

1 **Large-scale analysis of interindividual variability in single and paired-**
2 **pulse TMS data: results from the ‘Big TMS Data Collaboration’**

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Abstract

Objective: Interindividual variability of single and paired-pulse TMS data has limited the clinical and experimental applicability of these methods. This study brought together over 60 TMS researchers to create the largest known sample of individual participant single and paired-pulse TMS data to date, enabling a more comprehensive evaluation of factors driving response variability.

Methods: 118 corresponding authors provided deidentified individual TMS data. Mixed-effects regression investigated a range of individual and study level variables for their contribution to variability in response to single and pp TMS data.

Results: 687 healthy participant's TMS data was pooled across 35 studies. Target muscle, pulse waveform, neuronavigation use, and TMS machine significantly predicted an individual's single pulse TMS amplitude. Baseline MEP amplitude, M1 hemisphere, and biphasic AMT significantly predicted SICl response. Baseline MEP amplitude, test stimulus intensity, interstimulus interval, monophasic RMT, monophasic AMT, and biphasic RMT significantly predicted ICF response. Age, M1 hemisphere, and TMS machine significantly predicted motor threshold.

Conclusions: This large-scale analysis has identified a number of factors influencing participants' responses to single and paired pulse TMS. We provide specific recommendations to increase the standardisation of TMS methods within and across laboratories, thereby minimising interindividual variability in single and pp TMS data.

1 **Abbreviations and nomenclature**

2 TMS: Transcranial magnetic stimulation

3 MEP: motor evoked potential

4 pp: paired-pulse

5 SICI: short-interval intracortical inhibition

6 ICF: intracortical facilitation

7 IV: independent variable

8 DV: dependent variable

9 Normalised MEP: DV for SICI and ICF analyses (conditioned MEP amplitude expressed as a
10 percentage of the baseline MEP amplitude)

11 CS: conditioning stimulus (initial pulse for paired-pulse TMS protocols)

12 TS: test stimulus (second pulse for pp TMS protocols, or unconditioned / baseline MEPs for
13 pp protocol)

14 ISI: interstimulus interval

15 RMT: resting motor threshold

16 AMT: active motor threshold

17 Pulse waveform: monophasic or biphasic pulse waveforms

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20 **Highlights**

21 • 687 healthy participant's TMS data was pooled across 35 studies

22 • Significant relationships between age and resting motor threshold

23 • Significant relationships between baseline MEP amplitude and

24 SICI/ICF

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1 **1. Introduction**

2 Single and paired-pulse (pp) TMS protocols are used to measure neural
3 excitability within the primary motor cortex (M1) (Hallett 2000). However,
4 these measures of M1 excitability have been shown to vary significantly
5 between individuals (Iskan et al. 2016, Orth et al. 2003). A lack of
6 understanding of the factors driving this variability has restricted greater
7 application of single and pp TMS as a clinical and experimental tool (Iskan et
8 al. 2016). Many studies have investigated this issue, yet there are conflicting
9 findings in relation to the role of individual factors such as age (Cahn et al.
10 2003, Peinemann et al. 2001) and gender (Cahn et al. 2003, Shibuya et al.
11 2016), and also methodological factors such as the stimulus intensity used
12 (Cosentino et al. 2018, Ibáñez et al. 2020, Ilić et al. 2002), and the
13 hemisphere stimulated (Ilic et al. 2004, Maeda et al. 2002). Some of these
14 conflicting findings are likely caused by small sample sizes inherent to most
15 single-site studies (Fried et al. 2017a, Gilbert et al. 2005). To attempt to
16 overcome this limitation, we recently formed the ‘Big TMS Data collaboration’
17 (Supplementary file 1) to combine individual participant TMS data across
18 multiple studies. In the first instance, we used mixed-model regression to
19 analyse data across 22 distinct datasets and demonstrate the variables
20 driving interindividual variability in response to theta-burst stimulation (TBS)
21 (Corp et al. 2020). Here we employ the same method, combining data from 35
22 TMS studies, to investigate the factors accounting for interindividual variability
23 in response to single and pp TMS. The collation of multiple data-sets allowed
24 us to more thoroughly examine sources of variability demonstrated by
25 previous single and pp TMS studies, such as age, gender, and baseline MEP

1 amplitude (Cahn et al. 2003, Shibuya et al. 2016, Strube et al. 2015), and also
2 to further explore the possible influence of less examined variables on single
3 and pp response, such as TMS machine, target muscle, and neuronavigation.

4

5 **2. Methods**

6 This project was deemed exempt from ethical review by the Deakin University
7 Human Research Ethics Committee because it involved only the use of pre-
8 existing, non-identifiable or re-identifiable data. All primary studies had been
9 approved by local institutional review boards, and all participants had provided
10 informed consent.

11

12 *2.1 Article identification strategy*

13 This analysis comes from a larger project collecting individual participant
14 single and pp TMS data, input-output (I/O) curve data, and TBS data.
15 Systematic search procedures are described in detail our companion paper
16 (Corp et al. 2020), and the full search syntax is provided in Supplementary file
17 2. Inclusion criteria were: studies using a figure-of-eight coil; studies
18 measuring TMS responses from intrinsic hand muscles of humans; and
19 studies that collected baseline and conditioned MEP amplitudes. If an article
20 met inclusion criteria, the corresponding authors of studies were emailed to
21 ask for participants' age, gender, motor threshold, and baseline and
22 conditioned MEP amplitudes. Corresponding authors were asked to deidentify
23 data prior to sending. A number of other studies were also included via
24 informal data sharing with colleagues (Corp et al. 2020).

25

1 2.2 *Variables of interest and data used for present analyses*

2 Only healthy participant data were analysed within the present paper. To
3 investigate interindividual variability for single pulse MEP amplitude, we used
4 baseline MEP responses collected at 120% of RMT as our dependent
5 variable (DV), collected across TBS, paired-pulse, and I/O curve datasets.
6 This intensity was chosen as the DV because it was the most commonly used
7 single-pulse TMS intensity, enabling comparison across multiple studies (see
8 Results, Table 3). We were not able to collect sufficient input/output curve
9 data to analyse MEP amplitudes across a range of TS intensities. For SICI
10 and ICF, each individual's mean conditioned MEP amplitude was normalised
11 to their mean baseline MEP amplitude ('normalised MEP') using the equation:
12 (conditioned MEP amplitude / baseline MEP amplitude) x 100 (Amandusson
13 et al. 2017, Di Lazzaro et al. 2006), where a value of 100% represents no
14 change in conditioned MEP amplitudes. Note that the use of a 'normalised
15 MEP' value or a percentage of change value (Fried et al. 2017b) (0% = no
16 change in conditioned MEPs) provide the exact same results after regression
17 analyses (Corp et al. 2020).

18
19 Because MT is extensively used as a measure of corticospinal excitability
20 (Fried et al. 2017a, Kammer et al. 2001), we also investigated interindividual
21 variability for four types of MT for which we had data: monophasic RMT,
22 monophasic AMT, biphasic RMT and biphasic AMT. In addition to these four
23 MTs being used as DVs (as above), MT may also predict single and pp TMS
24 outcomes (Amandusson et al. 2017, Chen et al. 1998), thus these four MTs
25 were also used as independent variables (IV) for our analyses of factors

1 predicting single pulse MEP amplitude, and pp normalised MEP. Other IVs
2 investigated were: age, gender, target muscle, M1 hemisphere, conditioning
3 stimulus (CS) intensity, test stimulus (TS) intensity, pulse waveform (i.e.
4 monophasic or biphasic), inter-stimulus interval (ISI), baseline MEP
5 amplitude, the use/absence of neuronavigation, and TMS machine (Corp et
6 al. 2020). Studies used either a Magstim 200² TMS machine, a Magstim
7 Rapid TMS machine, a Nexstim NBS TMS, or a MagPro TMS machine. We
8 could not determine the specific MagPro model used in all studies, therefore
9 these machines were grouped based on the brand. We controlled for pulse
10 waveform in regression analyses to ensure that the effect of TMS machine
11 was not due the differential use of monophasic or biphasic pulses. For TS
12 intensity, studies used either 120% of RMT or a machine stimulus output
13 evoking an MEP amplitude of 0.5 mV, 0.5 - 1 mV, 1 mV MEP, or 0.5 - 1.5 mV.
14 To increase statistical power, we grouped these intensities into machine
15 stimulus output evoking an MEP amplitude of 0.5 - 1.5 mV. Three studies did
16 not use a TS intensity evoking 0.5 - 1.5 mV or 120% of RMT (Corp et al.
17 2015, Puri et al. 2016, Singh et al. 2016), and were therefore excluded from
18 this comparison. We were not able to obtain baseline MEP amplitude data
19 from one study (Munneke et al. 2013), thus these values were imputed as per
20 the method of Corp et al. (2020). For studies that tested the effect of external
21 interventions on TMS outcomes (e.g. exercise Singh et al. (2016)), only
22 control/baseline data were analysed. We collected handedness data for 21
23 studies, yet there were only nine left handers represented across five studies,
24 therefore this IV could not be analysed statistically.

25

1 We verified the accuracy of the data sent to us by comparing the results to
2 group mean data in the corresponding published paper. In cases where we
3 could not verify based on this group mean data, corresponding authors were
4 contacted for clarification. In instances where data could not be verified, the
5 study was excluded (n = 1).

6

7 All statistical analyses were conducted using Stata 13.0 (StataCorp, USA).

8 First, data were checked for outliers using histograms and descriptive
9 statistics. A number of outliers were detected in single and pp MEP data,
10 therefore values falling outside of the 2nd and 98th percentiles were winsorized
11 (Field 2009, Tukey 1962). Histograms prior to outlier winsorization are
12 provided in Supplementary file 3.

13

14 2.3 *Variability analyses*

15 Prior to our main analyses investigating IVs predicting interindividual
16 variability in single and pp TMS responses, we sought to characterise the
17 variability of the data across our collected sample. As per the method of
18 Brown et al. (2017), we calculated intraclass correlation coefficient (ICC),
19 standard deviation (SD), and coefficient of variation (CV) (Brasil-Neto et al.
20 1992) values to assess within study, and between study variability of single
21 and pp TMS data. Within study SDs and CVs were calculated using the mean
22 MEP amplitude (or MT) of participants, and between study SDs and CVs were
23 calculated using the mean MEP amplitude (or MT) of each study (Brown et al.
24 2017). ICC values < 0.50 were considered low; values 0.50 – 0.75 considered
25 moderate; and > 0.75 considered high (Portney and Watkins 2009). High

1 'within study' ICC values reflect smaller variance within studies relative to
2 larger variance between studies (Kline 2000).

3

4 Only one study (Beynel et al. 2014) assessed participants' corticospinal
5 excitability at multiple time-points, restricting an analysis of within-participant
6 reliability over time. Yet, with the corresponding authors' permission, we
7 provide these (unpublished) data in Supplementary file 4.

8

9 *2.4 Main regression analysis*

10 Our main analyses investigated IVs predicting the aforementioned single, pp,
11 and MT data. To do this, we employed the same regression analyses as
12 described in detail in Corp et al. (2020). Briefly here, we used mixed-effects
13 linear regression using a 'one-step' model as described by Riley et al. (2010),
14 using 'study ID' as a random factor. Some data contained multiple entries by
15 the same participants due to studies collecting multiple data-points across
16 certain measures, such as ISI (e.g., 2 ms and 4 ms) (Croarkin et al. 2013).
17 Thus, in these regressions we also included a random factor of 'participant ID'
18 to maintain the nesting of these data-points within individual participants.

19

20 We used forward-stepwise regression in two stages for each TMS protocol
21 (Bendel and Afifi 1977). Stage 1 regressions analysed the variance explained
22 in the DV by each IV separately, while controlling for the age and gender of
23 participants. IVs with p-values < 0.10 were added to the regression model in
24 stage 2, while IVs with p-values > 0.10 were dropped (Corp et al. 2020). The
25 stage 2 starting regression model comprised of all IVs that were $p < 0.10$ in

1 stage 1. Consecutive regressions then iterated through IVs that were dropped
2 in stage 1, to see whether these IVs now obtained a p-value < 0.10 controlling
3 for IVs in the starting stage 2 model. Thus, the final regression model
4 comprised of IVs that obtained a p-value < 0.10 in predicting the DV in either
5 stage 1 or 2 regressions (Corp et al. 2020).

6

7 IVs were omitted from regression analyses for three possible reasons. First,
8 an IV was omitted if it was not comprised of at least three studies within each
9 IV level, given that unreliable estimates may have resulted from a smaller
10 number of studies per level (Corp et al. 2020). For example, the IV 'ISI' was
11 included only if all ISIs for which we had data (e.g. for SICl: 2 ms, 2.5 ms, 3
12 ms, and 4 ms) were used in at least three separate studies. Where some, but
13 not all, levels of a given IV were represented across three or more studies, we
14 compared these levels post-hoc (see below). Second, an IV was omitted if its
15 inclusion led to a substantial reduction in the overall sample size of the
16 regression analysis for that DV, due to that IV only being measured in a
17 subset of studies. We defined a 'substantial reduction of the regression
18 sample size' as cases where two or more studies were excluded from the
19 regression analysis. Third, an IV was omitted because of collinearity, which
20 occurred if two types of MTs were included in the same regression model. To
21 avoid this, if two or more types of MTs had a p-value < 0.10 in stage 1
22 regressions, for stage 2 we included only the MT that was the strongest
23 predictor of normalised MEP for that particular regression analysis.

24

1 Given the presence of non-linearity and non-normality, robust variance
2 estimates were used for all regressions (Graubard and Korn 1996). Adjusted
3 marginal means (just ‘marginal means’ henceforth) estimated the mean
4 normalised MEP amplitude adjusted/controlled for all other variables in the
5 regression model (Williams 2012). This allowed an interpretable estimate of
6 the mean across the sample, and also for each level of categorical IVs (e.g.
7 the levels ‘left’ and ‘right’ for the IV ‘M1 hemisphere’) (Williams 2012).

8

9 2.5 *Post-hoc analyses*

10 Where sufficient data, post-hoc analyses were run on IVs that were omitted
11 from the main regression analyses for any of the three aforementioned
12 reasons. In relation to reason three for omission (i.e. collinearity), different
13 types of MT were always analysed in separate regression models, to assess
14 their independent relationship to normalised MEP. Next, post-hoc pairwise
15 comparisons were performed on significant IVs that had 3 or more levels
16 (given that results from IVs with only 2 levels can be interpreted from the main
17 regression output). Given their exploratory nature, these pairwise analyses
18 were not corrected for multiple comparisons. Finally, scatterplots indicated
19 possible non-linear relationships between normalised MEP and some
20 continuous variables (e.g. age). Therefore, we re-analysed all (continuous
21 variable) relationships that were included in the final regression model, or
22 were significant in post-hoc analyses, using quadratic and cubic regression
23 models (Davidson and MacKinnon 1993). All post-hoc analyses controlled for
24 all other IVs in the final regression model.

25

1 2.6 Additional analyses

2 A number of additional analyses were performed to further explore the data.
3 Marginal means following single pulse regression analysis indicated that
4 120% RMT MEP data did not reach 1 mV in amplitude. Therefore, we then
5 assessed whether these MEP amplitudes were significantly lower in
6 comparison to MEP amplitudes collected using the 1 mV method (i.e. stimulus
7 intensity required to evoke a 1 mV MEP amplitude). To do this, we performed
8 two-stage mixed-effects linear regression analysis, as above, including TS
9 intensity (with levels of 120 RMT method and 1 mV method) as an IV. Given
10 that controlling for other IVs may cause unwanted influence on 1 mV values,
11 which were already adjusted by TMS operators to attain a 1 mV amplitude
12 regardless of age, gender etc., we also repeated this analysis without the
13 inclusion of these IVs (i.e. including only the TS intensity IV, and 'study ID'
14 and 'Participant ID' as a random factors). This analysis did not include the
15 imputed data of Munneke et al. (2013).

16

17 We then assessed a possible difference in MEP amplitude *variance* between
18 these TS intensity methods. Here we used the same method as in our
19 'variability analysis', calculating SD and CV values of single pulse MEP
20 amplitudes, yet split the sample to analyse SD and CV separately for studies
21 that used the 120% RMT method, and the 1 mV method. Significance
22 between the TS intensity methods was assessed using Levene's robust test
23 for equality of variances (Levene 1961). While lower variance may be
24 expected for the 1mV method, given that operators specifically set the

1 machine intensity to evoke a 1mV amplitude, we still thought it valuable to
2 quantify these (possible) differences.

3

4 Lastly, we analysed correlations between the four types of MT. Because
5 different studies use different methods for obtaining MTs and therefore vary in
6 their average MT values, we normalised MTs to z-values within study, then
7 performed Pearson's correlation analyses on these z-values across the
8 sample. This gives similar results to correlating MT values within studies, then
9 taking the average of these correlations (Supplementary file 5).

10

11 **3. Results**

12 See Corp et al. (2020) for the PRISMA flowchart describing our initial
13 systematic search. In total, 38 studies contributed individual participant data.
14 Three studies were removed because they either included clinical populations
15 only (2) (Kuppuswamy et al. 2015, Murdoch et al. 2016), or we were unable
16 verify the accuracy of the sent data through email correspondence (1)
17 (Malcolm et al. 2015). MT and single-pulse data were drawn from this larger
18 sample of 35 studies and 687 healthy participants, which included theta-burst
19 stimulation and I/O curve datasets in addition to pp data (Table 1). Pp TMS
20 data were drawn from 16 studies, including 15 SICI and 14 ICF datasets
21 comprising 295 healthy participants. Figure 1 shows the distribution of single,
22 pp, and MT data.

23

24 < Table 1 here. Study characteristics >

25

Table 1. Characteristics of included studies.

Study	Author/s	Participants	TMS protocols
1	Barhoun (unp.)	13 healthy (5F, 22.1 ± 3.0 y)	cTBS
2	Beynel et al. (2014)	20 younger (14F, 26.4 ± 7.9 y), 19 older healthy (12F, 63.7 ± 1.7 y)	SICI, ICF
3	Busan et al., (2013)	40 healthy adults (12F, 26.2 ± 6.6 y)	I/O curves
4	Capone et al. (2009)	22 healthy (13F, 27.6 ± 9.0 y)	SICI, ICF
5	Corp et al. (2015)	14 healthy (3F, 29.6 ± 6.7 y)	SICI, ICF
6	Cosentino et al. (2015)	25 cluster headache patients (4F, 37.7 ± 10.5 y), 13 healthy (2F, 35.2 ± 11.2 y)	SICI, ICF
7	Croarkin et al. (2013)	24 MDD (14F, 13.9 ± 2.1 y), 22 healthy (11F, 13.8 ± 2.2 y)	SICI, ICF
8	Di Lazzaro (unp.)	17 healthy (5F, 23.9 ± 5.1 y)	SICI, ICF
9	Di Lazzaro et al. (2008)	12 stroke patients (5F, 69.4 ± 9.5 y), 12 controls (2F, 63.2 ± 5.3 y)	iTBS & cTBS
10	Di Lazzaro et al. (2011)	10 healthy (7F, 26.6 ± 4.1 y)	SICI, ICF, iTBS, cTBS
11	Dickins et al. (2015)	20 younger (10F, 22.9 ± 2.5 y) and 20 older participants (10F, 70.2 ± 3.1 y)	iTBS
12	Dileone et al. (2016)	16 healthy (10F, 23.2 ± 3.8 y)	iTBS
13	Do et al. (2018)	20 healthy (14F, 26.5 ± 3.1 y)	cTBS
14	Fried et al. (2017)	28 type 2 diabetes patients (12F, 65.8 ± 7.7 y), 22 AD patients (13F, 69.6 ± 7.4 y), 26 healthy (13F, 62.9 ± 8.9 y)	SICI, ICF, iTBS
15	Fuhl et al., (2015)	10 healthy (1F, 24.6 ± 3.9 y)	I/O curves
16	Goldsworthy et al. (2016)	18 healthy (10F, 22.1 ± 4.4 y)	iTBS
17	Gomes-Osman (unp.)	17 healthy (10F, 30.0 ± 12.9 y)	SICI, ICF, iTBS
18	Helm et al. (2015)	11 healthy (2F, 25 ± 4.3 y)	ICF
19	Hoseini et al., (2016)	18-40 y	I/O curves
20	Jannati et al. (2017)	30 healthy (3F, 36.0 ± 14.4 y)	cTBS
21	Koch et al. (2016)	40 AD patients (17F, 71.0 ± 6.4 y) and 24 healthy (12F, 69.3 ± 2.3 y)	iTBS, cTBS
22	Lee et al. (2014)	18 healthy (12F, 73.8 ± 5.1 y)	cTBS
23	Li et al. (2017)	26 GAD patients (13F, 42 ± 9.7 y), 35 controls (20F, 41 ± 10.6 y)	SICI, ICF
24	McDonnell et al. (2013)	25 healthy (9F, 26.8 ± 8.1 y)	cTBS
25	Lücke et al., (2014)	9 healthy (3F, 25 ± 4.2 y)	I/O curves
26	Morris (unp.)	15 healthy (9F, 25 ± 2.7 y)	SICI, ICF, iTBS
27	Munneke et al. (2013)	10 ALS patients (10M, 57.8 ± 1.8 y) and 10 controls (0F, 49.0 ± 3.6 y)	SICI, ICF, cTBS
28	Nettekoven et al. (2014)	16 healthy (9F, 27.0 ± 3.0 y)	iTBS
29	Opie et al. (2013)	13 sleep apnoea patients (2F, 42.6 ± 10.2 y), 11 controls (2F, 43.0 ± 10.3 y)	SICI, cTBS
30	Opie et al. (2015)	13 younger (7F, 22.3 ± 3.8 y) and 15 older healthy (7F, 73.7 ± 4.0 y)	SICI
31	Puri et al. (2016)	33 healthy (21F, 66.0 ± 4.8 y)	iTBS
32	Singh et al. (2016)	10 healthy (6F, 25.4 ± 4.0 y)	SICI, ICF, cTBS
33	Vallence et al. (2015)	18 healthy (10F, 23.1 ± 4.0 y)	cTBS
34	Vernet et al. (2014)	10 healthy (5F, 33.0 ± 18.0 y)	cTBS
35	Young-Bernier et al. (2014)	20 younger (13F, 22.3 ± 3.2 y) and 18 older healthy (9F, 70.1 ± 5.6 y)	iTBS

Note: age mean and standard deviation are shown. Studies without paired-pulse data were used in single pulse and/or motor threshold analyses. Abbreviations: F = females; y = years old; GAD = generalised anxiety disorder; AD = Alzheimer's disease; ALS = amyotrophic lateral sclerosis; MDD = major depressive disorder; I/O = input/output; FDI = first dorsal interosseous; APB = abductor pollicis brevis.

1 < Figure 1 here. Histograms for all protocols >

2

3 3.1 *Variability analyses*

4 Table 2 shows measures of reliability for all TMS outcomes. 120% of RMT

5 MEP amplitudes, SICI, and ICF demonstrated higher within, than between,

6 study variance. This is also demonstrated by low ICC values for these

7 outcomes, reflecting little grouping of within study values relative to the overall

8 sample. Consistent with previous reports (Davila-Pérez et al. 2018, Fried et al.

9 2017a), within and between study reliability was higher for MTs than the

10 aforementioned (120% of RMT) single pulse and pp TMS outcomes.

11

12 < Table 2 here – variability analysis >

13

14 3.2 *Single pulse TMS regression analysis*

15 The inclusion of any MT in the model would have substantially reduced the

16 regression sample size. Thus, see post-hoc analyses for these relationships.

17

18 The final regression model showed that muscle, pulse waveform, the use of

19 neuronavigation, and TMS machine were all significant predictors of 120% of

20 RMT single-pulse MEP amplitude (Table 3). See Figure 2 for single pulse

21 TMS marginal means.

22

23 < Table 3 here. Single pulse regression >

24

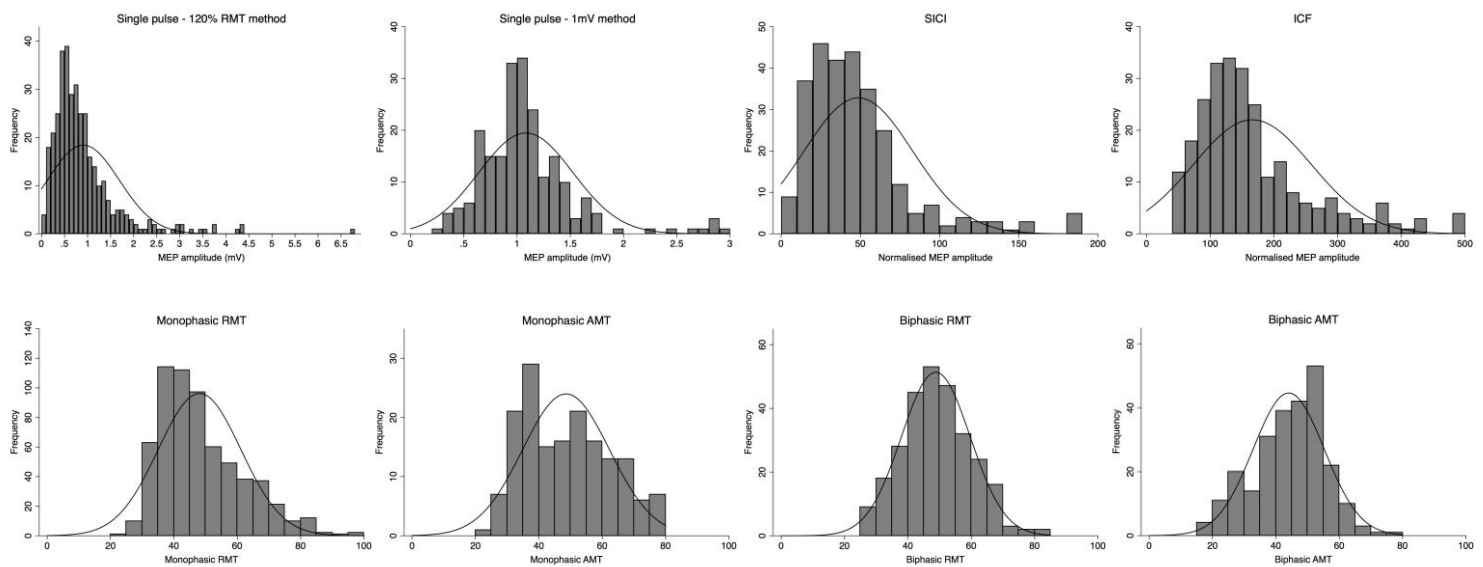


Figure 1. Distribution plots. Histograms of single pulse, paired pulse, and motor threshold data. 120% RMT data was used for single-pulse main regression analysis. These data were then compared to single pulse data using the 1 mV method in the 'additional analyses'. In addition to differences in amplitude and variance (see Results), 120% RMT data appear positively skewed, also evidenced by low median value (0.73 mV). 1 mV method data median = 1.03 mV. So that each participant was only represented once within all histograms and scatterplots (multiple data points due to some studies using multiple ISIs, muscles, etc. – see Methods) we take each participant's mean normalised MEP value across their multiple measurements. Note that in regression analyses, multiple measurements were dealt with by including 'participant ID' as a random factor – see Methods.

Table 2. Variability of single and paired-pulse TMS data. ICC = intraclass correlation coefficient; SD = standard deviation; CV = coefficient of variation %.

	<i>ICC within studies</i>	<i>SD within studies</i>	<i>SD between studies</i>	<i>CV within studies (%)</i>	<i>CV between studies (%)</i>
120% RMT MEP	0.14	0.49	0.28	51.80	28.52
SICI	0.10	28.86	14.96	58.34	30.95
ICF	0.10	75.43	38.39	46.15	24.23
Monophasic RMT	0.50	7.78	9.15	19.36	19.67
Biphasic RMT	0.27	8.47	5.82	17.43	11.84
Monophasic AMT	0.56	10.16	7.28	17.62	24.05
Biphasic AMT	0.52	7.45	8.16	17.99	19.25

Table 3. Final single pulse MEP amplitude regression model. B-values for categorical IVs show the differences between the IV levels in mV. e.g. the APB demonstrated 0.27 mV lower MEP amplitudes than the FDI. Bold denotes significance ($p < 0.05$). Participants = 341; studies = 17. *TMS machine had 3 levels (Magstim 200², MagPro, and Nextstim), therefore main effect: $\chi^2 = 11.62$, $df = 2$. See post-hocs for pairwise comparisons between levels.

IV	B	SE	95% CIs		β	p
Muscle	-0.27	0.11	-0.49	- -0.05	-0.40	0.016
Pulse waveform	0.30	0.05	0.20	- 0.39	0.44	<0.001
Neuronavigation use	0.11	0.04	0.20	- 0.03	0.17	0.011
Machine*						0.003

1 Other IVs not included in final regression model had p-values > 0.10 in both
2 stage 1 and 2 regressions (see Supplementary file 6 for all stage 1 and 2
3 results).

4 < Figure 2 here. Single pulse marginal means >

5

6

7 3.3 *Single pulse TMS post-hoc analyses*

8 When controlling for all IVs in the final regression model, all four types of MT
9 were significantly negatively associated with single pulse MEP amplitude at
10 120% RMT. Monophasic RMT, $B = -0.015$; $SE = 0.004$; $\beta = 0.31$; $p < 0.001$
11 (studies = 13; $N = 248$). Biphasic RMT, $B = -0.020$; $SE = 0.005$; $\beta = -0.31$; $p <$
12 0.001 (studies = 8; $N = 174$). Monophasic AMT, $B = -0.010$; $SE = 0.004$; $\beta = -$
13 0.20 ; $p = 0.024$ (studies = 3; $N = 62$). Biphasic AMT, $B = -0.017$; $SE = 0.006$;
14 $\beta = -0.29$; $p = 0.005$ (studies = 9; $N = 174$). Figure 3 shows bivariate
15 relationship between single-pulse MEP amplitude and monophasic RMT.

16

17 < Figure 3 here. Single pulse scatterplot >

18

19 In addition, non-linear analyses demonstrated a significant quadratic
20 relationship between single pulse MEP amplitude and biphasic AMT ($p =$
21 0.042), and significant cubic relationships between single pulse MEP
22 amplitude and biphasic RMT, and monophasic AMT ($p = 0.001$ and $p = 0.010$,
23 respectively) (see Supplementary file 7 for scatterplots).

24

25 3.4 *SICI regression analysis*

Figure2

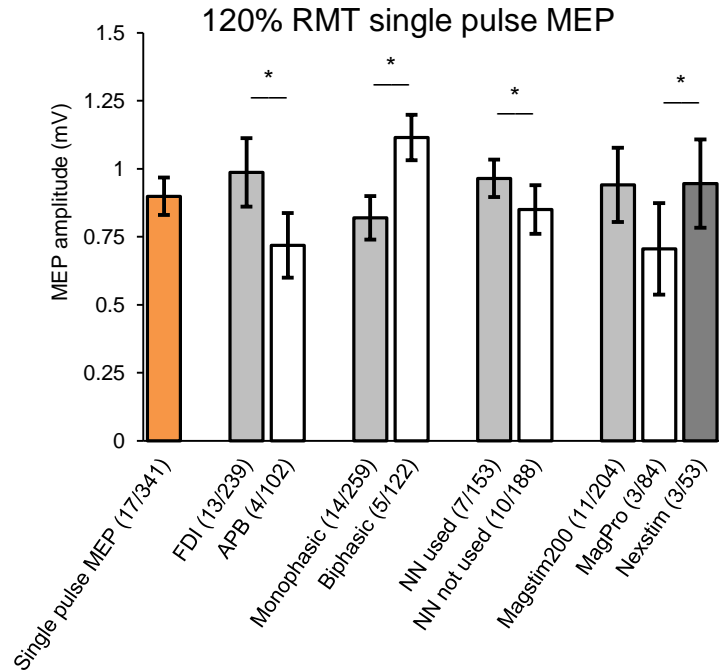


Figure 2. Marginal means for 120% RMT single pulse MEPs. Marginal means provide an estimate of normalised MEP, adjusted for all variables in the final model. Orange bar shows the overall marginal mean for single pulse MEPs. Grey and white bars show marginal means for each level of the IVs muscle, pulse waveform, neuronavigation (NN), and TMS machine. * denotes a significant difference between levels ($p < 0.05$). Error bars show 95% confidence intervals. Brackets show (studies/participants). Difference between Magstim 2002 and MagPro was close to significance ($p = 0.078$).

Figure3

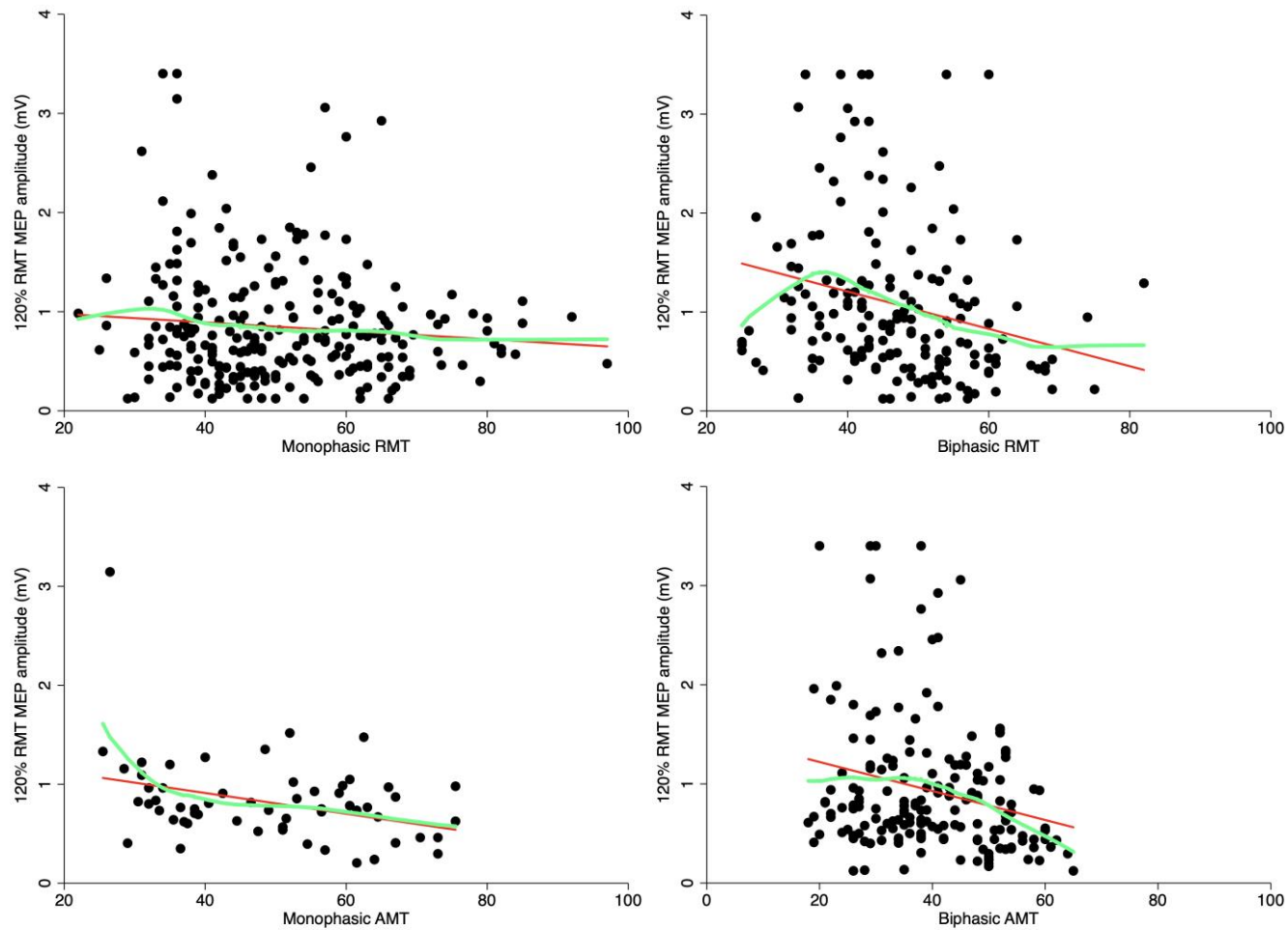


Figure 3. Relationships between 120% RMT single pulse MEPs and MTs. All relationships were significant in post-hoc regression analyses. Note that these scatterplots show raw bivariate relationships to give an indication of relationships only, see post-hoc section for results controlled for other IVs in the single pulse TMS model. Green lines fit a smoothed 'lowess' curve through data (smoothing level = 0.8, default).

1 IVs 'TMS machine', 'CS intensity', 'pulse waveform', and 'ISI' were omitted
2 because they did not include at least three studies within each IV level, while
3 biphasic AMT and biphasic AMT were $p < 0.10$ in stage 1 regressions but
4 substantially reduced regression sample size, thus were analysed post-hoc.
5 The final SICI regression model showed that baseline MEP and M1
6 hemisphere were both significant predictors of SICI normalised MEP (Table
7 4). M1 hemisphere was still significant when re-analysed including only data
8 from only right handers (from the sample in which we had handedness data)
9 (studies = 9; N = 144; B = -9.04; SE = 2.85; $p = 0.002$).

10

11 Figure 4 shows bivariate relationships for continuous IVs baseline MEP and
12 age, which were included in the final regression model. See Figure 5 for SICI
13 marginal means.

14

15 < Insert Table 4 here. SICI regression >

16

17 < Insert Figure 4 here. SICI scatterplots >

18

19 Other IVs not included in final regression model had p-values > 0.10 in both
20 stage 1 and 2 regressions (see Supplementary file 8 for all stage 1 and 2
21 results).

22

23 < Figure 5. SICI marginal means >

24

25 3.5 *SICI post-hoc analyses*

Table 4. Final SICI regression model. B-values for continuous IVs show the amount of increase in normalised MEP, for a one unit increase in the IV, after adjusting for all other variables in the model. i.e. a 1mV increase in baseline MEP resulted in a 23.29% reduction in SICI normalised MEP (greater inhibition). Bold denotes significance ($p < 0.05$). Participants = 283; studies = 15. See Figure 5 for IV levels.

IV	B	SE	95% CIs		β	p
Age	0.11	0.11	-0.11	- 0.34	0.04	0.334
Gender	5.67	3.63	-1.45	- 12.78	0.15	0.119
Baseline MEP	-23.29	8.22	-39.41	- -7.17	-0.33	0.005
Hemisphere	-4.01	1.73	-7.41	- -0.62	-0.10	0.021

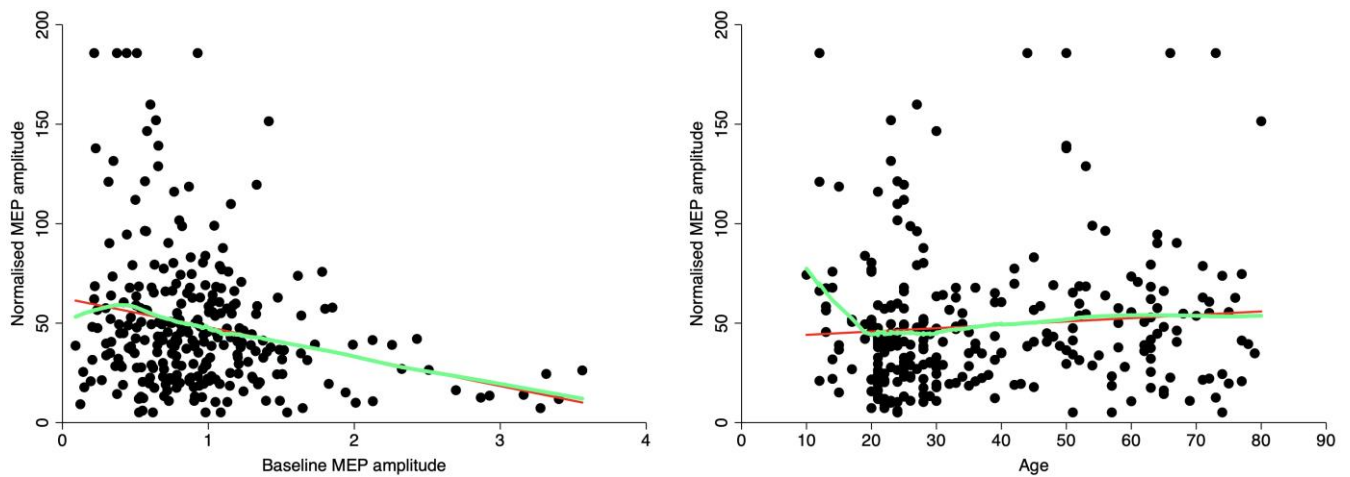


Figure 4. Relationships between continuous IVs and SICI. Baseline MEP amplitude was a significant predictor of SICI. Bivariate scatterplots give an indication of results only; see Table 4 for results controlled for other IVs. Green lines fit a smoothed 'lowess' curve through data. The appearance of a line of datapoints at the top (and to a lesser extent the bottom) of these (and other) scatterplots is due to winsorization; where small and large value outliers are converted to the value of the datapoint at the 2nd and 98th percentile (Field 2009, Tukey 1962) (see Methods).

Figure5

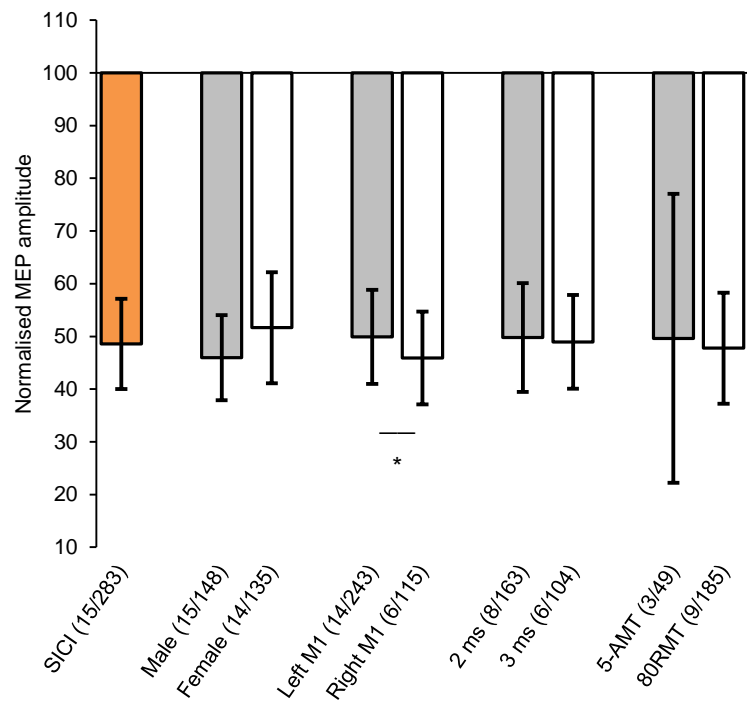


Figure 5. Marginal means for SICI normalised MEP. Orange bar shows the overall marginal mean for SICI. Grey and white bars show marginal means for each level of the IVs gender, M1 hemisphere, interstimulus interval and CS intensity (5% of machine intensity below AMT and 80% of RMT), which were included in the final model or post-hoc tests. * denotes a significant difference between levels ($p < 0.05$). All samples demonstrated significant inhibition ($p < 0.001$). Error bars show 95% confidence intervals. Brackets show (studies/participants).

1 CS intensity and ISI were omitted from the main analysis, yet we had
2 sufficient data to compare SICI normalised MEP between studies that used an
3 intensity of 80% of RMT to those that used a machine intensity 5% below
4 AMT (5-AMT), and also ISI of 2 ms and 3 ms (> 3 studies for these levels).
5 Neither comparison was significant ($p = 0.900$ and $p = 0.778$, respectively;
6 Figure 5).

7

8 Biphasic AMT was a significant predictor of SICI normalised MEP when
9 controlling for all IVs in the final model: 6 studies, 85 participants; $B = -0.86$;
10 $SE = 0.30$; $\beta = -0.24$; $p = 0.004$. Biphasic RMT was not a significant predictor
11 of normalised MEP: 3 studies, 78 participants; $B = 0.24$; $SE = 0.31$; $\beta = 0.07$;
12 $p = 0.426$.

13

14 There were no significant non-linear relationships between SICI and age,
15 baseline MEP amplitude, or biphasic AMT. Although the quadratic relationship
16 between SICI and baseline MEP amplitude almost reached significance ($p =$
17 0.053).

18

19 3.6 ICF regression analysis

20 IVs 'TMS machine', 'CS intensity', 'pulse waveform', and 'ISI' were omitted
21 from ICF regression due to insufficient data. The inclusion of any the MTs as
22 IVs would have led to a substantial reduction in regression sample size,
23 therefore these were analysed post-hoc.

24

25 < Insert Table 5 here. ICF regression

Table 5. Final ICF regression model. Bold denotes significance ($p < 0.05$).
Participants = 242; studies = 13. See Figure 7 for IV levels.

IV	B	SE	95% CIs		β	p
Gender	-4.46	8.24	-20.61	- 11.69	-0.05	0.588
Baseline MEP	-80.82	32.66	-144.83	- -16.81	-0.46	0.013
TS intensity	-33.32	16.43	-65.52	- -1.11	-0.34	0.043

1

2

3 The final regression model showed that baseline MEP amplitude and TS
4 intensity (i.e. 120% RMT vs 0.5 - 1.5 mV methods) were significant predictors
5 of ICF normalised MEP (Table 5 and Figure 6). See Figure 7 for ICF marginal
6 means. Other IVs not included in final regression model had p-values > 0.10
7 in both stage 1 and 2 regressions (see Supplementary file 8 for all stage 1
8 and 2 results).

9

10 < Insert Figure 6 here. ICF scatters >

11

12 < Figure 7. ICF marginal means >

13

14

15 3.7 ICF post-hoc analyses

16 While CS intensity and ISI were omitted from the main analysis, we had
17 sufficient data to compare 80% of RMT to 5-AMT CS intensities and to
18 compare 10 ms, 12, ms, and 15 ms ISIs. The CS intensity comparison was
19 not significant ($p = 0.303$), however for ISI, there was significantly higher ICF
20 for 12 ms ISI data compared to both 10 ms ($p = 0.043$) and 15 ms ISI data (p
21 = 0.042) (Figure 7).

22

23 Of the four types of MT, only biphasic AMT was not significantly positively
24 associated with ICF normalised MEP. Monophasic RMT, $B = 2.09$; $SE = 0.55$;
25 $\beta = 0.29$; $p < 0.001$ (studies = 11; $N = 193$). Biphasic RMT, $B = 1.46$; $SE =$

Figure6

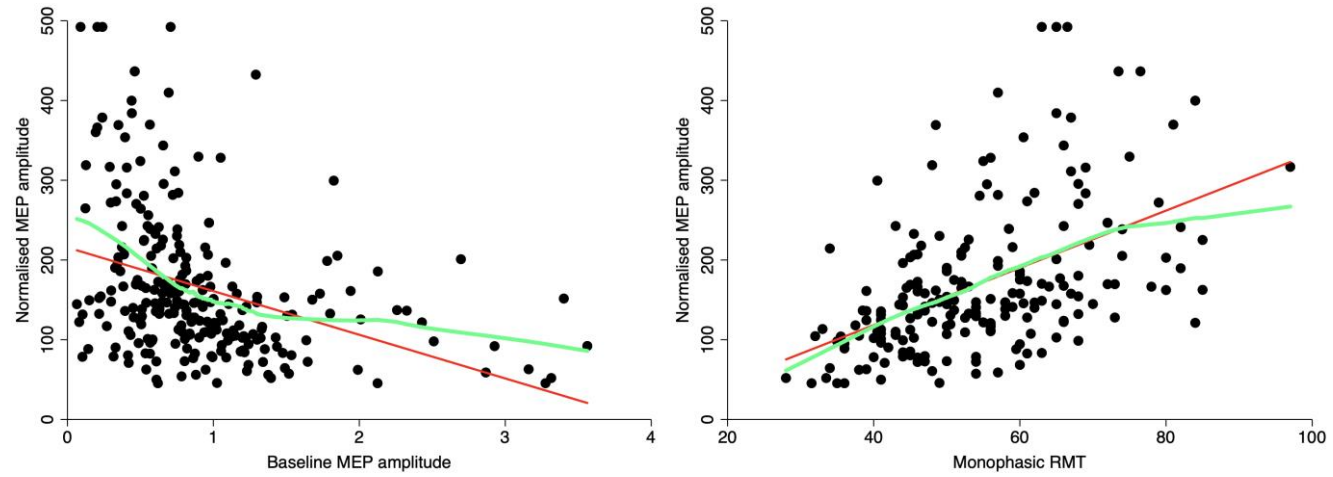


Figure 6. Relationships between continuous IVs and ICF. Baseline MEP and monophasic RMT were significant predictors of ICF MEP change. Bivariate scatterplots give an indication of results only; see Table 5 for results controlled for other IVs. Green lines fit a smoothed 'lowess' curve through data.

Figure 7

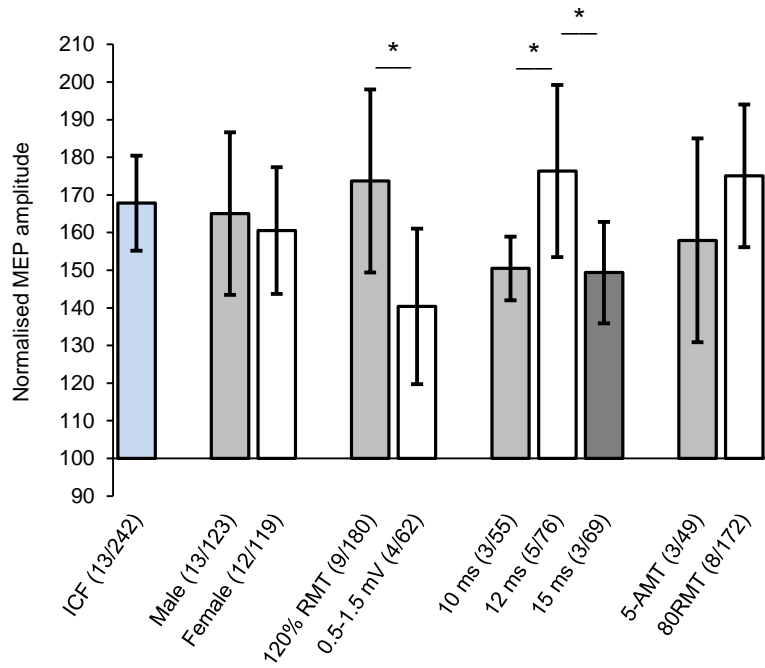


Figure 7. Marginal means for ICF normalised MEP. Blue bar shows the overall marginal mean for ICF. Grey and white bars show marginal means for each level of the IVs gender, TS intensity, ISI, and CS intensity (5% machine intensity below AMT vs. 80% of RMT) which were included in the final model or post-hoc tests. * denotes a significant difference between levels ($p < 0.05$). All samples demonstrated significant facilitation ($p < 0.001$). Error bars show 95% confidence intervals. Brackets show (studies/participants).

1 0.30; $\beta = 0.16$; $p < 0.001$ (studies = 3; N = 79). Monophasic AMT, B = 1.33;

2 SE = 0.48; $\beta = 0.19$; $p < 0.005$ (studies = 3; N = 84).

3

4 Non-linear analyses demonstrated a significant quadratic and cubic

5 relationship between ICF and baseline MEP amplitude ($p = 0.025$ and $p =$

6 0.044, respectively) (Figure 6). There was also a significant quadratic

7 relationship between ICF and monophasic AMT ($p = 0.001$), and a significant

8 cubic relationship between ICF and biphasic RMT (scatterplots in

9 Supplementary file 9).

10

11 3.8 *MT regression analyses*

12 Table 6 shows the four final regression models, demonstrating IVs predicting

13 each type of MT (see captions for IVs omitted due to insufficient data). Age,

14 M1 hemisphere, and TMS machine were significant predictors of different

15 types of MT. There was still higher monophasic RMT for the left hemisphere

16 when including only data from only right handers (from the restricted sample

17 in which we had handedness data), however this effect was now non-

18 significant (studies = 18; N = 319; B = -0.69; SE = 0.39; $p = 0.079$). Age

19 demonstrated a significant positive relationship with monophasic RMT and

20 biphasic RMT (Figure 8). See Figure 9 for marginal means of each IV level.

21

22 < Insert Table 6 here. MT regressions >

23

24 < Insert Figure 8 here. Scatterplots MT and age >

25

Table 6. Final MT regression models. Separate analyses were conducted to investigate IVs explaining variability in each of the four types of MT. Bold denotes significance ($p < 0.05$). IVs omitted because of insufficient data are listed below. See Figure 9 for all IV levels.

Monophasic RMT

Participants = 518; studies = 26. Omitted IV: TMS machine.

IV	B	SE	95% CIs		β	p
Age	0.08	0.02	0.03	- 0.13	0.12	0.001
Hemisphere	-2.17	0.89	-3.92	- -0.42	-0.17	0.015

Monophasic AMT

Participants = 123; studies = 6. Omitted IVs: target muscle, TMS machine, neuronavigation.

IV	B	SE	95% CIs		β	p
Age	0.09	0.05	-0.01	- 0.19	0.12	0.079

Biphasic RMT

Participants = 258; studies = 12. Omitted IV: target muscle, M1 hemisphere. *TMS machine had 3 levels (Magstim 200², MagPro, and Nextstim), therefore main effect: $\chi^2 = 24.97$, $df = 2$. See Figure 9 for pairwise comparisons between levels.

IV	B	SE	95% CIs		β	p
Age	0.14	0.06	0.02	- 0.27	0.25	0.026
Gender	2.62	1.49	-0.31	- 5.55	0.25	0.080
Neuronavigation use	-2.27	2.16	-1.97	- 6.50	0.21	0.295
Machine*						<0.001

Biphasic AMT

Participants = 277; studies = 14. Omitted IVs: M1 hemisphere, target muscle.

IV	B	SE	95% CIs		β	p
Machine	9.91	2.41	5.18	- 14.63	0.88	<0.001
Neuronavigation use	-3.60	3.32	-2.90	- 10.11	0.32	0.277

Figure8

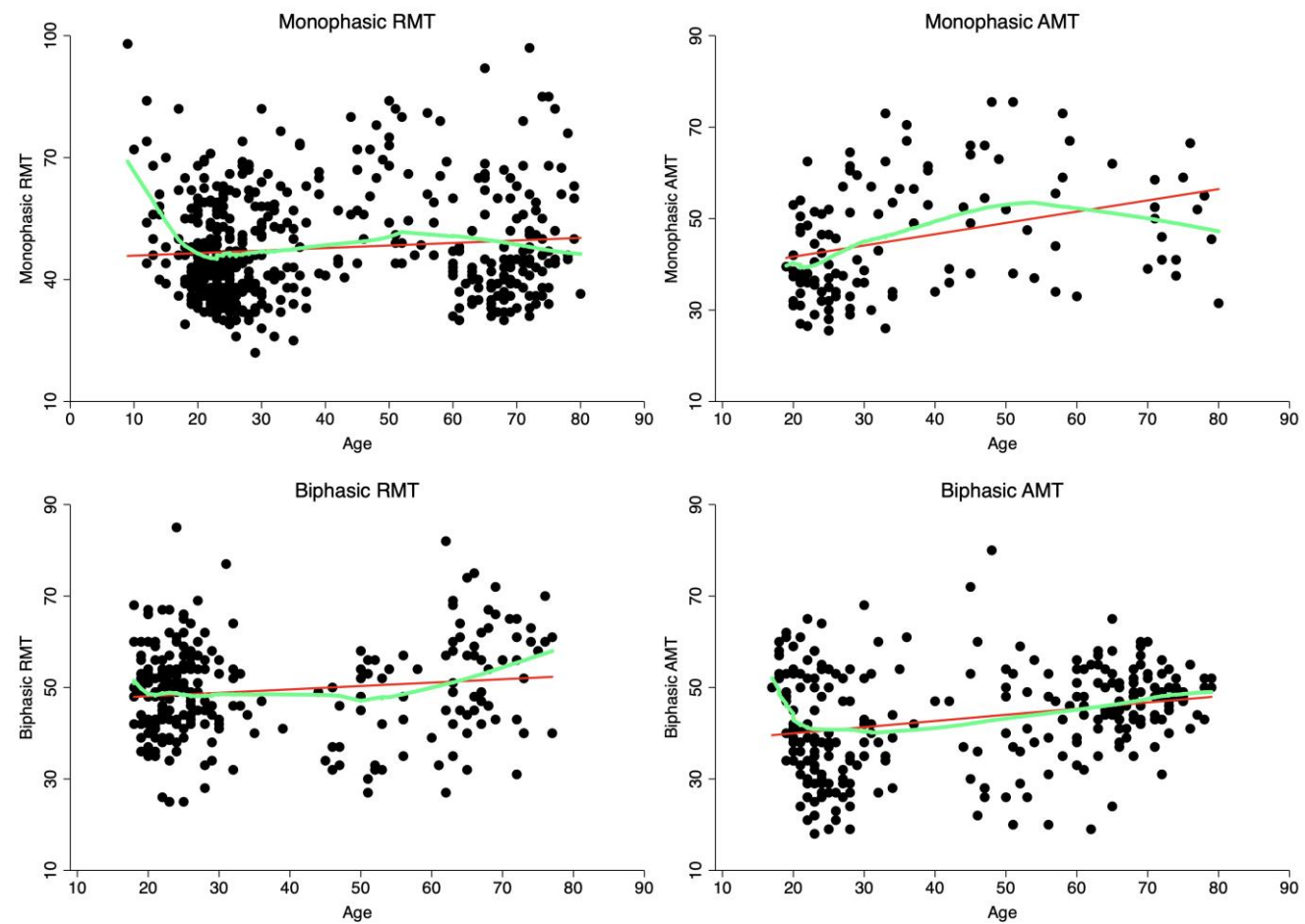


Figure 8. Relationship between age and motor threshold. Monophasic RMT and biphasic RMT showed a significant positive linear relationship with age (Table 6), indicating reduced corticospinal excitability in older adults. There were also significant non-linear relationships between age and monophasic AMT and biphasic AMT (see Results). Green lines fit a smoothed 'lowess' curve through data. Bivariate scatterplots give an indication of results only.

1

2 Other IVs not included in the final regression models had p-values > 0.10 in
3 both stage 1 and 2 regressions (see Supplementary file 10 for all stage 1 and
4 2 results).

5

6 < Insert Figure 9 here. MT marginal means >

7

8 3.9 *MT post-hoc analyses*

9 There was a significant quadratic and cubic relationship between monophasic
10 AMT and age ($p < 0.001$ and $p = 0.031$, respectively). A cubic relationship
11 between biphasic RMT and age did not reach significance ($p = 0.070$) (Figure
12 8).

13

14 3.10 *Additional analyses*

15 Two stage regression analysis demonstrated a significant difference between
16 single pulse TMS MEP amplitudes collected using 120% of RMT, compared
17 with those collected using the 1 mV method: 120% RMT marginal mean
18 (studies = 17; $N = 341$) = 0.87 mV; 95% CIs = 0.78 – 0.96; 1 mV method
19 marginal mean (studies = 9; $N = 189$) = 1.09 mV; 95% CIs = 0.97 – 1.21; $B =$
20 0.22; $SE = 0.09$; $p = 0.015$. This effect of TS intensity method was still
21 significant when not controlling for any covariates ($p = 0.013$) (see Figure 1 for
22 histograms of both methods).

23

24 Studies that employed the 120% RMT method also displayed higher average
25 variance between participants' MEP amplitudes: 120% RMT method studies

Figure9

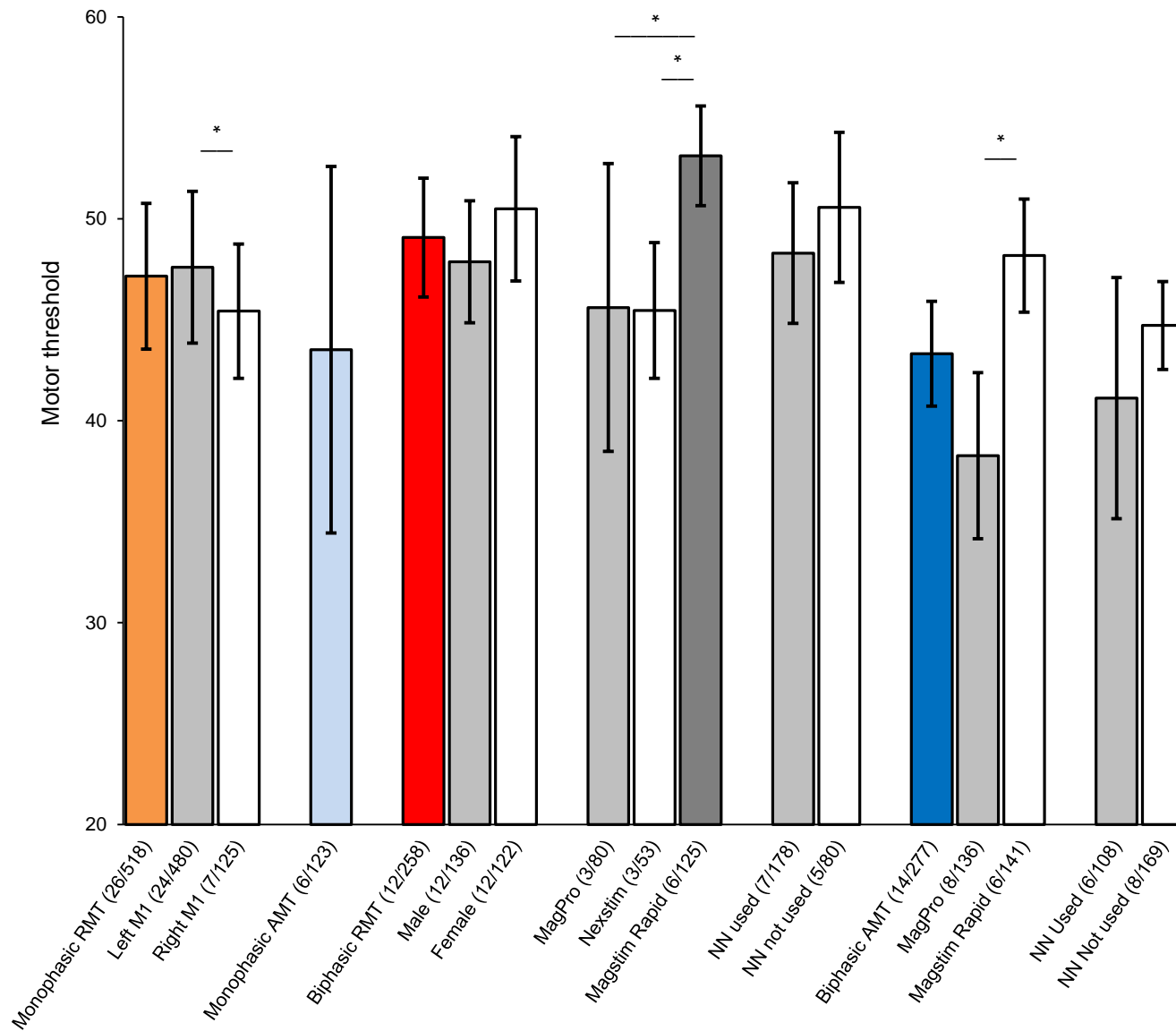


Figure 9. Marginal means for motor threshold. Coloured bars show overall marginal means for monophasic RMT, monophasic AMT, biphasic RMT, and biphasic AMT. Grey and white bars show marginal means of levels of the IVs M1 hemisphere, gender, TMS machine, and neuronavigation (NN), which were included in final regression models. * denotes a significant difference between levels ($p < 0.05$) Error bars show 95% confidence intervals. Brackets show (studies/participants).

1 average SD = 0.55 mV; average CV = 62.8%. 1 mV method studies average
2 SD = 0.39 mV; average CV = 33.8%. Levene's robust test demonstrated that
3 the higher MEP amplitude variance for the 120% RMT method was significant
4 ($F = 23.35$; $df = 1, 573$, $p < 0.001$). This lower variance for the 1mV method
5 was expected, given that operators set the machine intensity to evoke this
6 predefined 1mV amplitude output.

7

8 There were strong significant positive correlations between the four types of
9 MT (all $p < 0.001$): monophasic RMT x biphasic RMT, $N = 153$, $R = 0.856$;
10 monophasic RMT x monophasic AMT, $N = 123$, $R = 0.933$; monophasic RMT
11 x biphasic AMT, $N = 223$, $R = 0.659$; biphasic RMT x biphasic AMT, $N = 83$, R
12 $= 0.749$, monophasic AMT x biphasic AMT, $N = 21$, $R = 0.916$ (no
13 observations for biphasic RMT x monophasic AMT).

14

15 **4. Discussion**

16 This study pooled data from 35 studies to demonstrate factors explaining
17 interindividual variability in response to single and pp TMS. We suggest
18 reasons for these observed sources of variability and propose specific
19 methodological adjustments to reduce for their potential influence. We hope
20 that these findings will lead to greater standardisation of single and pp TMS
21 methods in the brain stimulation community, thereby increasing their utility as
22 a clinical and experimental tool.

23

24 **4.1 Baseline MEP amplitude**

1 As in Corp et al. (2020), who applied the present method to TBS data, this
2 study has demonstrated significant negative relationships between baseline
3 MEP amplitude and (SICI and ICF) normalised MEP. That is, lower baseline
4 responses resulted in higher amplitude conditioned MEPs, regardless of the
5 pp TMS or TBS protocol. We suggest three main reasons as to why these
6 relationships may occur in both pp TMS and TBS data (Corp et al. 2020):
7 regression to the mean; floor and ceiling effects; and different cortical
8 networks being probed between individuals. Regression to the mean is the
9 statistical phenomenon by which an initial extreme measurement is more
10 likely to be closer to the mean if measured for a second time (Bland and
11 Altman 1994, Stigler 1997). By this logic, conditioned MEP responses are
12 more likely to show facilitation (or ameliorated inhibition) if a person records
13 extremely low baseline MEP amplitudes, and vice versa (Corp et al. 2020).
14 Floor and ceiling effects occur when TMS intensities are too close to a floor
15 (minimal activation) or ceiling (maximal activation of neurons), and thus
16 further inputs fail to produce discernible changes in MEP amplitude (Devanne
17 et al. 1997). While TS intensities are individualised, usually to 120% RMT or a
18 1 mV value, there can be substantial variability in relation to where these
19 stimulus intensities occur in relation to each individual's input/output curve
20 (Goldsworthy et al. 2016b, Houdayer et al. 2008, Pitcher et al. 2015). In other
21 words, these individualised TS intensities can be a relatively low or high
22 between individuals. This can bias the effects of the CS, with 'inhibition' less
23 likely for individuals with low relative TS intensities, and 'facilitation' less likely
24 for those with high relative TS intensities (Amandusson et al. 2017,
25 Goldsworthy et al. 2016b). If we assume that those with low baseline MEP

1 amplitudes received TMS pulses at relatively low intensities, this would agree
2 with the negative relationship in the present study, where low baseline MEP
3 amplitudes resulted in greater ICF effects yet ameliorated SICI effects
4 (Figures 4 & 6). However, this is speculative given that we could not directly
5 assess the relative stimulus intensities at which the pulses were applied.
6 Lastly, it has been shown that TS intensity influences the cortical circuits
7 activated by the TMS pulse (Di Lazzaro et al. 1998). Thus, if the TS intensity
8 used for an individual does not probe the circuits activated by the initial CS,
9 SICI and ICF may not be revealed (Di Lazzaro et al. 1998, Garry and
10 Thomson 2009). Based on this, the negative relationship for baseline MEP
11 amplitude in the present study may suggest that SICI is best probed by high
12 relative TS intensities and ICF best probed by low relative TS intensities.
13 However, this does not agree with previous research showing that SICI and
14 ICF are maximal at moderate TS intensities (Cosentino et al. 2018, Garry and
15 Thomson 2009). This suggests that regression to the mean and floor and
16 ceiling effects may have been stronger influences on SICI and ICF response,
17 however again this is speculative, given that we could not directly test the
18 relative intensities at which the pulses were applied within individuals.

19

20 *4.2 Motor threshold predicts single and paired-pulse TMS response*

21 Our data demonstrated that MT predicted single pulse MEP amplitude, SICI,
22 and ICF response. For single pulse TMS, this is in agreement with Peterchev
23 et al. (2013), who showed that individuals with lower MTs have steeper I/O
24 slopes (Peterchev et al. 2013). We demonstrate a similar result here by
25 showing that individuals with lower MTs have higher MEP amplitudes at one

1 stimulus intensity along the I/O curve (120% RMT). For SICI and ICF, this
2 phenomenon may be in part caused by the fact that the conditioning stimulus
3 intensity (as a percentage of the machine output) is adjusted to an individual's
4 MT. This is designed to ensure the activation of a similar proportion of
5 corticospinal neurons between individuals. However, SICI and ICF
6 mechanisms are dependent on *intracortical*, rather than *corticospinal* neurons,
7 and the threshold for activation of these two networks does not necessarily
8 correlate (Chen et al. 1998). Thus, those with higher MTs receive a higher
9 intensity CS (as a percentage of machine output), and this could cause
10 stronger activation of intracortical mechanisms (Amandusson et al. 2017) (and
11 thus an increased SICI and ICF effect, as demonstrated here). However,
12 these relationships could also be caused by inherent differences in SICI and
13 ICF for individuals with low or high MTs, with the differential effects of stimulus
14 intensity and MT unable to be disentangled here due to machine output being
15 adjusted to MT in all studies.

16

17 4.3 *Effect of age on corticospinal excitability*

18 Linear regression showed that, on average, monophasic RMT and biphasic
19 AMT significantly increased with age. However, this reduction in corticospinal
20 excitability does not appear to be linear across the lifespan, demonstrated by
21 significant quadratic relationships for monophasic AMT, and biphasic AMT,
22 and fitted 'lowess' lines through MT data indicating curved patterns at
23 particular age points (Figure 8). These fitted lines suggest an initial stage of
24 hypoexcitability for people under ~20 years of age, with MT then reaching its
25 lowest point at about the age of 25. After this age, there seemed to be

1 different patterns in monophasic and biphasic data, with monophasic MTs
2 increasing through middle age, then reducing again in older age, as opposed
3 to biphasic MTs - which continued to increase with age. The divergent
4 patterns observed in monophasic and biphasic data could be due to different
5 cortical mechanisms activated by these pulse waveforms; biphasic pulses
6 may activate later I-waves compared to monophasic posterior-anterior
7 stimulation (Di Lazzaro et al. 2001). However, the pattern of activation may
8 also depend on stimulus intensity, and the initial current direction of the
9 biphasic pulse (Di Lazzaro et al. 2001), for which we had incomplete
10 information. The curved pattern of response for monophasic MTs is similar to
11 that of Shibuya et al. (2016), who demonstrated the lowest monophasic RMTs
12 for 20-25 year olds and older adults (study age range: 20-83), and maximal
13 RMT at approximately 50 years of age, and a significant quadratic effect.

14

15 Interestingly, the higher monophasic RMT for < 20 year olds (Figure 8) did not
16 translate to a significant quadratic or cubic effect. This may be because the
17 majority of these observations came from one study (Croarkin et al. 2013),
18 and these values would have been adjusted given that we included 'study ID'
19 as a random variable to account for the fact that data came from different
20 studies. However, the relationships between corticospinal excitability and age
21 observed in the present study should be interpreted with caution given the
22 relative dearth of data for adolescents and middle-aged adults (Figure 7).

23

24 *4.4 Effect of hemisphere on cortical excitability*

1 Our results demonstrated reduced SICl and increased monophasic RMT in
2 the left hemisphere. These effects were similar when including only data from
3 right handers from our restricted sample for which we had handedness data
4 (although the effect became non-significant for monophasic RMT, $p = 0.079$).
5 Thus, while we do observe these effects in right handers, we cannot say
6 whether they are driven by the fact that the left hemisphere is the dominant
7 M1, or whether it is simply an effect of the left hemisphere across both right
8 and left handers. The collection of additional data from left handers will be
9 required to answer this question. In regards to previous literature, Ilic et al.
10 (2004), also showed reduced SICl in the left M1 in right handed participants.
11 These authors suggested that less SICl in the dominant hemisphere for right
12 handers may provide an advantage for the readiness and ease to carry out
13 movements with the dominant hand (Ilic et al. 2004). In contrast, our
14 monophasic RMT findings differ to Ilic et al. (2004), who showed *reduced*
15 monophasic RMT in the left hemisphere for right handers. It is not clear as to
16 why we obtained conflicting MT results. However, given our non-significant
17 results when only including right handers, and the small sample size of Ilic et
18 al. (2004) (9 right handers), these effects are not conclusive, and additional
19 hemisphere and handedness data needs to be gathered.

20

21 4.5 *Effect of machine on corticospinal excitability*

22 We found that Nexstim machines were more powerful than MagPro machines
23 for single pulse MEP amplitude, yet observed higher biphasic RMT and
24 biphasic AMT for the Magstim Rapid machine than MagPro and Nexstim
25 machines. Much of this effect is likely due to the use of Magstim Rapid

1 machines for biphasic MT assessment prior to repetitive TMS protocols
2 (delivered with biphasic pulses), which have a reduced power output in
3 comparison to Magstim 200² (Kammer et al. 2001), and MagPro X100
4 machines (Koponen et al. 2020). These differential effects highlight the
5 importance of the inclusion of TMS machine (and study location if applicable)
6 as a covariate in statistical analyses on data that are pooled collaboratively
7 using different machines. Researchers should also be aware that the various
8 configurations of the Magstim BiStim machine (i.e. two connected Magstim
9 200² machines) produce different power outputs, which may confound
10 electrophysiological results if configured incorrectly (Do et al. 2019). We did
11 not collect information on these configurations in the present study, which
12 may have affected results.

13

14 4.6 *Limitations*

15 A number of limitations should be acknowledged. First, we were limited to
16 analysing the variables that were available to us, and so could not measure
17 the impact of IVs such as menstrual cycle (Hattemer et al. 2007), or
18 neuroimaging markers (Silbert et al. 2006) on corticospinal excitability.
19 Second, our approach pooled data from separate studies, and thus does not
20 have the precision of a repeated-measures design. Pooling different studies'
21 results increases the risk of between-study variability being caused by factors
22 such as sampling error, study setting, and experimenter behaviour (Higgins
23 and Green 2011). Next, of the nine studies using neuronavigation, none
24 reported coordinates of the motor hotspot, nor coil shift data from the motor
25 hotspot. Thus, unaccounted for differences in coil position may have

1 explained some unobserved intraindividual variability in TMS outcomes. Next,
2 we were limited by the incomplete dataset that we could gather for
3 handedness, and also the small number of left-handers within that dataset.
4 Thus, we do not know whether our ‘hemisphere’ effects were driven by
5 hemispheric differences between left and right handers, or by handedness.
6 Next, we did not measure the potential impact of TMS machine coil size or
7 type, or initial waveform direction (i.e. AP or PA), on cortical excitability.
8 Finally, it should be acknowledged that a portion of interindividual variability in
9 MEP amplitudes occurs due to differences in the excitability of spinal circuits
10 (Kiers et al. 1993, Lackmy and Marchand-Pauvert 2010), and we could not
11 account for this given that the included studies did not measure sub-cortical
12 responses such as the M-max or H-reflex.

13

14 *4.7 Recommendations*

15 We first propose some steps to counter the significant relationships observed
16 between baseline MEP amplitude and SIC/ICF. To avoid regression to the
17 mean caused by chance occurrences of high or low MEP amplitudes, we
18 recommend that investigators: 1) collect a sufficient number (20-30) of MEPs
19 in their TMS blocks (Chang et al. 2016, Goldsworthy et al. 2016a); 2) avoid
20 possible initial states of hyperexcitability within TMS sessions (Brasil-Neto et
21 al. 1994, Schmidt et al. 2009); and 3) include baseline MEP amplitude as a
22 covariate in statistical analyses. To avoid floor and ceiling effects, the CS
23 could be normalised to 50% of maximal inhibition/facilitation (McAllister et al.
24 2009), while the TS could be normalised to 50% of maximal MEP amplitude
25 (Goldsworthy et al. 2016b, Houdayer et al. 2008). This would also circumvent

1 the aforementioned issues with normalising the CS to MT (Chen et al. 1998).
2 However, it has previously been suggested that the use of this TS intensity
3 may still result in substantial between-subject differences in the in the neural
4 circuits probed by the TMS pulse (i.e. relative D- and I-wave contributions to
5 the MEP) (Goldsworthy et al. 2016b). Until this can be empirically investigated
6 (most likely through recordings from the cervical epidural space, e.g. Di
7 Lazzaro et al. (2001)), we recommend that researchers minimise the
8 aforementioned biases by collecting data across a range of stimulus
9 intensities (i.e. pp input/output curves) (Ilić et al. 2002, Orth et al. 2003).
10 However, in addition to the increased complexity in analysing pp input/output
11 curve data, their collection is time consuming, especially if varying both CS
12 and TS intensities. Thus, further effort should be directed towards the
13 formulation of time effective methods of collection of (single and) pp TMS
14 curve data, and increased standardisation in their analysis. Next, in order to
15 reduce possible variability due to coil position, we suggest that where
16 neuronavigation can be used, researchers should report the coordinates of
17 the motor hotspot, and report or analyse the impact of shifts from the motor
18 hotspot for individual participants. Lastly, when making age comparisons,
19 investigators should be aware that the relationship between age and
20 corticospinal excitability may not be linear across the lifespan.

21

22 4.8 Conclusions

23 The present study pooled individual participant data across 35 studies to
24 demonstrate sources of interindividual variability in single and pp TMS
25 measurements, including baseline MEP amplitude, age, TS intensity, M1

1 hemisphere, ISI, TMS machine, and MT. We have highlighted possible
2 reasons for these sources of variability and made specific methodological
3 recommendations to reduce their influence. These findings highlight the need
4 for increased standardisation of single and pp TMS methods across the brain
5 stimulation community, which we hope will be facilitated through this
6 collaborative approach. We are currently expanding the 'Big TMS Data
7 Collaboration' through the construction of an individual participant TMS data
8 repository at www.bigtmsdata.com, and welcome additional brain stimulation
9 researchers to contribute to this database.

10

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14

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16

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10

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20
21

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Supplementary file 2. Search syntax.

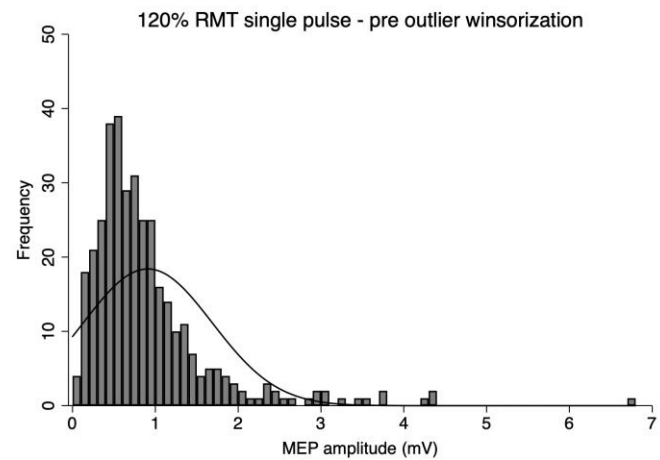
Search ((intermittent theta-burst stimulation OR intermittent theta burst stimulation OR iTBS)) AND (Transcranial magnetic stimulation OR TMS) Filters: Publication date from 2013/01/01 to 2016/12/31. Results = 126

((continuous theta-burst stimulation OR continuous theta burst stimulation OR cTBS)) AND (Transcranial magnetic stimulation OR TMS) Filters: Publication date from 2012/01/01 to 2016/12/31 Results = 239

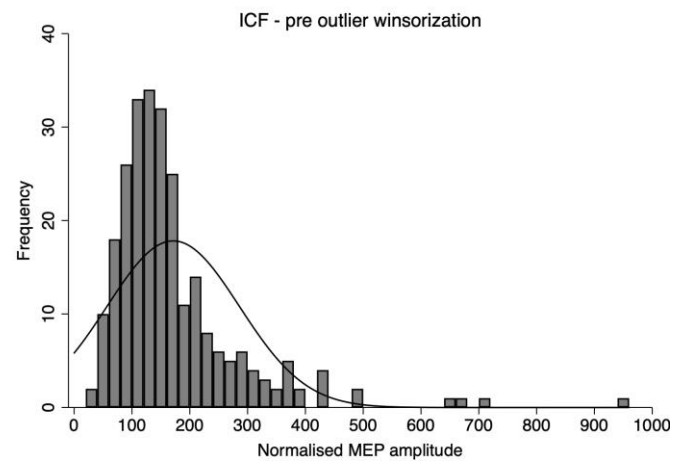
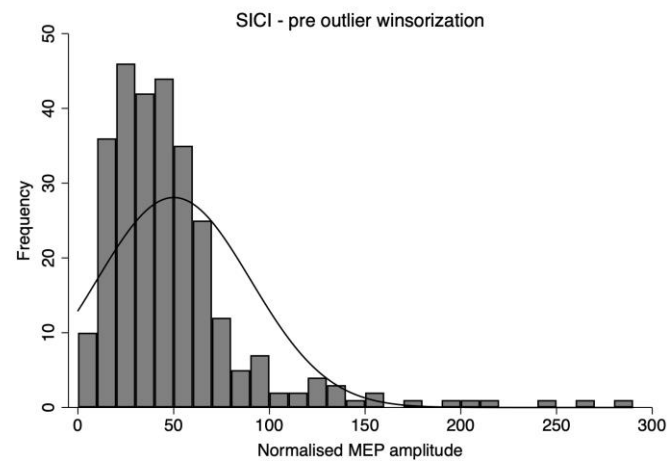
((short-interval intracortical inhibition OR short interval intracortical inhibition OR SICI)) AND (Transcranial magnetic stimulation OR TMS) Filters: Publication date from 2014/01/01 to 2016/12/31. Results = 218

((intracortical facilitation OR ICF)) AND (Transcranial magnetic stimulation OR TMS) Filters: Publication date from 2014/01/01 to 2016/12/31. Results = 152

((input-output curve* OR stimulus-response curve* OR I-O curve* OR IO curve* OR S-R curve* OR SR curve*)) AND (Transcranial magnetic stimulation OR TMS) Filters: Publication date from 2013/01/01 to 2016/12/31. Results = 69



Supplementary file 3. Distribution plots. Histograms show distribution of MEP data for single pulse, SICI and ICF protocols, prior to outlier winsorization.



Supplementary file 4: Reproducibility data from Beynel et al. (2014)

Methods

Test-retest data were taken from 35 healthy participants (19 females; mean age: 44.67 ± 20.12) at a month interval. Single pulse MEP data were assessed at 120% of RMT, while SICl and ICF were assessed at 80% and 120% of RMT, for conditioning and test stimuli, respectively, with interstimulus intervals of 2 ms (SICl) and 15 ms (ICF). Ten MEPs were collected per condition, per session. Please see the published study (Beynel et al., 2014) for further methodological details. As in the main manuscript (Corp et al.), for SICl and ICF, each individual's mean conditioned MEP amplitude was normalised to their mean baseline MEP amplitude.

Results

The intraclass correlation coefficients (McGraw et al., 1996) for each TMS protocol were as follows: biphasic RMT = 0.845; single pulse MEP amplitude = 0.375; ICF = 0.376; and SICl = 0.367.

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Supplementary file 5. The use of z-scores grouped by study to run correlation analyses. Table shows an example of this method, using the correlations between monophasic RMT and biphasic RMT.

Study	R-value
Dickins et al. (2015)	0.913
Do et al. (2018)	0.880
Fried et al. (2016)	0.902
Goldsworthy et al. (2016)	0.904
Gomes-Osman (unpublished)	0.826
Nettekoven et al. (2014)	0.607
Vallence et al. (2015)	0.838
Average R-value across studies	<hr/> 0.839 <hr/>
R-value of correlated z-scores across sample, first grouped by study (used in manuscript)	0.856
*R-value of correlated MTs across sample (without obtaining z-scores grouped by study)	0.127

*We include this analysis to demonstrates the importance of using z-scores to calculate these correlations. If not, variance is caused by the different methods used for obtaining MTs between studies.

*Step 1 regressions for 120% RMT single pulse MEP amplitude. Examining the variance in MEP amplitudes explained by each IV separately, while controlling for the age and gender of participants.

Abbreviations:

MEP change = Normalised MEP (DV)
 Age
 Gender
 BaseMEP_wins = 120% RMT single pulse MEP amplitude
 Machine_spulse = TMS machine
 Muscle = Target muscle
 Hemisphere = M1 hemisphere
 ppCSint = paired pulse conditioning stimulus intensity
 ppTSint = paired pulse test stimulus intensity
 PulseType/PulseType2 = Pulse waveform
 ISI = interstimulus interval
 MonoRMT = Monophasic RMT
 MonoAMT = Monophasic AMT
 BiRMT = Biphasic RMT
 BiAMT = Biphasic AMT
 TSint_comparison = denotes the analysis of 120% RMT data
 Studyno = Study ID
 newPartID = Participant ID

*IVs omitted because of insufficient data (did not include at least three studies within each IV level):

Machine Muscle PulseType2 MonoRMT MonoAMT BiRMT BiAMT

```
.
. for var Hemisphere Muscle Machine_spulse PulseType2 Neuronavigation
MonoRMT BiRM
> T MonoAMT BiAMT : mixed BaseMEP_wins Age Gender c.X if
TSint_comparison ==0 ///
> || Studyno: || newPartID:,robust norettable

-> mixed BaseMEP_wins Age Gender c.Hemisphere if TSint_comparison ==0 ||
Studyno: |
> | newPartID:,robust norettable
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -429.45103
Iteration 1: log pseudolikelihood = -429.43954
Iteration 2: log pseudolikelihood = -429.43954
```

Computing standard errors:

```
Mixed-effects regression          Number of obs    =
462
```

```
-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
      Studyno  |          17          10      27.2      70
    newPartID |         347           1       1.3       2
-----
```

```
Wald chi2(3) =
1.78
Log pseudolikelihood = -429.43954    Prob > chi2 =
0.6190
```

(Std. Err. adjusted for 17 clusters in Studyno)

```
-----
BaseMEP_wins |      Coef.      Robust      z      P>|z|      [95% Conf.
Interval]
-----+-----
Age |  -.0027805   .0033584   -0.83   0.408   -.0093628
.0038019
Gender | -.0087345   .0740265   -0.12   0.906   -.1538238
.1363548
Hemisphere | .0273188   .0333839    0.82   0.413   -.0381124
.09275
_cons |  .9897414   .1289038    7.68   0.000   .7370946
1.242388
-----
```

```
-> mixed BaseMEP_wins Age Gender c.Muscle if TSint_comparison ==0 ||
Studyno: || ne
> wPartID:,robust norettable
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -434.6118
Iteration 1: log pseudolikelihood = -434.59578
Iteration 2: log pseudolikelihood = -434.59578
```


Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	17	10	26.8	70
newPartID	341	1	1.3	2

Wald chi2(3) = 38.91
 Log pseudolikelihood = -414.93492 Prob > chi2 = 0.0000

(Std. Err. adjusted for 17 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Age	-.0038426	.0028052	-1.37	0.171	-.0093407 .0016555
Gender	-.0293734	.0699193	-0.42	0.674	-.1664127 .1076658
Machine_spulse	.2408224	.0420787	5.72	0.000	.1583496 .3232951
_cons	.9272276	.1144897	8.10	0.000	.702832 1.151623

```
-> mixed BaseMEP_wins Age Gender c.PulseType2 if TSint_comparison ==0 || Studyno: |
> | newPartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -424.34173
 Iteration 1: log pseudolikelihood = -424.33683
 Iteration 2: log pseudolikelihood = -424.33683

Computing standard errors:

Mixed-effects regression Number of obs = 474

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum

Studyno	18	10	26.3	70
newPartID	359	1	1.3	2

Wald chi2(3) = 177.91
 Log pseudolikelihood = -424.33683 Prob > chi2 = 0.0000

(Std. Err. adjusted for 18 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Age	-.0031481	.0029437	-1.07	0.285	-.0089176 .0026214
Gender	.0034524	.0689223	0.05	0.960	-.1316327 .1385376
PulseType2	.3376344	.0334713	10.09	0.000	.2720318 .403237
_cons	.926825	.1191044	7.78	0.000	.6933845 1.160265

```
-> mixed BaseMEP_wins Age Gender c.Neuronavigation if TSint_comparison ==0 || Study > no: || newPartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -434.25844
 Iteration 1: log pseudolikelihood = -434.24201
 Iteration 2: log pseudolikelihood = -434.24201

Computing standard errors:

Mixed-effects regression Number of obs = 474

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	18	10	26.3	70
newPartID	359	1	1.3	2

13.74 Wald chi2(3) =
 Log pseudolikelihood = -434.24201 Prob > chi2 =
 0.0033

(Std. Err. adjusted for 18 clusters in Studyno)

```
-----
```

BaseMEP_wins	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Age	-.0028702	.0028519	-1.01	0.314	-.0084598
Gender	-.0052331	.0692731	-0.08	0.940	-.141006
Neuronavigation	-.29488	.0954175	-3.09	0.002	-.4818949
_cons	1.180095	.112362	10.50	0.000	.959869

```
-----
```

```
-> mixed BaseMEP_wins Age Gender c.MonoRMT if TSint_comparison ==0 ||
Studyno: || n
> ewPartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -278.81131
Iteration 1: log pseudolikelihood = -278.80319
Iteration 2: log pseudolikelihood = -278.80319
```

Computing standard errors:

Mixed-effects regression Number of obs =
 363

```
-----
```

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	13	11	27.9	70
newPartID	248	1	1.5	2

```
-----
```

44.03 Wald chi2(3) =

Log pseudolikelihood = -278.80319 Prob > chi2 =
 0.0000

(Std. Err. adjusted for 13 clusters in Studyno)

```
-----
-----
BaseMEP_wins |          Coef.      Robust          z    P>|z|    [95% Conf.
Interval]     Std. Err.
-----+-----
Age |      .0030643    .0029831    1.03   0.304   -.0027824
.008911
Gender |    -.0092131    .0532958   -0.17   0.863   -.113671
.0952448
MonoRMT |   -.0146129    .0028081   -5.20   0.000   -.0201167  -
.0091092
_cons |    1.490094    .1688795    8.82   0.000    1.159097
1.821092
-----
-----
```

```
-> mixed BaseMEP_wins Age Gender c.BiRMT if TSint_comparison ==0 ||
Studyno: || new
> PartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0:  log pseudolikelihood = -235.75133
Iteration 1:  log pseudolikelihood = -235.56781
Iteration 2:  log pseudolikelihood = -235.56733
Iteration 3:  log pseudolikelihood = -235.56733
```

Computing standard errors:

Mixed-effects regression Number of obs =
 214

```
-----
-----
Group Variable |          No. of          Observations per Group
                Groups      Minimum   Average   Maximum
-----+-----
Studyno |              8              10      26.8      51
newPartID |             174              1       1.2       2
-----
-----
```

14.59 Wald chi2(3) =
 Log pseudolikelihood = -235.56733 Prob > chi2 =
 0.0022

(Std. Err. adjusted for 8 clusters in Studyno)

```
-----
-----
BaseMEP_wins |          Coef.      Robust          z    P>|z|    [95% Conf.
Interval]-----
-----
      Age |  -.0014456   .0035162   -0.41   0.681   -.0083372
.005446
      Gender |   .0284975   .1527012    0.19   0.852   -.2707914
.3277864
      BiRMT |  -.0193975   .0052949   -3.66   0.000   -.0297753  -
.0090197
      _cons |   2.029973   .2791479    7.27   0.000    1.482853
2.577093
-----
-----
```

```
-> mixed BaseMEP_wins Age Gender c.MonoAMT if TSint_comparison ==0 ||
Studyno: || n
> ewPartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0:  log pseudolikelihood = -67.441544
Iteration 1:  log pseudolikelihood = -67.389585
Iteration 2:  log pseudolikelihood = -67.371305
Iteration 3:  log pseudolikelihood = -67.37035
Iteration 4:  log pseudolikelihood = -67.37035
```

Computing standard errors:

```
Mixed-effects regression                               Number of obs    =
124
```

```
-----
-----
Group Variable |          No. of      Observations per Group
                Groups      Minimum   Average   Maximum
-----+-----
      Studyno |           3           20      41.3     70
      newPartID |          62            2       2.0      2
-----
-----
```

```
Wald chi2(2) =
.
Log pseudolikelihood = -67.37035      Prob > chi2 =
.
```

(Std. Err. adjusted for 3 clusters in Studyno)

```

-----
-----
BaseMEP_wins |          Coef.      Robust          z    P>|z|    [95% Conf.
Interval]
-----+-----
Age |    -.0032472    .0024551    -1.32    0.186    -.0080591
.0015647
Gender |    .0360827    .0363064     0.99    0.320    -.0350766
.107242
MonoAMT |   -.0079267    .0029001    -2.73    0.006    -.0136109  -
.0022425
_cons |    1.295731    .2591768     5.00    0.000     .7877538
1.803708
-----
-----

```

```

-> mixed BaseMEP_wins Age Gender c.BiAMT if TSint_comparison ==0 ||
Studyno: || new
> PartID:,robust norettable

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:  log pseudolikelihood = -204.47578
Iteration 1:  log pseudolikelihood = -204.45425
Iteration 2:  log pseudolikelihood = -204.45425

```

Computing standard errors:

```

Mixed-effects regression          Number of obs    =
214

```

```

-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
Studyno |           9           10      23.8      51
newPartID |          174           1       1.2       2
-----

```

```

Wald chi2(3) =
34.74
Log pseudolikelihood = -204.45425    Prob > chi2 =
0.0000

```

(Std. Err. adjusted for 9 clusters in Studyno)

```

-----
-----
|          Robust

```

BaseMEP_wins	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Age	.002146	.0024305	0.88	0.377	-.0026177
Gender	-.0775646	.08062	-0.96	0.336	-.2355768
BiAMT	-.0154547	.0026378	-5.86	0.000	-.0206247
_cons	1.515444	.2121489	7.14	0.000	1.099639

*Step 2 regressions for single pulse.

*This is the starting step 2 model for single pulse - all variables that obtained a p-value < 0.10 in stage 1 regressions.

```
. mixed BaseMEP_wins i.Muscle i.Machine_spulse i.PulseType2
i.Neuronavigation if TSint_comparison ==0 || ///
    Studyno: || newPartID:,robust cformat(%5.4f)
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -404.44997
Iteration 1: log pseudolikelihood = -404.31675
Iteration 2: log pseudolikelihood = -404.31339
Iteration 3: log pseudolikelihood = -404.3133
Iteration 4: log pseudolikelihood = -404.3133
```

Computing standard errors:

Mixed-effects regression Number of obs = 456

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	17	10	26.8	70

```

newPartID |          341          1          1.3          2
-----
Wald chi2(5)          =
864.57
Log pseudolikelihood = -404.3133      Prob > chi2          =
0.0000

```

(Std. Err. adjusted for 17 clusters in Studyno)

```

-----
BaseMEP_wins |          Coef.      Robust      z      P>|z|      [95% Conf.
Interval]
-----+-----
Muscle
  APB |      -0.2685      0.1112     -2.41     0.016     -0.4865
-0.0504
Machine_spulse
  MagPro |      -0.2358      0.1340     -1.76     0.078     -0.4984
0.0269
  Nexstim |       0.0045      0.1347      0.03     0.973     -0.2594
0.2684
PulseType2
  Biphasic |       0.2955      0.0488      6.05     0.000      0.1998
0.3912
Neuronavigation
  No |      -0.1146      0.0448     -2.56     0.011     -0.2025
-0.0267
  _cons |       1.0168      0.1112      9.14     0.000      0.7987
1.2348
-----

```

```

-----
Random-effects Parameters |          Estimate      Robust      [95% Conf.
Interval]
-----+-----
Studyno: Identity
  var(_cons) |          0.0004      0.0121      0.0000
5.1e
newPartID: Identity
  var(_cons) |          0.3334      0.0853      0.2020
0.5505

```



```

-----+-----
-----
                                var(Residual) |      0.0992      0.0105      0.0805
0.1221
-----
-----

```

```

.
. *Iterating

```

```

. mixed BaseMEP_wins i.Muscle i.Machine_spulse i.PulseType2
i.Neuronavigation Age i
> f TSint_comparison ==0 || Studyno: || newPartID:,robust
cformat(%5.4f)

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:  log pseudolikelihood = -403.41713
Iteration 1:  log pseudolikelihood = -403.16827
Iteration 2:  log pseudolikelihood = -403.16497
Iteration 3:  log pseudolikelihood = -403.16497

```

Computing standard errors:

```

Mixed-effects regression                                Number of obs      =
456

```

```

-----+-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum      Average      Maximum
-----+-----
      Studyno |           17           10           26.8           70
newPartID |           341            1            1.3            2
-----+-----

```

```

                                                                Wald chi2(6)      =
4381.19
Log pseudolikelihood = -403.16497                                Prob > chi2      =
0.0000

```

(Std. Err. adjusted for 17 clusters in Studyno)

```

-----+-----
BaseMEP_wins |      Coef.      Robust      z      P>|z|      [95% Conf.
Interval]
-----+-----

```

0.0080	Muscle APB	-0.2258	0.1193	-1.89	0.058	-0.4596
0.1045	Machine_spulse MagPro	-0.1602	0.1351	-1.19	0.236	-0.4250
0.4305	Nexstim	0.1092	0.1639	0.67	0.505	-0.2120
0.3845	PulseType2 Biphasic	0.2980	0.0441	6.75	0.000	0.2115
0.0645	Neuronavigation No	-0.0672	0.0672	-1.00	0.317	-0.1990
0.0028	Age	-0.0032	0.0031	-1.04	0.299	-0.0092
1.2887	_cons	1.0603	0.1165	9.10	0.000	0.8319

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	0.0000	.	.
newPartID: Identity			
var(_cons)	0.3307	0.0800	0.2059
var(Residual)	0.0993	0.0105	0.0807


```

. mixed BaseMEP_wins i.Muscle i.Machine_spulse i.PulseType2
i.Neuronavigation i. Gen
> der if TSint_comparison ==0 || ///
> Studyno: || newPartID:,robust cformat(%5.4f)

```

Performing EM optimization:


```

      Female |    -0.0074    0.0713   -0.10   0.917   -0.1472
0.1323
      _cons |     1.0205    0.1234    8.27   0.000    0.7786
1.2624
-----
-----
-----

```

```

-----
-----
-----
Random-effects Parameters |      Estimate   Robust
Std. Err.   [95% Conf.
Interval]
-----+-----

```

```

-----
Studyno: Identity |
      var(_cons) |      0.0004    0.0120    0.0000
5.1e
-----+-----

```

```

-----
newPartID: Identity |
      var(_cons) |      0.3335    0.0853    0.2019
0.5507
-----+-----

```

```

-----
      var(Residual) |      0.0992    0.0105    0.0805
0.1221
-----+-----
-----

```

```

.
. mixed BaseMEP_wins i.Muscle i.Machine_spulse i.PulseType2
i.Neuronavigation i. Hem
> isphere if TSint_comparison ==0 || ///
> Studyno: || newPartID:,robust cformat(%5.4f)

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -396.44941
Iteration 1: log pseudolikelihood = -396.35985
Iteration 2: log pseudolikelihood = -396.35867
Iteration 3: log pseudolikelihood = -396.35867

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
444

```

```

-----
Group Variable |      No. of      Observations per Group
Groups         Minimum   Average   Maximum
-----+-----
      Studyno |          16          10      27.8      70

```

newPartID	329	1	1.3	2

			Wald chi2(6)	=
998.22	Log pseudolikelihood = -396.35867		Prob > chi2	=
0.0000				
(Std. Err. adjusted for 16 clusters in Studyno)				

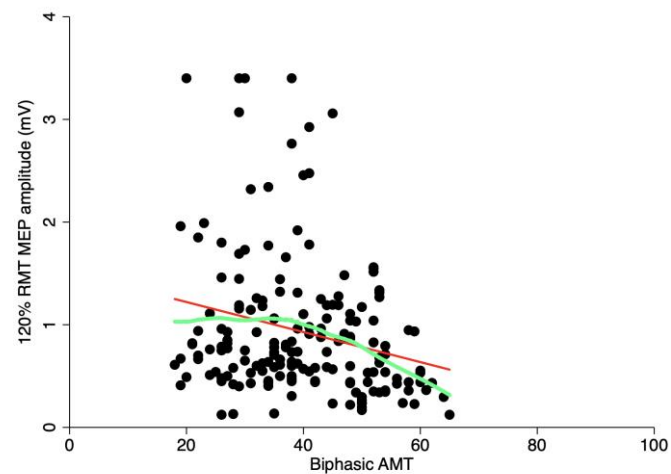
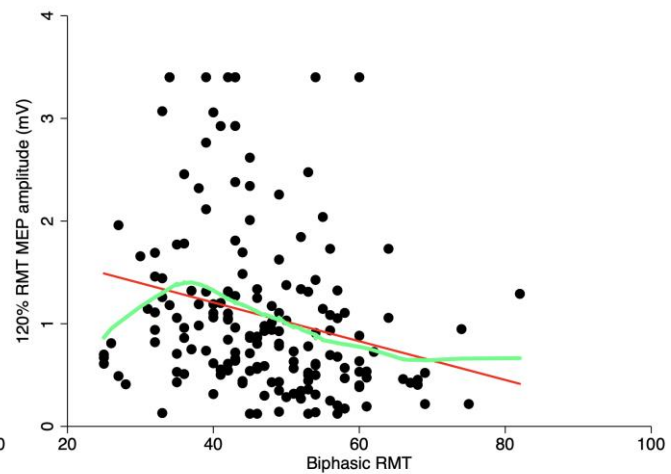
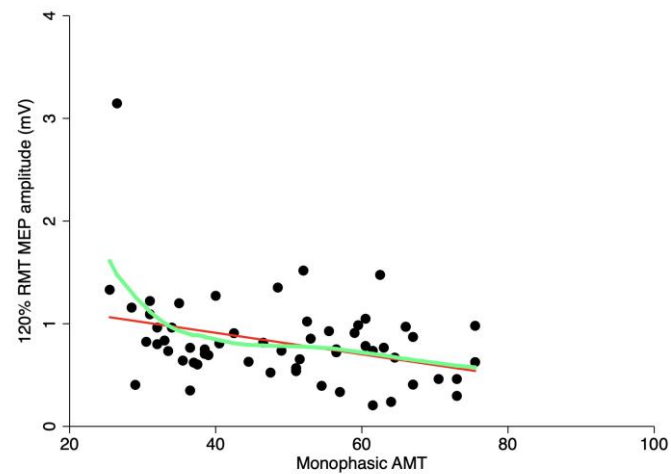
		Robust		
BaseMEP_wins	Coef.	Std. Err.	z	P> z
Interval]				[95% Conf.

Muscle				
APB	-0.2591	0.1245	-2.08	0.037
-0.0151				-0.5030
Machine_spulse				
MagPro	-0.2296	0.1467	-1.57	0.117
0.0579				-0.5171
Nexstim	0.0141	0.1458	0.10	0.923
0.2999				-0.2717
PulseType2				
Biphasic	0.2966	0.0485	6.12	0.000
0.3916				0.2017
Neuronavigation				
No	-0.1213	0.0419	-2.89	0.004
-0.0392				-0.2034
Hemisphere				
R	0.0210	0.0329	0.64	0.524
0.0854				-0.0435
_cons	1.0074	0.1245	8.09	0.000
1.2513				0.7634

. *Final model

```
. mixed BaseMEP_wins i.Muscle i.Machine_spulse i.PulseType2
i.Neuronavigation if TSint_comparison ==0 || ///
```


-0.0267	No		-0.1146	0.0448	-2.56	0.011	-0.2025
1.2348	_cons		1.0168	0.1112	9.14	0.000	0.7987



Supplementary file 7. Non-linear relationships for 120% RMT single pulse MEP amplitude. Post-hoc analyses demonstrated significant non-linear relationships between single pulse MEP amplitude and monophasic AMT, biphasic RMT, and biphasic AMT.

*Step 1 regressions for SICI. Examining the variance in SICI explained by each IV separately, while controlling for the age and gender of participants.

Abbreviations:

MEP change = Normalised MEP (DV)
 Age
 Gender
 BaseMEP = Baseline MEP amplitude
 Machine_ppulse = TMS machine
 Muscle = Target muscle
 Hemisphere = M1 hemisphere
 ppCSint = paired pulse conditioning stimulus intensity
 ppTSint = paired pulse test stimulus intensity
 PulseType/PulseType2/ppPulseType = Pulse waveform
 ISI = interstimulus interval
 MonoRMT = Monophasic RMT
 MonoAMT = Monophasic AMT
 BiRMT = Biphasic RMT
 BiAMT = Biphasic AMT
 Mono_cmb = Monophasic MT combined
 Bi_cmb = Biphasic MT combined
 RMTcmb = RMT combined
 AMTcmb = AMT combined
 MTcmb = MT combined
 TSint_comparison = denotes the analysis of 120% RMT data
 Studyno = Study ID
 newPartID = Participant ID

*IVs omitted because of insufficient data (did not include at least three studies within each IV level):
 Machine ppCSint PulseType ISI

```
. for var      BaseMEP Muscle Hemisphere ppTSint Neuronavigation
MonoRMT BiRMT MonoAMT BiAMT: mixed
>             MEPchange c.X Age Gender if Protocol == 0 &
Dx==0 || Studyno: || newPartID:,robust
```

```
-> mixed MEPchange c.BaseMEP Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || new
> PartID:,robust
```

Performing EM optimization:


```

                                var(_cons) |    211.1977    79.42076    101.0638
441.3499
-----+-----
----
newPartID: Identity           |
                                var(_cons) |    449.2635    100.4846    289.8124
696.4426
-----+-----
----
                                var(Residual) |    679.1771    155.2948    433.865
1063.191
-----+-----
-----

```

```

-> mixed MEPchange c.Muscle Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || newP
> artID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:  log pseudolikelihood = -2268.3673
Iteration 1:  log pseudolikelihood = -2268.3479
Iteration 2:  log pseudolikelihood = -2268.3479

```

Computing standard errors:

```

Mixed-effects regression                                Number of obs    =
456

```

```

-----+-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
      Studyno  |           15           10      30.4      70
    newPartID |          283            1       1.6       4
-----+-----

```

```

                                                                Wald chi2(3)    =
4.10
Log pseudolikelihood = -2268.3479                            Prob > chi2     =
0.2505

```

(Std. Err. adjusted for 15 clusters in Studyno)

```

-----+-----
MEPchange      |      Robust
                |      Coef.   Std. Err.      z    P>|z|    [95% Conf.
Interval]
-----+-----

```


Studyno	15	10	30.4	70
newPartID	283	1	1.6	4

Wald chi2(3) = 16.12
 Prob > chi2 = 0.0011
 Log pseudolikelihood = -2267.3419

(Std. Err. adjusted for 15 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Hemisphere	-5.273922	1.748358	-3.02	0.003	-8.700641 - 1.847202
Age	.220899	.1200631	1.84	0.066	-.0144204 .4562183
Gender	3.494108	3.30978	1.06	0.291	-2.992941 9.981156
_cons	40.70547	7.366821	5.53	0.000	26.26676 55.14417

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	139.5504	69.44456	52.61957 370.0966
newPartID: Identity			
var(_cons)	532.0593	147.2917	309.2568 915.3788
var(Residual)	742.8034	195.1739	443.8315 1243.168

```
-> mixed MEPchange c.pptSint Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || new
> PartID:,robust
```



```

Studyno: Identity |
                var(_cons) | 123.4359 45.64036 59.80123
254.7844
-----+-----
----
newPartID: Identity |
                var(_cons) | 554.4496 152.2201 323.721
949.6276
-----+-----
----
                var(Residual) | 757.9096 202.9583 448.4115
1281.026
-----+-----
-----

```

```

-> mixed MEPchange c.Neuronavigation Age Gender if Protocol == 0 & Dx==0
|| Studyno
> : || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -2268.3452
Iteration 1: log pseudolikelihood = -2268.3259
Iteration 2: log pseudolikelihood = -2268.3259

```

Computing standard errors:

```

Mixed-effects regression          Number of obs   =
456

```

```

-----+-----
Group Variable | No. of      Observations per Group
                | Groups      Minimum   Average   Maximum
-----+-----
Studyno       | 15          10        30.4      70
newPartID     | 283         1         1.6       4
-----+-----

```

```

3.78
Log pseudolikelihood = -2268.3259      Wald chi2(3)      =
0.2866                                Prob > chi2      =

```

(Std. Err. adjusted for 15 clusters in Studyno)

```

-----+-----
MEPchange     | Coef.      Robust      z    P>|z|    [95% Conf.
Interval]    | Std. Err.
-----+-----

```

```

Neuronavigation | -2.980393  7.835779  -0.38  0.704  -18.33824
12.37745
      Age | .2272705  .1231058  1.85  0.065  -.0140124
.4685535
      Gender | 3.33641  3.282533  1.02  0.309  -3.097236
9.770055
      _cons | 41.2268  9.153757  4.50  0.000  23.28577
59.16783

```

```

Random-effects Parameters | Estimate      Robust      [95% Conf.
Interval]          Std. Err.
-----+-----

```

```

Study: Identity          |
      var(_cons) | 150.0159    66.1064    63.24769
355.8197
-----+-----

```

```

newPartID: Identity     |
      var(_cons) | 529.4786   146.6327   307.6936
911.126
-----+-----

```

```

      var(Residual) | 747.3772   197.8844   444.8009
1255.781
-----+-----

```

```

-> mixed MEPchange c.MonoRMT Age Gender if Protocol == 0 & Dx==0 ||
Study: || new
> PartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:  log pseudolikelihood = -2027.8725
Iteration 1:  log pseudolikelihood = -2027.8662
Iteration 2:  log pseudolikelihood = -2027.8662

```

Computing standard errors:

```

Mixed-effects regression          Number of obs      =
407

```

```

-----+-----
Group Variable | No. of      Observations per Group
Groups         Minimum     Average     Maximum
-----+-----

```


Studyno		13	10	31.3	70
newPartID		234	1	1.7	4

Wald chi2(3) = 1.17

Log pseudolikelihood = -2027.8662 Prob > chi2 = 0.7608

(Std. Err. adjusted for 13 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
MonoRMT	.1084704	.236866	0.46	0.647	-.3557785
Age	.1210917	.1127784	1.07	0.283	-.0999499
Gender	2.468356	3.36346	0.73	0.463	-4.123904
_cons	38.00508	16.24395	2.34	0.019	6.167529

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	157.0305	65.08373	69.6932
newPartID: Identity			
var(_cons)	558.6721	178.3212	298.8574
var(Residual)	758.9709	212.5291	438.3987

```
-> mixed MEPchange c.BiRMT Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || newPa
> rtID:,robust
```



```

      var(_cons) |    100.9924    111.1754    11.67511
873.608
-----+-----
----
newPartID: Identity |
      var(_cons) |    1467.58    426.827    829.9287
2595.153
-----+-----
----
      var(Residual) |    206.6208    79.56925    97.13552
439.5113
-----+-----
-----

```

```

-> mixed MEPchange c.MonoAMT Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || new
> PartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -1294.0376
Iteration 1: log pseudolikelihood = -1294.0375

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
263

```

```

-----+-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
      Studyno |           6           20     43.8     70
newPartID |          123           1     2.1     4
-----+-----

```

```

2.46
Log pseudolikelihood = -1294.0375           Wald chi2(3)   =
0.4820                                       Prob > chi2   =

```

(Std. Err. adjusted for 6 clusters in Studyno)

```

-----+-----
MEPchange |      Robust
Interval |      Coef.   Std. Err.   z   P>|z|   [95% Conf.
-----+-----
MonoAMT |  -.490092   .4207196   -1.16  0.244   -1.314687
.3345032

```

```

      Age |   .1233373   .0812742   1.52   0.129   -.0359572
.2826318
      Gender |   3.201804   4.477844   0.72   0.475   -5.574608
11.97822
      _cons |   63.16403   18.60141   3.40   0.001   26.70593
99.62213

```

```

-----
-----
Random-effects Parameters |      Estimate      Robust
Interval]               Std. Err.      [95% Conf.
-----+-----
Studyno: Identity       |
      var(_cons) |      178.3565      101.5413      58.43668
544.3675
-----+-----
newPartID: Identity     |
      var(_cons) |      436.5358      265.2162      132.7011
1436.036
-----+-----
      var(Residual) |      729.7473      306.515      320.3637
1662.271
-----
-----

```

```

-> mixed MEPchange c.BiAMT Age Gender if Protocol == 0 & Dx==0 ||
Studyno: || newPa
> rtID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:  log pseudolikelihood = -542.54893
Iteration 1:  log pseudolikelihood = -541.89134
Iteration 2:  log pseudolikelihood = -541.85954
Iteration 3:  log pseudolikelihood = -541.85928
Iteration 4:  log pseudolikelihood = -541.85928

```

Computing standard errors:

```

Mixed-effects regression              Number of obs      =
107

```

```

-----
Group Variable |      No. of      Observations per Group
               |      Groups      Minimum      Average      Maximum
-----+-----

```

Studyno	6	10	17.8	33
newPartID	85	1	1.3	3

5.17 Wald chi2(3) =

Log pseudolikelihood = -541.85928 Prob > chi2 =

0.1599

(Std. Err. adjusted for 6 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
BiAMT	-.6226971	.3247755	-1.92	0.055	-1.259245
.0138512					
Age	.4843482	.2664709	1.82	0.069	-.0379252
1.006622					
Gender	9.836636	7.351436	1.34	0.181	-4.571914
24.24519					
_cons	55.12375	12.62634	4.37	0.000	30.37658
79.87092					

Random-effects Parameters Interval]	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	1.52e-18	6.41e-15	0
.			
newPartID: Identity			
var(_cons)	269.623	10006.22	6.94e-30
1.05e			
var(Residual)	1210.3	50865.76	2.04e-33
7.19e			

*Step 2 regressions for SICI.

*This is the starting step 2 model for SICI - all variables that obtained a p-value < 0.10 in stage 1 regressions.

```
. mixed MEPchange Age Gender BaseMEP Hemisphere if  
(Protocol == 0)  
> & Dx==0 || Studyno: || newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2243.7127  
Iteration 1: log pseudolikelihood = -2243.6731  
Iteration 2: log pseudolikelihood = -2243.6731
```

Computing standard errors:

```
Mixed-effects regression Number of obs =  
456
```

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
Studyno	15	10	30.4	70
newPartID	283	1	1.6	4

```
Wald chi2(4) =  
20.22  
Log pseudolikelihood = -2243.6731 Prob > chi2 =  
0.0005
```

(Std. Err. adjusted for 15 clusters in Studyno)

MEPchange	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Age	.1107418	.1146213	0.97	0.334	-.1139117 .3353954
Gender	5.665736	3.632083	1.56	0.119	-1.453015 12.78449
BaseMEP	-23.28733	8.223553	-2.83	0.005	-39.4052 7.169461

```

Hemisphere | -4.013009  1.732368  -2.32  0.021  -7.408388  -
.6176303
_cons | 65.08157  13.67916  4.76  0.000  38.27091
91.89222

```

```

-----
-----
Random-effects Parameters | Estimate Robust Std. Err. [95% Conf. Interval]
-----+-----
Studyno: Identity
var(_cons) | 195.8329 85.9892 82.81851
463.0669
-----+-----
newPartID: Identity
var(_cons) | 452.7606 101.2762 292.0564
701.8924
-----+-----
var(Residual) | 676.0384 154.0466 432.5247
1056.652
-----
-----

```

*Iterating

```

for var Muscle ppTSint MonoRMT BiRMT MonoAMT BiAMT: mixed
MEPchange
> c.X Age Gender BaseMEP Hemisphere if Protocol == 0 ///
> & Dx==0 || Studyno: || newPartID:,robust

```

```

-> mixed MEPchange c.Muscle Age Gender BaseMEP Hemisphere if Protocol ==
0 & Dx==0
> || Studyno: || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -2243.6699
Iteration 1: log pseudolikelihood = -2243.6302
Iteration 2: log pseudolikelihood = -2243.6301

```

Computing standard errors:


```

              var(_cons) |    452.8735    101.1909    292.269
701.7317
-----+-----

```

```

              var(Residual) |    676.0504    153.9417    432.6674
1056.341
-----+-----

```

```

-> mixed MEPchange c.ppTSint Age Gender BaseMEP Hemisphere if Protocol
== 0 & Dx==0
> || Studyno: || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:    log pseudolikelihood = -2176.7583
Iteration 1:    log pseudolikelihood = -2176.7255
Iteration 2:    log pseudolikelihood = -2176.7254

```

Computing standard errors:

```

Mixed-effects regression              Number of obs    =
442

```

```

-----+-----
Group Variable |    No. of      Observations per Group
              |    Groups      Minimum   Average   Maximum
-----+-----
      Studyno |         14         10      31.6      70
    newPartID |        269         1       1.6       4
-----+-----

```

```

              Wald chi2(5)    =
17.30
Log pseudolikelihood = -2176.7254    Prob > chi2    =
0.0040

```

(Std. Err. adjusted for 14 clusters in Studyno)

```

-----+-----
MEPchange |          Robust
Interval] |          Coef.  Std. Err.      z    P>|z|    [95% Conf.
-----+-----
      ppTSint | -8.031322    8.808018   -0.91  0.362   -25.29472
9.232076
      Age |  .0921402   .1233165    0.75  0.455   -.1495558
.3338361
      Gender |  5.559368    3.72985    1.49  0.136   -1.751004
12.86974

```

```

      BaseMEP | -25.74774   9.044947   -2.85   0.004   -43.47551   -
8.019972
      Hemisphere | -4.110605   1.684179   -2.44   0.015   -7.411535   -
.8096746
      _cons |    71.8413   15.80493    4.55   0.000    40.8642
102.8184

```

```

-----
-----
-----
Random-effects Parameters |      Estimate      Robust      [95% Conf.
Interval]
-----+-----
Studyno: Identity |
      var(_cons) |    204.9906    72.52314    102.4682
410.0894
-----+-----
newPartID: Identity |
      var(_cons) |    466.0944    103.4138    301.7277
720.0003
-----+-----
      var(Residual) |    678.809    153.7985    435.4015
1058.291
-----
-----

```

```

-> mixed MEPchange c.MonoRMT Age Gender BaseMEP Hemisphere if Protocol
== 0 & Dx==0
> || Studyno: || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:   log pseudolikelihood = -2000.6636
Iteration 1:   log pseudolikelihood = -2000.6426
Iteration 2:   log pseudolikelihood = -2000.6426

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
407

```

```

-----
Group Variable |      No. of      Observations per Group
               |      Groups      Minimum      Average      Maximum
-----+-----
      Studyno |           13           10           31.3           70
newPartID |          234            1            1.7            4

```

28.84 Wald chi2(5) =

Log pseudolikelihood = -2000.6426 Prob > chi2 =

0.0000

(Std. Err. adjusted for 13 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
MonoRMT	-.349762	.3247811	-1.08	0.282	-.9863212
.2867972					
Age	.1424259	.1185159	1.20	0.229	-.089861
.3747128					
Gender	4.353436	4.096342	1.06	0.288	-3.675246
12.38212					
BaseMEP	-29.64184	10.55421	-2.81	0.005	-50.32772
8.955958					
Hemisphere	-5.605659	1.897601	-2.95	0.003	-9.324888
1.88643					
_cons	89.87277	28.39005	3.17	0.002	34.2293
145.5162					

Random-effects Parameters Interval]	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	282.1264	104.4826	136.5243
583.0117			
newPartID: Identity			
var(_cons)	443.2318	111.2133	271.0516
724.786			
var(Residual)	673.8053	156.6797	427.1741
1062.83			

```
-> mixed MEPchange c.BiRMT Age Gender BaseMEP Hemisphere if Protocol ==
0 & Dx==0 |
> | Studyno: || newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -397.78284
Iteration 1: log pseudolikelihood = -397.78282 (not concave)
Iteration 2: log pseudolikelihood = -397.78282 (backed up)
```

Computing standard errors:

```
Mixed-effects regression                               Number of obs   =
78
```

```
-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum      Average      Maximum
-----+-----
      Studyno |           3          15          26.0          39
    newPartID |          78           1           1.0           1
-----
```

```
Wald chi2(2) =
Log pseudolikelihood = -397.78282      Prob > chi2 =
.
```

(Std. Err. adjusted for 3 clusters in Studyno)

```
-----
MEPchange |      Robust
Interval] |      Coef.   Std. Err.      z    P>|z|    [95% Conf.
-----+-----
      BiRMT |   .2470882   .3100845     0.80   0.426   -.3606662
.8548427
      Age |   .1444077   .1741899     0.83   0.407   -.1969982
.4858136
      Gender |  15.61687   4.818079     3.24   0.001    6.173611
25.06013
      BaseMEP | -18.17106   9.119013    -1.99   0.046   -36.044 -
.2981202
      Hemisphere | -2.415782   2.125187    -1.14   0.256   -6.581073
1.749508
      _cons |   47.3614   36.95123     1.28   0.200   -25.06168
119.7845
-----
```

```

-----
-----
Random-effects Parameters | Estimate      Robust      [95% Conf.
Interval]           Std. Err.
-----+-----
Studyno: Identity      |
var(_cons) | 91.40858    148.2462    3.806362
2195.148
-----+-----
newPartID: Identity   |
var(_cons) | 1315.182    315.9672    821.274
2106.122
-----+-----
var(Residual) | 204.8791    117.1965    66.77083
628.6495
-----
-----

```

```

-> mixed MEPchange c.MonoAMT Age Gender BaseMEP Hemisphere if Protocol
== 0 & Dx==0
> || Studyno: || newPartID:,robust

```

Performing EM optimization:
Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -1270.5645
Iteration 1: log pseudolikelihood = -1270.5636
Iteration 2: log pseudolikelihood = -1270.5636

```

Computing standard errors:

```

Mixed-effects regression           Number of obs   =
263

```

```

-----
Group Variable | No. of      Observations per Group
Groups         Minimum     Average     Maximum
-----+-----
Studyno | 6          20         43.8       70
newPartID | 123        1          2.1        4
-----

```

```

Wald chi2(5) =
429.73
Log pseudolikelihood = -1270.5636   Prob > chi2 =
0.0000

```

(Std. Err. adjusted for 6 clusters in Studyno)

```

-----
-----
MEPchange |           Coef.      Robust
Interval] |           Std. Err.      z    P>|z|      [95% Conf.
-----+-----
MonoAMT |  -.9197529   .7011269   -1.31   0.190   -2.293936
.4544306
Age |    .192005   .1362812    1.41   0.159   -.0751012
.4591112
Gender |    7.086305   7.54868    0.94   0.348   -7.708835
21.88145
BaseMEP |  -37.90118  18.88504   -2.01   0.045  -74.91517  -
.8871883
Hemisphere |  -5.014506   1.640793   -3.06   0.002  -8.230402  -
1.79861
_cons |   113.7038   45.2527    2.51   0.012   25.01012
202.3975
-----
-----

```

```

-----
-----
Random-effects Parameters |           Estimate      Robust
Interval] |           Std. Err.      [95% Conf.
-----+-----
Studyno: Identity
var(_cons) |   294.2187   150.6621   107.8428
802.6928
-----+-----
newPartID: Identity
var(_cons) |   333.4856   126.739   158.3374
702.3777
-----+-----
var(Residual) |   617.1795   188.3234   339.3748
1122.389
-----
-----

```

```

-> mixed MEPchange c.BiAMT Age Gender BaseMEP Hemisphere if Protocol ==
0 & Dx==0 |
> | Studyno: || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:   log pseudolikelihood = -537.39432
Iteration 1:   log pseudolikelihood = -536.72862

```



```

                var(_cons) |    108.7552    283.307    .6592848
17940.2
-----+-----
----
newPartID: Identity |
                var(_cons) |    144.245    103.915    35.14713
591.9862
-----+-----
----
                var(Residual) |    1129.344    163.3617    850.5473
1499.527
-----
-----

```

. *This is the final model

```

. mixed MEPchange Age i.Gender BaseMEP i.Hemisphere if (Protocol == 0) &
Dx==0 || Studyno: || newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:   log pseudolikelihood = -2243.7127
Iteration 1:   log pseudolikelihood = -2243.6731
Iteration 2:   log pseudolikelihood = -2243.6731

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
456

```

```

-----+-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
      Studyno |           15           10    30.4     70
    newPartID |           283            1     1.6      4
-----+-----

```

```

                Wald chi2(4)   =
20.22
Log pseudolikelihood = -2243.6731   Prob > chi2   =
0.0005

```

(Std. Err. adjusted for 15 clusters in Studyno)


```

-----
-----
MEPchange |           Coef.      Robust
Interval] |           Std. Err.      z      P>|z|      [95% Conf.
-----+-----
Age |      .1107418      .1146213      0.97      0.334      -.1139117
.3353954
Gender |
Female |      5.665736      3.632083      1.56      0.119      -1.453015
12.78449
BaseMEP |     -23.28733      8.223553      -2.83      0.005      -39.4052  -
7.169461
Hemisphere |
R |     -4.013009      1.732368      -2.32      0.021      -7.408388  -
.6176303
_cons |      65.08157      13.67916      4.76      0.000      38.27091
91.89222
-----
-----

```

*Step 1 regressions for ICF. Examining the variance in ICF explained by each IV separately, while controlling for the age and gender of participants.

*IVs omitted because not enough studies: Machine_ppulse ppCSint ppPulseType ISI

```

.
.
. for var      BaseMEP Muscle Hemisphere  ppTSint Neuronavigation
MonoRMT MonoAMT : mixed MEPchange      ///
>      c.X Age Gender if      Protocol ==      1 &      Dx==0
|| Studyno: || newPartID:,robust noretale

```

```
-> mixed MEPchange c.BaseMEP Age Gender if Protocol == 1 & Dx==0 ||
Studyno: || new
> PartID:,robust norettable
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2294.6159
Iteration 1: log pseudolikelihood = -2294.5463
Iteration 2: log pseudolikelihood = -2294.5463
```

Computing standard errors:

```
Mixed-effects regression          Number of obs    =
393
```

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	14	10	28.1	70
newPartID	256	1	1.5	3

```
Wald chi2(3) =
6.41
Log pseudolikelihood = -2294.5463    Prob > chi2 =
0.0931
```

(Std. Err. adjusted for 14 clusters in

Studyno)

MEPchange	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
BaseMEP	-71.83875	28.90853	-2.49	0.013	-128.4984 - 15.17908
Age	-.0014924	.4610102	-0.00	0.997	-.9050559 .9020711
Gender	-4.805832	8.276008	-0.58	0.561	-21.02651 11.41485
_cons	227.2174	38.17283	5.95	0.000	152.4 302.0347

```
-> mixed MEPchange c.Muscle Age Gender if Protocol == 1 & Dx==0 ||
Studyno: || newP
```

> artID:,robust noretale

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -2327.4999
Iteration 1: log pseudolikelihood = -2327.4307
Iteration 2: log pseudolikelihood = -2327.4307

Computing standard errors:

Mixed-effects regression Number of obs =
393

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	14	10	28.1	70
newPartID	256	1	1.5	3

10.30 Wald chi2(3) =
Log pseudolikelihood = -2327.4307 Prob > chi2 =
0.0162

(Std. Err. adjusted for 14 clusters in

Studyno)

	MEPchange	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Muscle	1.376667	28.52563	0.05	0.962	-54.53254	57.28588
Age	.5851793	.3642238	1.61	0.108	-.1286862	1.299045
Gender	-12.14622	8.690536	-1.40	0.162	-29.17936	4.886914
_cons	146.1589	17.15735	8.52	0.000	112.5312	179.7867

-> mixed MEPchange c.Hemisphere Age Gender if Protocol == 1 & Dx==0 ||
Studyno: ||
> newPartID:,robust noretale

Performing EM optimization:

Iteration 2: log pseudolikelihood = -2245.3709

Computing standard errors:

Mixed-effects regression Number of obs = 379

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	13	10	29.2	70
newPartID	242	1	1.6	3

Wald chi2(3) = 7.33
 Log pseudolikelihood = -2245.3709 Prob > chi2 = 0.0621

(Std. Err. adjusted for 13 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
ppTSint	-31.27347	20.60984	-1.52	0.129	-71.66801
Age	.4298185	.34591	1.24	0.214	-.2481526
Gender	-12.51507	8.949082	-1.40	0.162	-30.05495
_cons	165.8492	17.05441	9.72	0.000	132.4231

```
-> mixed MEPchange c.Neuronavigation Age Gender if Protocol == 1 & Dx==0
|| Studyno
> : || newPartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -2326.7597
 Iteration 1: log pseudolikelihood = -2326.6911
 Iteration 2: log pseudolikelihood = -2326.6911

Computing standard errors:

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	12	10	28.7	70
newPartID	207	1	1.7	3

57.35
 Log pseudolikelihood = -2014.7426
 0.0000

Wald chi2(3) =
 Prob > chi2 =

(Std. Err. adjusted for 12 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
MonoRMT	2.963653	.6799572	4.36	0.000	1.630962
Age	.5288319	.5960899	0.89	0.375	-.6394829
Gender	-16.31275	7.716366	-2.11	0.035	-31.43655
_cons	-1.168291	22.69199	-0.05	0.959	-45.64378

```
-> mixed MEPchange c.MonoAMT Age Gender if Protocol == 1 & Dx==0 ||
Studyno: || new
> PartID:,robust noretale
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -1008.8916
Iteration 1: log pseudolikelihood = -1008.7753
Iteration 2: log pseudolikelihood = -1008.7717
Iteration 3: log pseudolikelihood = -1008.7717
```

Computing standard errors:

Mixed-effects regression
 168

Number of obs =

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum

Studyno		4	20	42.0	70
newPartID		84	2	2.0	2

Wald chi2(3) = 241480.47

Log pseudolikelihood = -1008.7717 Prob > chi2 = 0.0000

(Std. Err. adjusted for 4 clusters in Studyno)

MEPchange Interval]	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
MonoAMT	2.951797	.5354576	5.51	0.000	1.90232
Age	.6873275	.61033	1.13	0.260	-.5088973
Gender	-26.80652	6.322692	-4.24	0.000	-39.19877 -
_cons	42.1005	11.17352	3.77	0.000	20.20081

```

. .
. * Doing this separately here bc have to take out the newPartID
. mixed MEPchange c.BiAMT c.Age i.Gender if (Protocol ==
1) & Dx==0
> || Studyno: ,robust

```

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -442.40142
Iteration 1: log pseudolikelihood = -442.3021
Iteration 2: log pseudolikelihood = -442.3021

Computing standard errors:

Mixed-effects regression Number of obs = 75
Group variable: Studyno Number of groups = 5
Obs per group: min = 10


```

15.0
25
8.07
Log pseudolikelihood = -442.3021
0.0446
                                Wald chi2(3) =
                                Prob > chi2 =
                                avg =
                                max =

```

(Std. Err. adjusted for 5 clusters in Studyno)

```

-----
-----
      MEPchange |           Coef.   Robust
      Interval] |           Std. Err.   z   P>|z|   [95% Conf.
-----+-----
-----
      BiAMT |    3.663754   2.684226   1.36   0.172   -1.597232
8.92474
      Age |   -.0134243   1.033459   -0.01   0.990   -2.038967
2.012118
      Gender |
      Female |  -18.24444   35.65254   -0.51   0.609   -88.12214
51.63325
      _cons |    44.28037   74.17977    0.60   0.551   -101.1093
189.67
-----
-----

```

```

-----
-----
      Random-effects Parameters |           Estimate   Robust
      Interval] |           Std. Err.   Std. Err.   [95% Conf.
-----+-----
-----
Studyno: Identity |
      var(_cons) |    8.70e-15   2.29e-12   3.6e-239
2.1e□
-----+-----
-----
      var(Residual) |    7760.838   2052.043   4622.133
13030.91
-----
-----

```

```

. mixed MEPchange c.BiRMT c.Age i.Gender if (Protocol ==
1) & Dx==0
> || Studyno: ,robust

```

Performing EM optimization:

(Std. Err. adjusted for 14 clusters in

Studyno)

```

-----
-----
      MEPchange |           Robust
      Interval] |      Coef.   Std. Err.      z    P>|z|    [95% Conf.
-----+-----
      BaseMEP |   -71.8332   28.93723   -2.48  0.013   -128.5491  -
15.11728
      Gender |
      Female |   -4.802347   8.188739   -0.59  0.558   -20.85198
11.24729
      _cons |    227.1622   34.26389    6.63  0.000    160.0062
294.3182
-----
-----

```

```

-----
-----
      Random-effects Parameters |           Robust
      Interval] |      Estimate   Std. Err.    [95% Conf.
-----+-----
Studyno: Identity |
      var(_cons) |    859.9823   387.4785    355.6045
2079.753
-----+-----
newPartID: Identity |
      var(_cons) |   3415.069   947.5544    1982.544
5882.693
-----+-----
      var(Residual) |    3837.627  1319.951    1955.655
7530.665
-----
-----

```

*Iterating

```

.
. for var      Age  ppTSint Muscle Hemisphere: mixed MEPchange ///
>             c.X BaseMEP Gender if Protocol ==    1 &    Dx==0
|| Studyno: || newPartID:,robust norettable

```

```
-> mixed MEPchange c.Age BaseMEP Gender if Protocol == 1 & Dx==0 ||
Studyno: || new
> PartID:,robust norettable
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2294.6159
Iteration 1: log pseudolikelihood = -2294.5463
Iteration 2: log pseudolikelihood = -2294.5463
```

Computing standard errors:

```
Mixed-effects regression          Number of obs    =
393
```

```
-----
```

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	14	10	28.1	70
newPartID	256	1	1.5	3

```
-----
```

```
6.41                                Wald chi2(3)      =
Log pseudolikelihood = -2294.5463    Prob > chi2      =
0.0931
```

(Std. Err. adjusted for 14 clusters in

Studyno)

```
-----
```

	MEPchange	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
	Age	-.0014924	.4610102	-0.00	0.997	-.9050559
	BaseMEP	-71.83875	28.90852	-2.49	0.013	-128.4984
	Gender	-4.805832	8.276008	-0.58	0.561	-21.02651
	_cons	227.2174	38.17283	5.95	0.000	152.4

```
-----
```

```
-> mixed MEPchange c.ppTSint BaseMEP Gender if Protocol == 1 & Dx==0 ||
Studyno: ||
> newPartID:,robust norettable
```



```

Iteration 0: log pseudolikelihood = -2294.5445
Iteration 1: log pseudolikelihood = -2294.4752
Iteration 2: log pseudolikelihood = -2294.4752

```

Computing standard errors:

```

Mixed-effects regression          Number of obs    =
393

```

```

-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum      Average      Maximum
-----+-----
      Studyno |           14          10          28.1          70
    newPartID |          256           1           1.5           3
-----

```

```

                                Wald chi2(3)    =
11.74
Log pseudolikelihood = -2294.4752          Prob > chi2    =
0.0083

```

(Std. Err. adjusted for 14 clusters in Studyno)

```

-----
MEPchange |      Coef.      Robust      z      P>|z|      [95% Conf.
Interval]
-----+-----
Muscle | -7.852723      23.7672      -0.33      0.741      -54.43558
38.73013
BaseMEP | -71.99152      28.69792      -2.51      0.012      -128.2384 -
15.74464
Gender | -5.000234      8.025518      -0.62      0.533      -20.72996
10.72949
      _cons |      229.7268      30.53341      7.52      0.000      169.8824
289.5712
-----

```

```

-> mixed MEPchange c.Hemisphere BaseMEP Gender if Protocol == 1 & Dx==0
|| Studyno:
> || newPartID:,robust norettable

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -2294.5567
Iteration 1: log pseudolikelihood = -2294.4875
Iteration 2: log pseudolikelihood = -2294.4875

```



```
> : || newPartID:,robust noretale
```

```
Performing EM optimization:
```

```
Performing gradient-based optimization:
```

```
Iteration 0: log pseudolikelihood = -2209.5674  
Iteration 1: log pseudolikelihood = -2209.5174  
Iteration 2: log pseudolikelihood = -2209.5174
```

```
Computing standard errors:
```

```
Mixed-effects regression Number of obs =  
379
```

```
-----  
Group Variable | No. of Observations per Group  
                | Groups Minimum Average Maximum  
-----+-----  
    Studyno |      13      10      29.2      70  
    newPartID |     242       1       1.6       3  
-----
```

```
Wald chi2(4) =  
8.01  
Log pseudolikelihood = -2209.5174 Prob > chi2 =  
0.0914
```

```
(Std. Err. adjusted for 13 clusters in  
Studyno)
```

```
-----  
MEPchange | Robust  
Interval] | Coef. Std. Err. z P>|z| [95% Conf.  
-----+-----  
Age | -.1797049 .4539419 -0.40 0.692 -1.069415  
.7100049  
BaseMEP | -81.56248 32.36383 -2.52 0.012 -144.9944 -  
18.13054  
Gender | -4.877201 8.339107 -0.58 0.559 -21.22155  
11.46715  
ppTSint | -34.70664 16.96814 -2.05 0.041 -67.96358 -  
1.44971  
_cons | 252.5945 41.95015 6.02 0.000 170.3737  
334.8153  
-----
```

```
-> mixed MEPchange c.Muscle BaseMEP Gender ppTSint if Protocol == 1 &  
Dx==0 || Stud  
> yno: || newPartID:,robust noretale
```



```
. mixed MEPchange c.BaseMEP i.ppTSint i.Gender if
(Protocol == 1) &
> Dx==0 || Studyno: || newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2209.6579
Iteration 1: log pseudolikelihood = -2209.607
Iteration 2: log pseudolikelihood = -2209.607
```

Computing standard errors:

```
Mixed-effects regression Number of obs =
379
```

```
-----
```

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	13	10	29.2	70
newPartID	242	1	1.6	3

```
-----
```

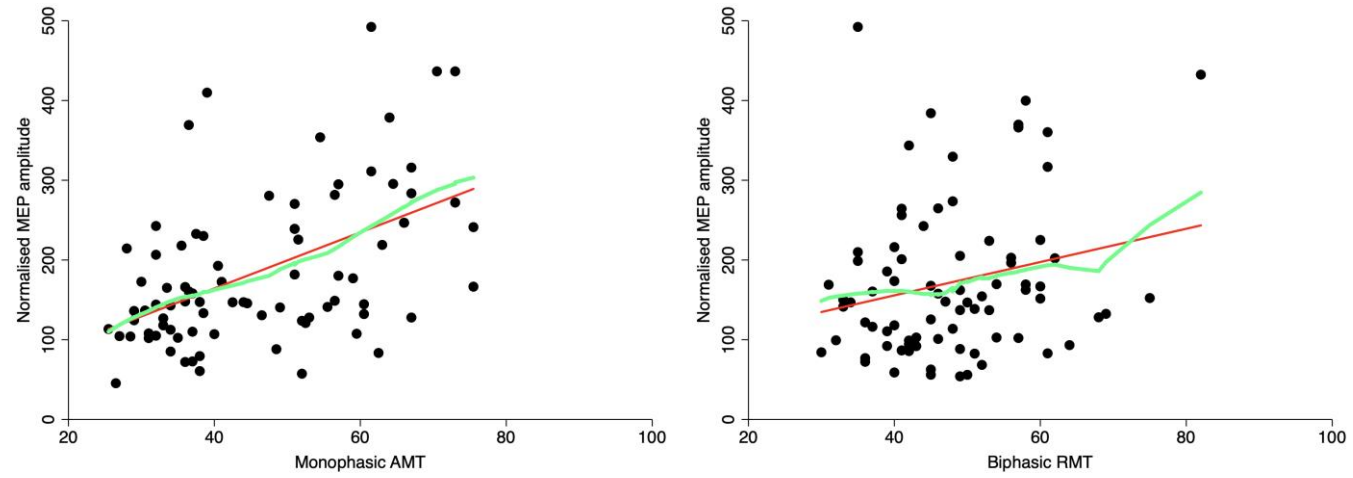
```
7.46 Wald chi2(3) =
Log pseudolikelihood = -2209.607 Prob > chi2 =
0.0586
```

(Std. Err. adjusted for 13 clusters in Studyno)

```
-----
```

	MEPchange	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
BaseMEP	-80.82001	32.65889	-2.47	0.013	-144.8303 -	
ppTSint						
0.5-1.5MV	-33.31513	16.43076	-2.03	0.043	-65.51884 -	
Gender						
Female	-4.461701	8.240202	-0.54	0.588	-20.6122	
_cons	245.4519	38.38918	6.39	0.000	170.2105	

```
-----
```



Supplementary file 9. Non-linear relationships for ICF. Post-hoc analyses demonstrated significant non-linear relationships between ICF normalised MEP and monophasic AMT and biphase RMT.

*Step 1 regressions for Monophasic RMT. Examining the variance in Monophasic RMT explained by each IV separately, while controlling for the age and gender of participants.

Abbreviations:

MEP change = Normalised MEP (DV)
 Age
 Gender
 BaseMEP = Baseline MEP amplitude
 Machine_MonoRMT = TMS machine
 Muscle = Target muscle
 Hemisphere = M1 hemisphere
 ppCSint = paired pulse conditioning stimulus intensity
 ppTSint = paired pulse test stimulus intensity
 PulseType/PulseType2 = Pulse waveform
 ISI = interstimulus interval
 MonoRMT = Monophasic RMT
 MonoAMT = Monophasic AMT
 BiRMT = Biphasic RMT
 BiAMT = Biphasic AMT
 Mono_cmb = Monophasic MT combined
 Bi_cmb = Biphasic MT combined
 RMTcmb = RMT combined
 AMTcmb = AMT combined
 MTcmb = MT combined
 TSint_comparison = denotes the analysis of 120% RMT data
 Studyno = Study ID
 newPartID = Participant ID

*IVs omitted because of insufficient data (did not include at least three studies within each IV level):

Machine_MonoRMT

```
. for var Muscle Hemisphere Neuronavigation: mixed MonoRMT c.X Age
Gender || Stud
> yno: || newPartID:,robust noretale
```

```
-> mixed MonoRMT c.Muscle Age Gender || Studyno: || newPartID:,robust
noretale
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2158.0198
Iteration 1: log pseudolikelihood = -2157.8946
Iteration 2: log pseudolikelihood = -2157.8946
```


Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
Studyno	26	9	23.2	70
newPartID	516	1	1.2	2

15.87
 Log pseudolikelihood = -2152.824
 0.0012

Wald chi2(3) =
 Prob > chi2 =

(Std. Err. adjusted for 26 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Hemisphere	-2.167551	.8941427	-2.42	0.015	-3.920038 - .4150636
Age	.0877955	.0250402	3.51	0.000	.0387177 .1368733
Gender	.8295988	.8551474	0.97	0.332	-.8464594 2.505657
_cons	43.8205	2.032247	21.56	0.000	39.83737 47.80363

```
-> mixed MonoRMT c.Neuronavigation Age Gender || Studyno: ||
newPartID:,robust nore
> table
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2157.1211
Iteration 1: log pseudolikelihood = -2156.9948
Iteration 2: log pseudolikelihood = -2156.9948
```

Computing standard errors:

Mixed-effects regression
 603

Number of obs =

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum

Studyno		26	9	23.2	70
newPartID		516	1	1.2	2

Wald chi2(3) = 13.06
 Prob > chi2 = 0.0045

(Std. Err. adjusted for 26 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Neuronavigation	-5.554583	5.132827	-1.08	0.279	-15.61474 4.505573
Age	.0876297	.0243342	3.60	0.000	.0399355 .1353238
Gender	.8071669	.851408	0.95	0.343	-.8615621 2.475896
_cons	47.73867	4.603463	10.37	0.000	38.71605 56.7613

*Step 2 regressions for Monophasic RMT.

*This is the starting step 2 model for Monophasic RMT - all variables that obtained a p-value < 0.10 in stage 1 regressions.

```
. for var Gender Neuronavigation Muscle : mixed MonoRMT c.X Age
Hemisphere || Stu
> dyno: || newPartID:,robust
```

```
-> mixed MonoRMT c.Gender Age Hemisphere || Studyno: ||
newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2152.894
Iteration 1: log pseudolikelihood = -2152.824
Iteration 2: log pseudolikelihood = -2152.824
```



```
-----+-----
-----
var(Residual) | 19.07504 7.344056 8.969026
40.56817
-----
```

```
-> mixed MonoRMT c.Neuronavigation Age Hemisphere || Studyno: ||
newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -2175.4234
Iteration 1: log pseudolikelihood = -2175.3661
Iteration 2: log pseudolikelihood = -2175.3661
```

Computing standard errors:

```
Mixed-effects regression          Number of obs    =
605
```

```
-----+-----
Group Variable | No. of      Observations per Group
                | Groups      Minimum   Average   Maximum
-----+-----
Studyno | 26          9        23.3     70
newPartID | 518         1        1.2      2
-----
```

```
13.89                                Wald chi2(3)    =
Log pseudolikelihood = -2175.3661    Prob > chi2    =
0.0031
```

(Std. Err. adjusted for 26 clusters in Studyno)

```
-----+-----
MonoRMT | Robust
Interval] Coef. Std. Err. z P>|z| [95% Conf.
-----+-----
Neuronavigation | -4.980313 5.229877 -0.95 0.341 -15.23068
5.270059
Age | .082273 .023767 3.46 0.001 .0356905
.1288556
Hemisphere | -2.141702 .9041601 -2.37 0.018 -3.913823 -
.3695807
_cons | 48.37788 4.655561 10.39 0.000 39.25315
57.50261
```


(Std. Err. adjusted for 26 clusters in Studyno)

```
-----
-----
      MonoRMT |           Coef.      Robust
Interval]    |           Std. Err.      z    P>|z|    [95% Conf.
-----+-----
-----
      Muscle |  -.3326077    4.704501    -0.07    0.944    -9.553259
8.888044
      Age |    .083011    .0246176     3.37    0.001     .0347614
.1312606
      Hemisphere | -2.172428    .8909239    -2.44    0.015    -3.918607  -
.4262489
      _cons |   44.61384    2.055979    21.70    0.000     40.5842
48.64349
-----
-----
```

```
-----
-----
      Random-effects Parameters |           Estimate      Robust
Interval]    |           Std. Err.      [95% Conf.
-----+-----
-----
Studyno: Identity |
      var(_cons) |   80.05252    17.88173    51.66993
124.0258
-----+-----
-----
newPartID: Identity |
      var(_cons) |   57.87658    14.14898    35.84357
93.45327
-----+-----
-----
      var(Residual) |   19.22974     7.514983     8.93972
41.36405
-----
-----
```

```
.
. *Final model
. mixed MonoRMT Age i.Hemisphere || Studyno: || newPartID:,robust
```

```
Performing EM optimization:
Performing gradient-based optimization:
```



```

newPartID: Identity |
                var(_cons) | 57.87702 14.14931 35.84357
93.4547
-----+-----
-----
                var(Residual) | 19.22993 7.515469 8.93943
41.36619
-----
-----

```

*Step 1 regressions for Monophasic AMT. Examining the variance in Monophasic AMT explained by each IV separately, while controlling for the age and gender of participants.

*IVs omitted because of insufficient data (did not include at least three studies within each IV level):

Machine_MonoAMT Neuronavigation Muscle

```

. for var Hemisphere: mixed MonoAMT c.X Age Gender || Studyno: ||
newPartID:,robus
> t

```

```

-> mixed MonoAMT c.Hemisphere Age Gender || Studyno: ||
newPartID:,robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -643.86716
Iteration 1: log pseudolikelihood = -643.86501
Iteration 2: log pseudolikelihood = -643.86501

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
185

```

```

-----+-----
Group Variable |      No. of      Observations per Group
              |      Groups      Minimum      Average      Maximum
-----+-----
      Studyno |           6           11           30.8           70
newPartID |          123           1            1.5            2
-----

```

16.56
 Log pseudolikelihood = -643.86501
 0.0009

Wald chi2(3) =
 Prob > chi2 =

(Std. Err. adjusted for 6 clusters in Studyno)

```
-----
```

		Robust				
	MonoAMT	Coef.	Std. Err.	z	P> z	
	Interval]				[95% Conf.	
	Hemisphere	-2.044264	1.406067	-1.45	0.146	-4.800104
	.7115761					
	Age	.0881807	.0461307	1.91	0.056	-.0022337
	.1785952					
	Gender	.1843289	1.909437	0.10	0.923	-3.558099
	3.926756					
	_cons	40.02314	4.788737	8.36	0.000	30.63739
	49.40889					

```
-----
```

*Step 2 regressions for Monophasic AMT.

```
. for var Hemisphere Gender: mixed MonoAMT c.X Age || Studyno: ||
newPartID:,robust
```

```
-> mixed MonoAMT c.Hemisphere Age || Studyno: || newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -643.87551
Iteration 1: log pseudolikelihood = -643.87335
Iteration 2: log pseudolikelihood = -643.87335
```

Computing standard errors:

Mixed-effects regression
 185

Number of obs =

```
-----
```

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum

```
-----
```


Studyno	6	11	30.8	70
newPartID	123	1	1.5	2

Wald chi2(2) = 3.75

Log pseudolikelihood = -643.87335 Prob > chi2 = 0.1536

(Std. Err. adjusted for 6 clusters in Studyno)

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Hemisphere	-2.043988	1.408105	-1.45	0.147	-4.803822 .7158467
Age	.0876773	.0500413	1.75	0.080	-.0104019 .1857565
_cons	40.12775	4.312104	9.31	0.000	31.67618 48.57931

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	76.12289	49.24335	21.42294 270.4901
newPartID: Identity			
var(_cons)	38.35551	4.93975	29.79908 49.36883
var(Residual)	26.01736	11.17431	11.21185 60.37393

-> mixed MonoAMT c.Gender Age || Studyno: || newPartID:,robust

Performing EM optimization:

Performing gradient-based optimization:


```

                    var(_cons) |   36.97731   6.037561   26.85056
50.9234
-----+-----
                    var(Residual) |   28.04595   13.90795   10.6111
74.12759
-----

```

. *None became p<0.10

. *Final model

. mixed MonoAMT Age || Studyno: || newPartID:,robust

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0:   log pseudolikelihood = -646.29055
Iteration 1:   log pseudolikelihood = -646.28708
Iteration 2:   log pseudolikelihood = -646.28708

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs   =
185

```

```

-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
      Studyno |           6           11     30.8     70
newPartID |          123           1      1.5      2
-----

```

```

Wald chi2(1) =
3.08
Log pseudolikelihood = -646.28708      Prob > chi2 =
0.0792

```

(Std. Err. adjusted for 6 clusters in Studyno)

```

-----
MonoAMT |      Coef.      Robust      z      P>|z|      [95% Conf.
Interval] |      Std. Err.
-----+-----

```



```

          var(_cons) | 12.53973 6.461749 4.567327
34.42818
-----+-----
----
newPartID: Identity |
          var(_cons) | 33.78715 4.451385 26.09802
43.74169
-----+-----
----
          var(Residual) | 40.24614 1.19274 37.97501
42.65309
-----
-----

```

. contrast Machine

Contrasts of marginal linear predictions

Margins : asbalanced

```

-----
|          df          chi2      P>chi2
-----+-----
BiRMT |
Machine_BiRMT |          2          26.97      0.0000
-----

```

. mixed BiRMT c.Age i.Gender i.Neuronavigation || Studyno: ||
newPartID:,robust

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -972.37348
Iteration 1: log pseudolikelihood = -971.11579
Iteration 2: log pseudolikelihood = -971.10897
Iteration 3: log pseudolikelihood = -971.10895

```

Computing standard errors:

Mixed-effects regression Number of obs = 269

```

-----
|          No. of          Observations per Group
Group Variable |          Groups          Minimum          Average          Maximum
-----+-----
          Studyno |          12          10          22.4          40
          newPartID |          258          1          1.0          2
-----

```

8.58 Wald chi2(3) =

Log pseudolikelihood = -971.10895 Prob > chi2 =
 0.0355

(Std. Err. adjusted for 12 clusters in

Studyno)

```
-----
-----
      BiRMT |           Coef.      Robust
      Interval] |           Std. Err.      z    P>|z|      [95% Conf.
-----+-----
      Age |      .1398177      .0658581      2.12   0.034      .0107382
.2688973
      Gender |
      Female |      2.668809      1.40876      1.89   0.058      -.0923103
5.429929
      Neuronavigation |
      No |      6.090487      2.782046      2.19   0.029      .6377772
11.5432
      _cons |      40.70272      3.260771      12.48   0.000      34.31172
47.09371
-----
-----
```

```
-----
-----
      Random-effects Parameters |           Estimate      Robust
      Interval] |           Std. Err.      [95% Conf.
-----+-----
      Studyno: Identity |
      var(_cons) |           21.995      8.800499      10.0403
48.18383
-----+-----
      newPartID: Identity |
      var(_cons) |           33.69647      4.428642      26.04432
43.5969
-----+-----
      var(Residual) |           40.35693      1.177169      38.11444
42.73137
-----
-----
```

*Machine age gender Neuronav are p<0.10, so are all in the final model and no need for Step 2.

```
*Final model
mixed BiRMT c.Age i.Gender i.Neuronavigation i.Machine_BiRMT ||
Studyno: || newPartID:,robust
```

Performing EM optimization:

Performing gradient-based optimization:

```
Iteration 0: log pseudolikelihood = -969.32567
Iteration 1: log pseudolikelihood = -968.0294
Iteration 2: log pseudolikelihood = -968.02312
Iteration 3: log pseudolikelihood = -968.02311
```

Computing standard errors:

```
Mixed-effects regression          Number of obs    =
269
```

```
-----
Group Variable |      No. of      Observations per Group
                |      Groups      Minimum   Average   Maximum
-----+-----
          Studyno |           12          10      22.4      40
          newPartID |          258           1       1.0       2
-----
```

```
Wald chi2(5)          =
49.48
Log pseudolikelihood = -968.02311      Prob > chi2      =
0.0000
```

(Std. Err. adjusted for 12 clusters in Studyno)

```
-----
Robust
          BiRMT |      Coef.   Std. Err.      z    P>|z|    [95% Conf.
Interval]
-----+-----
          Age |   .1436453   .0645893     2.22   0.026   .0170525
          .2702381
          Gender
          Female |   2.619628   1.494448     1.75   0.080   -.3094365
          5.548692
          Neuronavigation
          No |   2.266546   2.162414     1.05   0.295   -1.971707
          6.5048
          Machine_BiRMT |
-----
```


Log pseudolikelihood = -964.26939 Prob > chi2 =
 0.0000

(Std. Err. adjusted for 14 clusters in

Studyno)

```
-----
-----
      BiAMT |           Coef.      Robust
      Interval] |           Std. Err.      z    P>|z|      [95% Conf.
-----+-----
Machine_BiAMT |
MagstimRapid | 11.47653  2.860075  4.01  0.000  5.870888
17.08218
      Age | .0102896  .0291013  0.35  0.724  -.0467479
.067327
      Gender |
      Female | 1.212589  .8673283  1.40  0.162  -.4873428
2.912522
      _cons | 36.43792  2.406274  15.14  0.000  31.7217
41.15413
-----
-----
```

```
-----
-----
      Random-effects Parameters |           Estimate      Robust
      Interval] |           Std. Err.      [95% Conf.
-----+-----
Studyno: Identity |
      var(_cons) | 25.89262  9.841236  12.29284
54.53806
-----+-----
      var(Residual) | 55.19693  7.153314  42.81564
71.15861
-----
-----
```

. mixed BiAMT i.Neuronavigation c.Age i.Gender || Studyno:, robust

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log pseudolikelihood = -967.26622
 Iteration 1: log pseudolikelihood = -967.26622

Computing standard errors:

Mixed-effects regression
 277
 Group variable: Studyno
 14

Number of obs =

Number of groups =

Obs per group:

min =

10

avg =

19.8

max =

38

Wald chi2(3) =

11.74

Prob > chi2 =

Log pseudolikelihood = -967.26622
 0.0083

(Std. Err. adjusted for 14 clusters in

Studyno)

```
-----+-----
```

	BiAMT	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
Neuronavigation	No	8.215334	3.889127	2.11	0.035	.592785
15.83788						
	Age	.0058006	.0295783	0.20	0.845	-.0521718
.063773						
	Gender					
	Female	1.207429	.8690058	1.39	0.165	-.4957914
2.910649						
	_cons	36.88192	3.047584	12.10	0.000	30.90877
42.85508						

```
-----+-----
```

```
-----+-----
```

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
-----+-----			
Studyno: Identity			
var(_cons)	41.76348	11.79172	24.01397
72.63222			

```
-----+-----
```

```

var(Residual) | 55.18199 7.155373 42.79797
71.14944
-----
-----

```

*Step 2 regressions for Biphasic AMT.

*This is the starting step 2 model for Biphasic AMT - all variables that obtained a p-value < 0.10 in stage 1 regressions.

```

. *iterating
. mixed BiAMT i.Machine_BiAMT i.Neuronavigation c.Age || Studyno:, robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -964.48931
Iteration 1: log pseudolikelihood = -964.48931

```

Computing standard errors:

```

Mixed-effects regression                               Number of obs      =
277                                                    Number of groups   =
Group variable: Studyno                               Number of groups   =
14                                                    Obs per group:
                                                    min =
10                                                    avg =
19.8                                                  max =
38                                                    Wald chi2(3)       =
20.17                                                  Prob > chi2        =
Log pseudolikelihood = -964.48931                    0.0002

```

(Std. Err. adjusted for 14 clusters in Studyno)

```

-----
-----

```

	BiAMT	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
--	-------	-------	------------------	---	------	----------------------

```

-----
-----

```

Machine_BiAMT |

```

MagstimRapid | 9.884012 2.375768 4.16 0.000 5.227592
14.54043
Neuronavigation |
No | 3.56965 3.31251 1.08 0.281 -2.922751
10.06205
Age | .004566 .0277584 0.16 0.869 -.0498394
.0589714
_cons | 35.91625 3.373647 10.65 0.000 29.30402
42.52848

```

```

Random-effects Parameters | Estimate Robust Std. Err. [95% Conf.
Interval]
-----+-----

```

```

Studyno: Identity |
var(_cons) | 24.44731 9.193287 11.69879
51.08826
-----+-----

```

```

var(Residual) | 55.43709 7.315971 42.80242
71.80134
-----

```

```

. mixed BiAMT i.Machine_BiAMT i.Neuronavigation i.Gender ||
Studyno:, robust

```

Performing EM optimization:

Performing gradient-based optimization:

```

Iteration 0: log pseudolikelihood = -963.7224
Iteration 1: log pseudolikelihood = -963.7224

```

Computing standard errors:

```

Mixed-effects regression          Number of obs      =
277
Group variable: Studyno           Number of groups   =
14
                                     Obs per group:
                                     min =
10
                                     avg =
19.8
                                     max =
38

```

30.30 Wald chi2(3) =
 Log pseudolikelihood = -963.7224 Prob > chi2 =
 0.0000

(Std. Err. adjusted for 14 clusters in

Studyno)

```
-----
```

	BiAMT	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
Machine_BiAMT						
MagstimRapid		9.841807	2.475184	3.98	0.000	4.990535
14.69308						
Neuronavigation						
No		3.597779	3.33627	1.08	0.281	-2.941191
10.13675						
Gender						
Female		1.189822	.8518392	1.40	0.162	-.4797519
2.859396						
_cons		35.51965	3.12057	11.38	0.000	29.40344
41.63585						

```
-----
```

```
-----
```

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]
Studyno: Identity			
var(_cons)	24.31386	8.664651	12.09244
48.88705			
var(Residual)	55.13081	7.159201	42.74238
71.1099			

```
-----
```

*Final model

