_s(1,11) < 4.32, ps > .062, \eta_G^2s < .035$. The grand mean frequency of the α_{Peak} was 7.17 Hz ($SD = 0.62$). Analysis of the relative magnitude of the α_{Peak} resulted in main effects of Vision Condition, $F(1,11) = 13.18, p = .004, \eta_G^2 = .235$, and Instruction Set, $F(1,11) = 11.90, p = .005, \eta_G^2 = .022$ (see *Figure 2*, panel b). In the full-vision conditions, the relative magnitude of the α_{Peak} was significantly larger (i.e., $M = 25.37\%, SD = 3.81$) compared to the no-vision conditions (i.e., $M = 20.68\%, SD = 4.43$). Additionally, the relative magnitude of the α_{Peak} was also significantly larger with the high-accuracy instruction set (i.e., $M = 23.66\%, SD = 3.70$) relative to the low-accuracy instruction set (i.e., $M = 22.39\%, SD = 3.36$). No significant interaction was observed between Vision Condition and Instruction Set, $F(1,11) = 0.42, p = .531, \eta_G^2s = .004$.

Because no observable β_{Peak} was present for the full-vision conditions, the frequency of

this peak was estimated based on the associated frequency observed in the no-vision conditions. The resulting preliminary analysis of the frequency of the β_{Peak} across the two no-vision conditions revealed no significant effect of Instruction Set, $F(1,11) = 1.73$, $p = .215$, $\eta_G^2 = .020$. The grand mean frequency for the β_{Peak} in the no-vision conditions was 18.27 Hz ($SD = 0.80$). The nearest resolvable frequency (i.e., 17.58 Hz) was chosen to represent the relative magnitude of the β_{Peak} in the forthcoming relative magnitude analysis for the two full-vision conditions. The analysis of the relative magnitude of the β_{Peak} resulted in a main effect of Vision Condition, $F(1,11) = 45.10$, $p < .001$, $\eta_G^2 = .562$ (see *Figure 2*, panel c). Reaches completed in the full-vision conditions yielded a significantly smaller pPower magnitude at the β_{Peak} frequency peak (i.e., $M = 2.20\%$, $SD = 1.02$) relative to those completed in the no-vision conditions (i.e., $M = 4.81\%$, $SD = 1.21$). No significant main effect or interaction involving Instruction set was observed, $F_s(1,11) < 0.93$, $p_s > .817$, $\eta_G^2_s < .005$.

In summary, when the vision conditions were employed in separate blocks of trials, the availability of online vision (i.e., vision during the movement) led to smaller endpoint variability, lower Z^2 correlation values, larger α_{Peak} magnitudes, and smaller β_{Peak} magnitudes. In contrast, neither endpoint position in the primary movement axis, nor time spent following peak limb velocity were significantly influenced by the vision manipulation. The inclusion of the high-accuracy instruction set significantly increased the α_{Peak} magnitude only. That is, no other dependent measure was significantly modulated by the Instruction Set manipulation. Further, none of the dependent measures exhibited an interaction between the two manipulations of

365 Vision Condition and Instruction Set.

366 **Experiment 2: Randomized vision conditions**

367   The analysis of the average movement endpoint in the primary movement axis yielded a
368 significant main effect of Vision Condition, $F(1,11) = 13.10$, $p = .004$, $\eta_G^2s = .247$. Performance
369 in the full-vision conditions exhibited a significantly farther mean endpoint position (i.e., $M =$
370 309.9 mm, $SD = 2.8$) relative to the no-vision conditions (i.e., $M = 303.3$ mm, $SD = 7.6$). No
371 significant main effect or interaction involving Instruction Set was observed, $F_s(1,11) < 3.50$, ps
372 $> .090$, $\eta_G^2s < .021$.

373   The analysis of variable error in the primary movement axis (i.e., VE) yielded a
374 significant main effect of Vision Condition, $F(1,11) = 43.72$, $p < .001$, $\eta_G^2 = .273$. Performance
375 in the full-vision conditions yielded significantly smaller VE values (i.e., $M = 4.63$ mm, $SD =$
376 1.64) relative to the no-vision conditions (i.e., $M = 6.85$ mm, $SD = 1.15$). No significant main
377 effect or interaction involving Instruction Set was observed, $F_s(1,11) < 3.03$, $ps > .101$, $\eta_G^2s <$
378 $.080$.

379   The analysis of the time spent following peak limb velocity (i.e., TAPV) resulted in a
380 significant effect of Vision Condition, $F(1,11) = 7.33$, $p = .020$, $\eta_G^2s < .068$. Performance in the
381 full-vision conditions yielded significantly longer TAPV values (i.e., $M = 294$ ms, $SD = 15$)
382 relative to the no-vision conditions (i.e., $M = 286$ ms, $SD = 14$). No significant main effect of
383 Instruction Set was observed, $F(1,11) = 1.90$, $p = .195$, $\eta_G^2 = .024$. Additionally, because the
384 interaction between Vision Condition and Instruction Set neared conventional levels of statistical

significance, $F(1,11) = 4.74$, $p = .052$, $\eta_G^2 = .009$, post-hoc pairwise comparisons were completed. This subsequent analysis revealed that a sole significant difference was observed in the high-accuracy Instruction Set, indicating significantly longer TAPV values in the full-vision relative to the no-vision condition (i.e., full-vision: $M = 298$ ms, $SD = 15$; no-vision: $M = 287$ ms, $SD = 14$; $p_{b4} = .025$). Conversely, the contrast between vision conditions did not reach significance in the low-accuracy Instruction Set (full-vision: $M = 290$ ms, $SD = 18$; no-vision: $M = 285$ ms, $SD = 16$; $p_{b4} = .565$).

The analysis of the Z^2 correlations yielded a significant main effect of Vision Condition, $F(1,11) = 23.10$, $p < .001$, $\eta_G^2 = .220$. Performance in the full-vision conditions yielded significantly smaller Z^2 values (i.e., $M = 0.39$, $SD = 0.34$) relative to the no-vision conditions (i.e., $M = 0.88$, $SD = 0.36$). No significant main effect or interaction involving Instruction Set was observed, $F_s(1,11) < 1.85$, $p_s > .602$, $\eta_G^2_s < .050$.

As was the case in Experiment 1, alpha (α_{Peak}) and beta peaks (β_{Peak}) were observable in the spectra (see *Figure 3*, panel a). Analysis of the frequency of the α_{Peak} resulted in no significant effects or interactions, $F_s(1,11) < 1.61$, $p_s > .231$, $\eta_G^2_s < .027$. The grand mean frequency of the α_{Peak} was 6.92 Hz ($SD = 0.49$).

Analysis of the relative magnitude of the α_{Peak} resulted in a main effect of Vision Condition, $F(1,11) = 26.98$, $p < .001$, $\eta_G^2 = .223$. In the full-vision conditions, the relative magnitude of the α_{Peak} was significantly larger (i.e., $M = 31.82$ %, $SD = 3.10$) relative to the no-vision conditions (i.e., $M = 28.39$ %, $SD = 2.70$). Also, the main effect of Instruction Set did not

reach conventional levels of statistical significance, $F(1,11) = 3.59$, $p = .085$, $\eta_G^2 = .059$ (see *Figure 3*, panel b). However, the pattern of means was consistent with the Experiment 1 findings (i.e., high-accuracy instruction set: $M = 30.91\%$, $SD = 3.11$; low-accuracy instruction set: $M = 29.30\%$, $SD = 2.98$). Additionally, no significant interaction between Vision Condition and Instruction Set was observed, $F(1,11) < 0.01$, $p = .989$, $\eta_G^2 < .001$.

Because no observable β_{Peak} was present for the full-vision conditions, the frequency of this peak was again estimated based on the two no-vision conditions. The analysis of the two no-vision conditions revealed no significant effect of Instruction Set, $F(1,11) = 0.16$, $p = .694$, $\eta_G^2 = .003$. The grand mean frequency for the β_{Peak} in the no-vision conditions was 17.75 Hz ($SD = 0.95$). The nearest resolvable frequency (i.e., 17.58 Hz) was chosen to represent the relative magnitude of the β_{Peak} in the forthcoming analysis for the two full-vision conditions.

The analysis of the relative magnitude of the β_{Peak} resulted in main effects of both Vision Condition, $F(1,11) = 108.45$, $p < .001$, $\eta_G^2 = .647$, and Instruction Set, $F(1,11) = 8.51$, $p = .014$, $\eta_G^2 = .152$ (see *Figure 3*, panel c). Reaches completed in the full-vision conditions yielded a significantly smaller β_{Peak} (i.e., $M = 1.47\%$, $SD = 0.42$) relative to the no-vision conditions (i.e., $M = 3.60\%$, $SD = 0.84$). Additionally, reaches completed under the high accuracy instruction set yielded a significantly smaller β_{Peak} (i.e., $M = 2.20\%$, $SD = 0.51$) relative to the low accuracy instruction set (i.e., $M = 2.86\%$, $SD = 0.83$). Additionally, no significant interaction between Vision Condition and Instruction Set was observed, $F(1,11) < 0.01$, $p = .988$, $\eta_G^2 < .001$.

In summary, when the vision conditions were employed randomly within a given block of

trials, the availability of online vision (i.e., vision during the movement) led to farther endpoint positions, smaller endpoint variability, longer times spent after peak limb velocity, lower Z^2 correlation values, larger α_{Peak} magnitudes, and smaller β_{Peak} magnitudes. In contrast to Experiment 1 (i.e., blocked trial schedule), the inclusion of the high-accuracy instruction set significantly decreased the β_{Peak} magnitude. No other dependent measure was significantly modulated by the Instruction Set manipulation. Further, the main effect of Vision Condition observed for time spent after peak limb velocity was likely mediated by the near-significant interaction between the Vision Condition and Instruction Set (i.e., $p = .052$). That is, only when online vision was available with a high accuracy instruction set were longer times after peak limb velocity observed.

Discussion

The current study sought to gain further insight into the nature of the processes contributing to the lower and higher frequency peaks previously observed in pPower spectra during full-vision and no-vision conditions respectively. This aim was accomplished via three main experimental manipulations: 1) the availability of online vision during reaching (i.e., full-vision and no-vision conditions); 2) the application of two instructions sets (i.e., high-accuracy and low-accuracy instructions); and 3) the predictability of online vision through blocked and randomized trial scheduling across experiments. It was hypothesized that if the processes associated with the two frequency peaks represented error-reducing online control mechanisms, then their contributions to reaching performance would be enhanced in full-vision (i.e., the lower

frequency peak) and no-vision (i.e., the lower frequency peak) conditions. Further, the addition of accuracy-focused instruction sets was anticipated to enhance these contributions. Lastly, the inclusion of a randomized trial scheduling with respect to vision conditions was expected to better isolate the contributions of control mechanisms by encouraging comparable planning across conditions. In most cases, these manipulations worked as expected, with the exception of the influence of accuracy-based instructions on the contributions of the non-visual frequency peak (i.e., the β_{Peak}). That is, the instructions to produce accurate movements suppressed the contributions of this higher frequency process, rather than enhance it. Thus, it appears that the visual and non-visual processes associated with the lower and higher frequency peaks in the pPower spectra represent processes that differ not only in their target modality, but also the nature of their normal contribution to online reaching performance.

To better associate the frequency peaks with corrective, online control processes, reaching performance was first evaluated using more traditional measures of performance. Considering average endpoint position, no significant differences were observed when the trial scheduling was blocked. However, when randomized trial scheduling was utilized, significantly shorter amplitude movements were observed in the no-vision vs. the full-vision conditions. Thus, in a situation of relative uncertainty regarding the possibility of visual feedback, participants completed their movements in a manner consistent with a conservative strategy associated with planning for the worst-case scenario (e.g., Elliott, et al., 2004; Hansen et al., 2006). That is, given the time constraints, target overshoots may be particularly costly, especially if visual feedback

were not to be available (e.g., Elliott et al., 2010, 2017). These results can be contrasted with those of Elliott et al. (2014), who recently reported that such undershooting could be maximized by using blocked trial scheduling with situations wherein overshoots would be more costly (i.e., a downward movement) without the provision of terminal feedback. The failure to replicate those findings in the current study likely stems from a combination of factors including the temporal constraints, and the use of only one potential target. That latter of which likely led to enhanced performance on a trial-to-trial basis. Nevertheless, performance differences observed in Experiment 2 likely better reflected differences in the utilization of online control across vision conditions. Subsequent analyses specifically addressed this possibility.

First, endpoint variability was significantly smaller in the presence of online visual information, which was expected (e.g., Elliott et al., 1991; Heath, 2005; de Grosbois & Tremblay, 2016; Zelaznik et al., 1983). Unexpectedly, the instructions to be accurate did not result in significant decreases in endpoint variability (cf., Adam, 1992; Elliott et al., 1991; Zhai et al., 2004). Yet, the pattern of results was in the expected direction for both experiments. High accuracy instructions tended toward smaller endpoint variability values. Notably, however, the magnitude of the variable error in the absence of online vision was apparently smaller when the trial scheduling was randomized (i.e., 6.8 vs 8.6 mm). Such reductions in variable error could result from a carry-over effect of performance on full-vision trials into performance on the subsequent no-vision trials when using a randomized schedule (e.g., Cheng et al., 2008). This benefit may have accrued in part, from partial terminal feedback available due to the closing of

the goggles at movement end (cf. earlier). This would allow for even greater similarity in the planning mechanisms across vision conditions in Experiment 2.

Second, the analysis of the time spent following peak limb velocity did not exhibit any significant effects or interactions when vision conditions were blocked. Although increased times spent following peak limb velocity (TAPV) has been associated with visual feedback utilization (e.g., Elliott et al., 1991), this finding has not been consistently replicated (e.g., de Grosbois & Tremblay, 2016; de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018; Heath, et al., 2004). In contrast, when vision conditions were randomized, a main effect of vision condition was observed. That is, longer TAPV values were observed in the presence relative to the absence of online vision. That is, participants likely incurred a cost associated with using online visual feedback when they had not planned to (see Kennedy, Bhattacharjee, Hansen, Reid, and Tremblay, 2015; see also Tremblay et al., 2013; cf., Hansen et al., 2006). Notably, the absence of this effect for the blocked vision conditions in Experiment 1 strengthens the notion that TAPV is influenced both by changes in planning and online control (see also de Grosbois & Tremblay, 2018; Plamondon & Alimi, 1992). Furthermore, it also strengthens the notion that changes motor planning mechanisms may influence online control processes (e.g., Khan et al., 1998; Khan et al., 2002; Roberts et al., 2016).

It was also hypothesized that TAPV would increase with instructions to be accurate (e.g., Adam, 1992; Elliott et al., 1991). Nevertheless, no significant differences were observed between instruction set conditions for either the blocked or the randomized vision condition experiments.

Yet, the pattern of means was in the expected direction for both experiments.

Third, the Z^2 analysis yielded only a significant effect only of Vision Condition in both experiments. That is, the presence of online visual information during movement yielded greater estimates of online control. Such an influence of online vision on this correlational measure was expected and has been replicated many times (e.g., de Grosbois & Tremblay, 2016; de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018; Heath, 2005; Heath et al., 2004; Khan, Lawrence, Franks, & Buckolz, 2004; Tremblay, et al., 2013; cf., Bernier et al., 2006). In contrast, the effect of Instruction Set was not found to be statistically significant, although the observed pattern of means was in the expected direction for both experiments.

The overall meagre influence of instructions on these dependent measures, relative to previous studies (e.g., Adam, 1992; Elliott et al., 1991), may have stemmed from the added temporal accuracy demand in the current study. That is, participants were instructed to move with a movement time bandwidth between 400 and 500 ms. Thus, participants may have inadvertently placed a stronger emphasis on the temporal aspect of the task rather than the spatial aspect. Additionally, differences in how the participants interpreted the instruction sets may have added to the observed variability in performance. However, despite the lack of significant differences for most of the dependent variables, the patterns of the means in all cases were consistent with an increased emphasis on movement accuracy. Nevertheless, such an influence of the temporal demands did not interfere with the pPower analyses, thereby providing greater validity to the instruction set manipulation overall.

Fourth and last, the analysis of the relative magnitude of the α_{Peak} when vision conditions were blocked indicated a significant increase in the contribution of online control processes in the presence of online vision and in the high-accuracy instructions conditions. Increased power at this peak has been previously associated with a greater relative contribution of visuomotor online control mechanisms (e.g., de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018). Notably, the increase in the high-accuracy instructions was unique across all measures. Importantly, the pPower analysis has been shown to be relatively more robust to planning-induced changes on the quantification of the contribution of online control as compared to the other considered measures (de Grosbois & Tremblay, 2018). Thus, the absence of significant differences between instruction set conditions in the traditional measures may stem from changes in movement planning across conditions. When vision conditions were randomized in Experiment 2, a comparable influence of online visual information was found. Conversely, no significant effect of Instruction were observed. However, the pattern of the means, and the size of the difference between the two instruction sets were consistent with the findings from Experiment 1 (i.e., when vision conditions were blocked). Nevertheless, it was only the pPower analysis that yielded significant differences in the expected direction in response to changes in instruction sets. As such the motor planning explanation is both possible and probable.

Overall, because the relative magnitude of the α_{Peak} was modulated by instructions to be accurate, the association between the magnitude of the α_{Peak} and the contribution of online control mechanisms was strengthened. In contrast, the finding of a main effect of instruction set

indicated that the α_{Peak} may be influenced by both visual and non-visual control processes. Such an assertion is consistent with the fact that the differences observed between full-vision and no-vision conditions have been in the relative magnitude, and not in the mere presence / absence of the α_{Peak} . Potential mechanistic explanations include efferent outflow control, voluntary non-visual control, and proprioceptive control (e.g., Elliott et al., 2010). However, the relative contribution of these distinct processes to the relative magnitude of the α_{Peak} is beyond the scope of the current study. Accordingly, studies manipulating proprioceptive feedback could prove insightful in future investigations.

The analysis of the relative magnitude of the β_{Peak} resulted in significant a main effect of Vision Condition for both experiments. That is, as previously reported (e.g., de Grosbois & Tremblay, 2017; de Grosbois & Tremblay, 2018), the relative magnitude of the β_{Peak} was larger in the absence of online visual information, as compared to when it was present. A main effect of Instruction Set was also observed only when vision conditions were randomized (i.e., Experiment 2). That is, when the high-accuracy instruction set was provided, the relative magnitude of the β_{Peak} was significantly smaller relative to the low-accuracy instruction set conditions. It had been hypothesized that if the β_{Peak} represented a control mechanism modifiable by changes in instructions, it would increase in both no-vision conditions and when participants were instructed to be accurate. Instead, the relative magnitude of the β_{Peak} increased with no-vision conditions and decreased when accuracy was stressed in the instructions. Thus, an alternative explanation is warranted.

Instead of viewing the presence of the β_{Peak} as evidence for the contributions of a control-related process, a parsimonious alternative is that its absence reflects the contribution of an inhibitory process. That is, under full-vision conditions, oscillations normally associated with this secondary peak were presumably suppressed to achieve a high level of movement accuracy. When online vision was not available, the decrease in contribution of visuomotor online control processes lessened this suppression. Further, when visual feedback was randomized, instructions to be accurate also significantly decreased the relative magnitude of the β_{Peak} . Although it is often stated that, under randomized visual feedback schedules, participants plan for the worst-case scenario (e.g., Elliott et al., 2004), these results indicate that it may not be so simple. Given that under blocked visual feedback scheduling (i.e., Experiment 1), the β_{Peak} was consistently larger in the no-vision conditions relative to the full-vision condition, a worst-case scenario prediction for Experiment 2 (i.e., randomized vision condition schedule) would be an overall β_{Peak} magnitude comparable in size to the no-vision conditions of Experiment 1. Instead, the relative magnitude of the β_{Peak} decreased in Experiment 2 relative to Experiment 1. That is, it appeared as if participants were preparing for the possibility of visual feedback utilization by suppressing the relative magnitude of the β_{Peak} , irrespective of the vision condition. Notably, although this explanation is not entirely consistent with a plan for the worst-case scenario hypothesis, it is consistent with the expectation that under randomized vision condition scheduling, participants

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3 Analysis of the relative magnitude of the β_{Peak} across experiments yielded a significant effect of Experiment, $F(1,22) = 10.23$, $p = .004$, $\eta_G^2 = .197$. That is, the relative magnitude of the β_{Peak} was larger in Experiment 1 (i.e., blocked scheduling; $M = 3.51\%$, $SD = 0.90$) relative to Experiment 2 (i.e., randomized scheduling; $M = 2.53\%$, $SD = 0.56$).

may prepare their movements more comparably across conditions. This hypothesis of inhibition of the β_{Peak} during movement is also consistent with existing neurophysiological data.

Fink et al. (2014) examined reaching movements in mice and reported that presynaptic inhibition of interneurons in the spinal cord were important for the maintenance of smooth reaching performance. When the specific GABA-ergic interneurons were genetically ablated, the mice exhibited forelimb oscillations in the 18 to 22 Hz range during movement. The authors argued that the interneurons normally reduced the gain of proprioceptive spinal feedback loops during movement. Although the current experiment examined human reaching behaviours, such an inhibitory process is consistent with the data described above. This idea of a modulation of short-latency spinal reflex pathway in a task-specific manner has previously been observed for mechanical perturbations of a reaching limb in humans (e.g., Mutha, Boulinguez, & Sainburg, 2008). Further, such reflexes have been found to be dynamically modulated during goal-directed reaches (e.g., Liu & Todorov, 2007). As such, it is likely that the β_{Peak} represents the contribution of proprioceptive feedback loops, which can be suppressed in a task-relevant manner via online-vision during reaching and / or instructions to complete accurate movements. Accordingly, future work examining the magnitude of responses to mechanical perturbations during movements paired with accuracy-based instructions could be used to directly test this hypothesis.

Overall, the influence of instruction set across the frequency peaks differed between Experiments 1 and 2. That is, when the availability of vision was provided in a blocked manner, the magnitude of the α_{Peak} was significantly increased with high accuracy instructions. In

contrast, when the availability of vision was provided in a randomized fashion, the magnitude of the β_{Peak} was decreased with high accuracy instructions. Thus, it appears that under blocked conditions, the online control process represented by the α_{Peak} may be up-regulated by changes in movement planning. This is consistent with the idea that planning can influence the contributions of online control (e.g., Khan et al., 1998; Khan, Elliott, Coull, Chua, & Lyons, 2002; Roberts et al., 2016). In contrast, under randomized conditions, it has been suggested that individuals plan for the worst-case scenario (e.g., Elliott, Hansen, Mendoza, & Tremblay, 2004; Hansen et al., 2006). Indeed, the TAPV findings in Experiment 2 were consistent with this hypothesis. However, the β_{Peak} findings from Experiment 2 are not entirely consistent with this suggestion. When provided with high-accuracy instructions, the magnitude of the β_{Peak} in the no-vision condition shifted closer to what one might expect from a full-vision condition. Thus, although the participants may have prepared some aspects of the forthcoming movements for the worst-case scenario, they also planned for the possibility of using visual feedback. Ultimately, these findings suggest that the interdependency of the planning and control of reaching movements more complex than previously thought.

Conclusion

The current study sought to characterize the nature of the two previously observed peaks observed in the frequency domain spectra for simple reaches. This was accomplished through the manipulations of online vision, accuracy-based instruction sets, and trial scheduling. It was hypothesized that if the peaks represented visual (i.e., the α_{Peak}) and non-visual (i.e., β_{Peak}) online

control processes voluntarily modifiable by instruction sets, then their relative contributions to the trajectories should increase in the presence (i.e., the α_{Peak}) and the absence (i.e., β_{Peak}) of online vision, respectively. Additionally, high-accuracy instructions were predicted to further facilitate the respective contributions in compatible sensory environments. In partial agreement with these hypotheses, the relative magnitude of the α_{Peak} increased in the presence of online visual information and also when participants were given high-accuracy instruction sets. However, this instruction-based modulation was more robust when vision conditions were blocked. In contrast, the results associated with the β_{Peak} indicated that its relative magnitude increased in the absence of online vision, but decreased with instructions to be accurate when vision conditions were also randomized. Thus, unlike the α_{Peak} , the magnitude of the β_{Peak} does not represent the direct contribution of an online control process, but rather, it likely represents the suppression of proprioceptive spinal feedback loops, which may otherwise interfere with the production of smooth and accurate movements.

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817 *Table 1.* Means and standard deviations (in parentheses) for all dependent variables across
 818 experimental manipulations of trial scheduling (i.e., blocked & random), accuracy instruction set
 819 (i.e., low & high), and vision condition (i.e., full-vision and no-vision).

	Experiment 1 (Blocked Vision)				Experiment 2 (Randomized Vision)			
	Low Accuracy		High Accuracy		Low Accuracy		High Accuracy	
	Full-Vision	No-Vision	Full-Vision	No-Vision	Full-Vision	No-Vision	Full-Vision	No-Vision
Endpoint (mm)	310.3 (4.3)	306.9 (11.3)	309.6 (3.9)	304.3 (12.7)	310.5 (3.3)	304.4 (8.9)	309.3 (3.0)	302.3 (6.6)
Variable Error (mm)	5.1 (1.3)	9.3 (2.9)	4.3 (0.9)	7.8 (2.0)	5.3 (2.8)	7.2 (1.9)	3.9 (1.3)	6.5 (1.1)
TAPV (ms)	284 (18)	288 (23)	290 (21)	291 (26)	290 (18)	285 (16)	298 (15)	287 (15)
Z^2	0.29 (0.24)	1.22 (0.84)	0.29 (0.18)	1.08 (0.41)	0.52 (0.60)	0.96 (0.65)	0.25 (0.26)	0.81 (0.32)
α_{Peak} Frequency (Hz)	7.1 (0.8)	7.2 (0.8)	7.4 (1.0)	6.9 (0.6)	6.8 (0.6)	6.8 (0.7)	7.1 (0.7)	6.9 (0.6)
α_{Peak} Magnitude (%)	25.0 (2.9)	19.8 (5.2)	25.7 (5.0)	21.6 (4.3)	31.0 (3.4)	27.6 (3.3)	32.6 (3.5)	29.2 (3.2)
β_{Peak} Frequency (Hz)	(-)	18.2 (0.8)	(-)	18.4 (0.9)	(-)	17.8 (0.8)	(-)	17.7 (1.3)
β_{Peak} Magnitude (%)	2.3 (1.0)	4.9 (1.5)	2.2 (1.2)	4.7 (1.1)	1.8 (0.6)	3.9 (1.1)	1.1 (0.3)	3.3 (0.9)

820 *Figure 1. A depiction of the experimental setup (Note. Not to scale).*

821 *Figure 2.* The main findings of Experiment 1: a) The mean pPower spectra of the four
 822 conditions; b) The relative magnitude of the α_{Peak} ; and c) the relative magnitude of the β_{Peak}
 823 across experimental conditions. * indicates $p < .05$. Error bars represent within-subject 95 %
 824 confidence intervals.

825 *Figure 3.* The main findings of Experiment 2: a) The mean pPower spectra of the four
826 conditions; b) The relative magnitude of the α_{Peak} ; and c) the relative magnitude of the β_{Peak}
827 across experimental conditions. * indicates $p < .05$. Error bars represent within-subject 95 %
828 confidence intervals.