

1 **Title:** Neuronal control of the fingertips is socially configured in touchscreen smartphone
2 users

3

4

5

6 **Authors:** Myriam Balerna and Arko Ghosh

7

8

9 **Affiliation:** Institute of Neuroinformatics, University of Zurich and ETH Zurich,

10 Winterthurerstr. 190, 8400 Zurich, Switzerland

11

12

13 **Corresponding author:** Arko Ghosh, Institute of Neuroinformatics, University of Zurich and

14 ETH Zurich, Winterthurerstr. 190, 8400 Zurich, Switzerland. Email: arko@ini.uzh.ch; Phone:

15 044 63 53098

16

17

18 **Author Contributions:** MB acquired the data, participated in data analysis, and edited this

19 manuscript. AG designed the study, helped in data acquisition, analyzed the data, and drafted

20 this manuscript.

21

22

23 **Abstract**

24

25 As a common neuroscientific observation, the more a body part is used, the less variable the
26 corresponding computations become. We here report a more complicated scenario concerning
27 the fingertips of smartphone users. We sorted 21-days histories of touchscreen use of 57
28 volunteers into social and non-social categories. Sensorimotor variability was measured in a
29 laboratory setting by simple button depressions and scalp electrodes (electroencephalogram,
30 EEG). The ms range trial-to-trial variability in button depression was directly proportional to
31 the number of social touches and inversely proportional to non-social touches. Variability of
32 the early tactile somatosensory potentials was also proportional to the number of social touches,
33 but not to non-social touches. The number of Apps and the speed of touchscreen use also
34 reflected this variability. We suggest that smartphone use affects elementary computations even
35 in tasks not involving a phone and that social activities uniquely reconfigure the thumb to
36 touchscreen use.

37

38 **Impact statement**

39 Unconstrained behavior on a smartphone is a powerful predictor of neuronal functions
40 measured in the laboratory and the details of the smartphone-neuronal association challenges
41 the established ideas of brain plasticity.

42

43

44

45 **Introduction**

46

47 Smartphones enable a remarkably broad range of activities. From the perspective of
48 higher cognition, smartphone behavior engages complex computations for decision-making,
49 language, and social interactions. From the perspective of lower-level sensorimotor control, the
50 thumb and the fingertips are repeatedly applied on the touchscreen to essentially either tap or
51 swipe. The observation that even toddlers can easily operate a touchscreen underscores the
52 simplicity of its sensorimotor control (1). According to a series of experiments, a repeated use
53 of the hand in either skillful or simple actions enhances the corresponding representation in the
54 sensorimotor cortex (2–6). Sensorimotor alterations have been observed in trained laboratory
55 monkeys, athletes, Braille readers, and concert string instrument players (3, 5, 7–9). A
56 prominent notion underlying these observations is that the sensorimotor cortex keeps track of
57 the amount of activity generated by the corresponding body part but the exact nature of this
58 tracking is unclear. For instance, in terms of touchscreen use, the cortex may keep track of the
59 number, frequency, and/or behavioral context of touchscreen actions.

60 In real-world observations, the role of the behavioral context in use-dependent plasticity
61 is difficult to establish, partly because of a poor quantification of human actions. For instance,
62 it is common to assess the extent of deliberate practice in elite musicians by using
63 questionnaires (6, 10, 11). Such qualitative approaches do not provide a measure of the amount
64 of activity nor do they capture the activity context. Under well-controlled laboratory conditions,
65 the precise extent of plasticity depends on whether the sensory information presented at the
66 fingertip is used towards a behavioral task or not (4). In general, the cortical plasticity can be
67 modulated by artificially stimulating neuromodulators, such as dopamine or serotonin, that are
68 naturally released according to the behavioral relevance (12). Social behavior strongly engages
69 such neuromodulators and the touchscreen smartphone is prominently used towards social
70 activities (13–15). Therefore, the use-dependent configuration of fingertips in touchscreen users

71 might not be a simple function of sensorimotor activity (16). In particular, touchscreen touches
72 used towards social activities may be distinctly weighted towards use-dependent plasticity of
73 the sensorimotor cortex. Social activities are well compartmentalized within specific Apps,
74 allowing us to quantitatively address use-dependent plasticity in distinct behavioral contexts.

75 In this report, we focused on the elementary property of neuronal variability, or noise,
76 in the sensorimotor system. Substantial theoretical and empirical support exists for the notion
77 that an increased use of a body part reduces the sensorimotor noise (17–21). According to one
78 prominent theory, the brain actively learns to suppress motor variability as if to eliminate
79 unwanted noise, albeit a different theory has been put forward on how the brain may exploit the
80 inherent noise towards learning (18, 22). Sensorimotor variability of the fingertips is diminished
81 with musical practice, by typing on the keyboard, or by deliberately practicing laboratory-
82 designed tasks (18, 23–25). Therefore, a clear-cut prediction would be that the sensorimotor
83 variability of the fingertips is diminished with increased touchscreen use, irrespective of the
84 actions being social or non-social. Alternatively, the complexity, neuromodulation, and the
85 overall significance of social activities may distinctly shape the sensorimotor variability.

86 To address these possibilities, we performed a multiple regression analysis to assess
87 the relationship between (a) Social App usage in the real world and sensorimotor variability
88 measured in the laboratory, and (b) Non-social App use and sensorimotor variability measured
89 in the laboratory. We also examined other variables that were likely to influence sensorimotor
90 variability. To alleviate the effect of development or aging on our measurements, we restricted
91 the analysis to a young adult population (26). Gender-associated differences exist in
92 sensorimotor processing from the fingertips and in the performance variability of a simple task
93 (27, 28). Therefore, we included a dummy variable representing the gender of participants in
94 the regression analysis. Since an accurate control of motor timing is important for rapid actions,
95 fast touchscreen operators may develop a more precise sensorimotor system (29). Therefore, a
96 typical rate of touchscreen touches was added as an explanatory variable. Finally, practicing

97 motor skills in various contexts leads to better performance in a previously not experienced
98 context (30). Since each App on the phone is associated with a distinct context, we quantified
99 the number of Apps in use as an explanatory variable. In summary, type of touchscreen activity
100 (social or non-social), the gender, a typical rate of touchscreen activity, and the number of Apps
101 may all impact sensorimotor computations measured in the laboratory. Incorporating these
102 factors in a single regression model allowed us to address if and how they are separately
103 weighing in on the sensorimotor variability.

104

105

106

107 **Results**

108

109 *Basic features of touchscreen use*

110

111 We quantified touchscreen use for a period of 21 d in a young adult population using a custom-
112 designed software operating in the background to record every touchscreen event and the App
113 targeted by the event. Social activity generated on the touchscreen was sorted based on the App
114 in use. We considered Apps that primarily enabled the communication of personal messages or
115 opinions to a circle of friends or acquaintances as “Social”, and Apps that did not fulfill these
116 functions as “Non-social” (for a sample of Social and Non-social Apps in the database see
117 *Supplementary List 1*). The usage statistics were as follows: the volunteers touched the screen
118 from 1540.3 (20th percentile) to 5562.3 (80th percentile) times per day, and generated between
119 429.1 (20th percentile) and 2486.9 (80th percentile) touches per day on the Social Apps.
120 Importantly, the number of social touches was only partly correlated with the number of non-
121 social touches [variables Log_{10} normalized, $R^2 = 0.29$, $f(1,55) = 22$, $p = 1.9 \times 10^{-6}$, robust linear
122 regression]. Furthermore, volunteers ranked the fingers used according to their preference.
123 Confirming previous findings for smartphone usage, the thumb was ranked by 73% of the users
124 as most preferred on the touchscreen; 16% preferred the index finger; and 10% preferentially
125 used both the thumb and the index finger (16, 31). Remarkably, only one user preferred their
126 middle finger to all the other fingers.

127

128 *Motor variability of the thumb, but not of the middle finger, is associated with touchscreen*
129 *use*

130

131 At the end of the touchscreen recording period, the volunteers performed a simple tactile
132 reaction task in the laboratory where the reaction involved micro switch press-down and
133 release-up actions (*Figure 1a,b*). In theory, the time taken to trigger the press-down action

134 (reaction time) reflects the sensory decision processes, and the time taken to complete the motor
135 act, from pressing down to releasing upwards (movement time), reflects the lower cognitive
136 levels of sensorimotor execution (32–35). The trial-to-trial variability was parametrized using
137 ex-Gaussian fits. Specifically, we estimated the variability of Gaussian curve region lacking
138 very slow actions driven by attention lapses (36, 37). In agreement with the notion that the
139 reaction and movement times reflect distinct neuronal computations, the corresponding
140 variabilities were unrelated to each other [$R^2 = 0.02$, $f(1,53) = 1.1$, $p = 0.299$, robust linear
141 regression]. Since we were interested in the low-level sensorimotor variability, we focused on
142 the movement time.

143 In our multiple linear regression analysis of movement time variability, we treated the
144 number of daily touches on the Social, Non-social, and Uncategorized Apps (all Log_{10} -
145 normalized), gender (dummy variable, female = 1), typical rate of touchscreen touches, and the
146 number of Apps used during the recording period, as explanatory variables. First, let us
147 elaborate on the thumb use analysis data (the thumb was most preferred for touchscreen
148 interactions). The full regression model was highly significant [$R^2 = 0.45$, $f(6,48) = 6.5$, $p =$
149 4.43×10^{-5} , robust multiple linear regression; for variation inflation factors see *Supplementary*
150 *Figure 1*]. The maximum variation inflation factor was 2.7, indicating that the regression model
151 was not affected by multicollinearity (38). According to the simple prediction of use-dependent
152 reduction in sensorimotor variability, the regression coefficient for social touches was expected
153 to be either zero, suggesting that social actions are not distinctly tracked by the brain, or
154 negative, suggesting that social actions are distinctly tracked but a higher number of social
155 touches leads to lower sensorimotor variability. Contrary to these predictions, we found that
156 higher number of social touches led to increased movement time variability [$t(1,48) = 3.96$, p
157 $= 0.00024$, *Figure 1c*]. The case for non-social touches was anticipated, with higher number
158 linked with smaller variability [$t(1,48) = -2.66$, $p = 0.011$, *Figure 1d*]. The same was observed
159 for uncategorized touches [$t(1,48) = -2.45$, $p = 0.018$].

160 To what extent does the social behavior-movement time variability relationship (**Figure**
161 **1c**) depend on App classification? We addressed this by repeating our analysis 10^5 times using
162 randomly shuffled categories. The relationship uncovered for social touches was well separated
163 from the distribution of relationships obtained by quantifying random category touches (**Figure**
164 **1e**). This result further supported the notion that the type of touchscreen behavior determines
165 how neuronal processes responsible for the thumb are configured.

166 To address whether the touchscreen behavior-movement time variability relationship
167 was specific to the thumb, a subset of volunteers also performed the task with their middle
168 finger (which was rarely indicated as the preferred finger for touchscreen use). We found a
169 strong association between the explanatory variables and movement time variability for the
170 thumb [$R^2 = 0.79, f(6,10) = 6.43, p = 0.0053$, robust linear regression], similarly to data for the
171 full set of volunteers. Importantly, here too the number of social touches was significantly
172 related with movement variability [$t(1,10) = 2.70, p = 0.022$, **Figure 1 – Supplement 1**].
173 However, the results for the middle finger were strikingly different. We found no correlation
174 between the explanatory variables and movement time variability [$R^2 = 0.28, f(6,10) = 0.66, p$
175 $= 0.683$, robust linear regression]. Moreover, the regression coefficient associated with the
176 number of social touches was non-significant [$t(1,10) = -0.30, p = 0.77$, **Figure 1 – Supplement**
177 **1**]. These results suggested that the putative impact of touchscreen use on movement time
178 variability is specific to the finger that is repeatedly engaged on the touchscreen.

179
180 *Social keypad touches distinctly impact on motor variability*
181

182 In the analyses conducted above, the touchscreen touches consisted of different gestures, i.e.,
183 keypad taps, swipes, and pinches. One interesting possibility was that the correlations identified
184 for social touches were driven by the different gestures used for Social Apps. Therefore, we
185 next restricted our analysis to pop-up keypad touches. It is safe to assume that for sensorimotor
186 control, i.e., the degrees of freedom for motor control and visuomotor coordination, keypad

187 touches for Social Apps are the same as the ones for Non-social Apps. The difference concerns
188 the specific content typed. Full regression model based on the keypad touches was significantly
189 related to motor time variability [$R^2 = 0.60, f(6,25) = 6.36, p = 0.0004$, robust linear regression].
190 We noted that the higher the number of social touches on the keypad, the larger the movement
191 time variability [$t(1,25) = 3.76, p = 0.0009$, **Supplementary Figure 2**]. This suggested that
192 gestures cannot simply account for the distinct imprint of social activities on motor time
193 variability.

194

195 *Social and non-social touches show distinct patterns of correlations as a function of time*

196

197 The continuously recorded touchscreen behavior made prior to the laboratory measurements
198 allowed us to address the question of whether the touchscreen-movement time variability
199 relationship changes as a function of time. Should the relationship be driven by rapid plasticity,
200 then it would simply decay as a function of time. However, if slow mechanisms were
201 operational, then the relationship would peak with older rather than the most recent touchscreen
202 experiences, as if indicating a delayed impact of touchscreen behavior. F-values, describing the
203 relationship strength, revealed a simple decay trend for non-social touches. This was well
204 described ($R^2 = 0.82$, **Figure 1f**) by:

205

$$206 \quad Y_{F\text{-value}} = 8.6 \times e^{\text{Time from lab measure} \times 0.15}$$

207

208 The relationship for social touches was more complicated, consisting of both an initial decay
209 and a strong relationship with older data. This dynamic was well described ($R^2 = 0.81$, **Figure**
210 **1f**) by:

211

212

213

$Y_{F-value}$

$$214 = [24.53 \times e^{-\left(\frac{\text{Time from lab measure} + 17.06}{1.97}\right)^2}] + [2.06 \times 10^{15} \times e^{-\left(\frac{\text{Time from lab measure} - 655.2}{114.7}\right)^2}]$$

215

216

217 The distinct pattern of time-dependent relationships for social vs. non-social touches suggested
218 that they engage different forms of plasticity.

219 We also revealed the dynamics of other explanatory variables that were significantly
220 related to touchscreen use recorded over the 21-d period. In brief, as anticipated, variability was
221 smaller with a higher typical rate of touchscreen touches [$t(1,48) = -5.10, p = 5.73 \times 10^{-6}$,
222 **Figure 1 – Supplement 2**] and with a larger number of Apps used [$t(1,48) = -3.29, p = 0.002$,
223 **Figure 1 – Supplement 2**]. Time-dependent dynamics for the typical rate of touchscreen
224 touches indicated slow plasticity but the “number of Apps” variable dynamics indicated both
225 rapid and slow plasticity (**Figure 1 – Supplement 2**). The gender of the user was not
226 significantly associated with the motor time variability [$t(1,48) = -0.90, p = 0.37$].

227

228 *Social touches distinctly affect the reaction time variability*

229

230 We opportunistically explored the variability of higher cognitive levels captured by the reaction
231 time. For the reaction time variability, the full regression model was significant but weak [$R^2 =$
232 $0.26, f(6,49) = 2.86, p = 0.02$, robust linear regression]. Similarly to the results for movement
233 time variability, we observed that a higher number of social touches was associated with greater
234 reaction time variability [$t(1,49) = 2.72, p = 0.009$, **Supplementary Figure 3**]. The only other
235 explanatory variable that significantly contributed to the regression model was the participant
236 gender, such that the females showed less variability [$t(1,49) = -3.25, p = 0.0002$] than the
237 males. Since the reaction and movement times measure different aspects of cognition, taken

238 together, they suggested that the putative impact of social touches is not restrained to the lower-
239 levels of sensorimotor cognition.

240

241 *The signal-to-noise ratio of the early somatosensory evoked potentials from the thumb strongly*
242 *corresponds with touchscreen use*

243

244 To address the neurophysiological predictions of use-dependent plasticity, we measured the
245 cortical potentials in response to tactile stimulation of the fingertips using
246 electroencephalography (EEG). The EEG signals were noisy at a single trial level and an
247 averaging method across several trials revealed an event-related potential (**Figure 2a**) (39). We
248 used the ratio between the average response and a trial-to-trial deviation from the average as a
249 measure of putative signal-to-noise ratio. Based on the observations from an electrode showing
250 the strongest response (according to the grand average), a distinctive rise in the signal-to-noise
251 ratio was observed, with a peak at 55 ms (latencies are reported from the onset of stimuli, **Figure**
252 **2b**).

253 We were interested in both the direction and timing of neuronal correlates of
254 touchscreen use. Based on the simplistic prediction of use-dependent plasticity, we anticipated
255 that the more the fingertips are used on the touchscreen (irrespective of the social category of
256 the activity), the larger the signal-to-noise ratio (6, 16, 40). Measurements at different latencies
257 reflect distinct stages of the cortical somatosensory processing, with the potentials between 40
258 and 100 ms dominated by the primary somatosensory cortex, and those between 100 and 200
259 ms dominated by the secondary somatosensory and frontal cortices (41, 42).

260 Multiple regression analysis included all time points from -30 to +200 ms and was
261 conducted across all electrodes. Significant relationships with social and non-social touches
262 were largely restricted to the electrodes above the contralateral sensorimotor cortex
263 (contralateral to the stimulated hand), i.e., the electrodes that also showed the highest signal-to-

264 noise ratio (*Figure 2c-f*). Our analysis revealed that the number of social touches was
265 correlated with the thumb-associated signal-to-noise ratio at time points between 70 and 100
266 ms, and then again between 125 and 150 ms (*Figure 2c*). Notably and contrary to the simplistic
267 prediction, the direction of the correlation was such that the higher the number of social touches,
268 the lower the signal-to-noise ratio (*Figure 2c*). In contrast, the history of non-social touches
269 was significantly related to the cortical signals in a narrow window between 135 and 150 ms,
270 so that the higher the number of touches, the larger the signal-to-noise ratio (the relationships
271 with other explanatory variables are presented in *Figure 2 – Supplement 1*). These results
272 suggested that social touches were tracked by the somatosensory cortex separately from non-
273 social touches, and that the social touches were encoded at multiple stages of somatosensory
274 processing.

275 To verify whether the uncovered relationship between the number of social touches on
276 the phone and signal-to-noise ratio for the thumb was based on the social category per se, we
277 once again employed random category shuffling. Based on the maximum signal-to-noise ratio,
278 for the signal-to-noise ratio at the chosen electrode, the distribution of relationships for the
279 number of touches on random categories was well separate from the relationship based on
280 touches on Social Apps (*Figure 2g*). We also explored the relationships between the number
281 of social touches on the phone and the somatosensory signal-to-noise ratios for the index and
282 middle fingers, in addition to the thumb (*Figure 2h*). In comparison with the thumb, the
283 relationships were substantially weaker for the index finger and absent for the middle finger. In
284 summary, these results suggested that engaging in social activity on the touchscreen diminishes
285 the cortical signal-to-noise ratio associated with the thumb, contrary to the anticipated
286 consequences based on a simplistic view of use-dependent plasticity.

287

288

289

290 *Neuronal correlates of social touches on the keypad*

291

292 The neuronal correlates of social touches described above were based on all touchscreen
293 gestures, leaving open the possibility that the correlates reflected the underlying differences in
294 the gestures used on Social vs. Non-social Apps. We matched the gesture type by restricting
295 the analysis to pop-up keypads. A near-identical pattern of correlates was observed as in the
296 original analysis that included all gestures. Briefly, with an increasing number of social touches
297 on the keypad, the signal-to-noise ratio associated with the thumb between 70 and 100 ms
298 decreased (*Supplementary Figure 4*).

299

300 *Social touches vs. somatosensory signal-to-noise ratio correlations as a function of time*

301

302 According to the results presented above, the signal-to-noise ratio at early stages of the cortical
303 somatosensory processing was significantly correlated with the number of social touches on the
304 touchscreen but not with the number of non-social touches. Touchscreen behavior was
305 continuously recorded prior to the EEG measurements. We leveraged this continuity to
306 establish the temporal dynamics in terms of the time elapsed between the touchscreen behavior
307 and the EEG measurement. Using the observations from the chosen electrode, we found the
308 following complex temporal dynamics: the relationships were strong when examining recent
309 social touches, followed by complex relationships decay, and the relationships picked up again
310 with older touches (*Figure 2i*). The dynamics, although apparently more complicated than what
311 was observed for the social touches vs. movement time variability relationships, were well
312 captured using the following formula ($R^2 = 0.83$):

313

314

315

316
317
318
319
320
321
322
323
324
325
326
327
328
329
330
331
332
333
334
335
336
337
338
339
340

$$Y_{F-value} = (24.1 \times e^{-\left(\frac{\text{Time from lab measure} + 6.68}{1.1}\right)^2}) + (21.3 \times e^{-\left(\frac{\text{Time from lab measure} + 2.01}{3.3}\right)^2}) + (22.5 \times e^{-\left(\frac{\text{Time from lab measure} + 24.76}{12.1}\right)^2})$$

This relationship pattern suggested that a complex mix of both fast and slow mechanisms of plasticity is employed when configuring the cortex according to the history of social touches.

Increased trial-to-trial variability in neuronal response amplitude is associated with social touches on the touchscreen

A reduction in somatosensory cortical signal-to-noise ratio associated with a larger number of social touches may be associated with two entirely different attributes of neuronal activity. First, the reduction may genuinely reflect an alteration in the amount of neuronal activity; and second, the reduction may reflect increased trial-to-trial temporal jitter, so that averaging of responses across trials results in a smaller amplitude (43). In theory, it would be possible to address these two possibilities by focusing on the shape of the evoked potentials at a single trial level to estimate the variability in peak amplitude separately from peak latency. However, in practice, the EEG signals intensely fluctuate at the single trial level, precluding facile analysis of the shape of the evoked potentials. To partly smooth the signals, we averaged a subset of 25 trials. Next, we detected the amplitude and latency of local maxima that immediately followed the temporal landmarks placed at 50 and 85 ms (**Figure 3a**). The landmarks were set so as to focus on the initial stages of somatosensory processing that did not encode the number of social touches according to the signal-to-noise ratio analysis (50 ms) and later stages that did (85 ms,

341 at the center of the correlated range of 70–100 ms). We repeated this with a different subset of
342 25 trials, 10^5 times for each volunteer, to estimate the trial-to-trial variability of the
343 corresponding latencies and amplitudes (**Figure 3b,c**).

344 The variability of cortical signal amplitudes detected by the 50 ms landmark was
345 unrelated to the explanatory variables that included movement time variability in addition to
346 the original set of variables derived from the touchscreen and gender [$R^2 = 0.31, f(7,33) = 2.11,$
347 $p = 0.07$, robust linear regression]. In particular, amplitude variability was clearly unrelated to
348 the number of social touches [$t(1,33) = 0.68, p = 0.5$] and non-social touches [$t(1,33) = -0.02,$
349 $p = 0.98$, **Supplementary Figure 5**]. The variability of signal latencies at this temporal landmark
350 was also unrelated to the social touches [$t(1,33) = 0.60, p = 0.6$] and non-social touches [$t(1,33)$
351 $= -0.23, p = 0.8$, **Supplementary Figure 5**]. In contrast, the variability of signal amplitudes
352 detected by the 85 ms landmark was strongly related to the explanatory variables [$R^2 = 0.45, f$
353 $(7,33) = 3.9, p = 0.003$, robust linear regression]. We observed that the higher the number of
354 social touches, the larger the variability [$t(1,33) = 4.62, p = 5.6 \times 10^{-5}$, **Figure 3d**]. There was
355 a weak trend linking the number of non-social touches and neuronal variability, such that the
356 higher the number, the lower the variability [$t(1,33) = -1.9, p = 0.07$, **Figure 3e**]. In terms of
357 variability of signal latencies at this landmark, a weak relationship with the explanatory
358 variables was observed [$R^2 = 0.34, f(7,33) = 2.5, p = 0.04$, robust linear regression], and the
359 higher the number of social touches, the larger the neuronal temporal variability [$t(1,33) = 2.3,$
360 $p = 0.03$, **Supplementary Figure 5**]. Finally, we did not find any significant links between
361 movement time variability and neuronal response variability [latency dispersion at 85 ms: $t(33)$
362 $= -1.8, p = 0.08$; amplitude dispersion at 85 ms: $t(33) = -1.91, p = 0.06$]. This raised the
363 possibility that although both movement time variability and neuronal variability increased with
364 social touches, the two measures themselves reflected largely separate neuronal process.

365 In summary, the results were consistent with the notion that trial-to-trial variability of
366 both, the degree and timing of neuronal activity, increased according to the number of social

367 touches. However, it must be noted that the evidence for increased temporal variability was
368 rather weak in contrast with the evidence for increased amplitude variability.

369

370 *Time-dependent structure of the relationships between touchscreen use and neuronal*
371 *variability*

372

373 As with the preceding time-dependent analyses, we reasoned that the putative plasticity
374 attributes could be studied by sampling touchscreen behavior at various times before laboratory
375 measurements. Since a tendency was observed linking non-social touches over the entire
376 recording period with neuronal variability, we first studied temporal dynamics of the
377 phenomenon using F-values associated with non-social touches. The relationship strength
378 simply decayed as a function of time and was well described by the following formula ($R^2 =$
379 0.81 , **Figure 3f**):

380

$$381 \quad Y_{F-value} = 9.9 \times e^{Time \text{ from lab measure} \times 0.34}$$

382

383 The social touches showed more complex dynamics, such that the relationship was
384 strong when using recent touchscreen data, weakening over time. The relationship was also
385 strong when using older data. This was well captured by the following equation ($R^2 = 0.72$,
386 **Figure 3f**):

387

$$388 \quad Y_{F-value} = (11.04 \times e^{-\left(\frac{Time \text{ from lab measure} + 16.6}{7.47}\right)^2}) + (1.2 \times 10^{15}$$
$$389 \quad \times e^{-\left(\frac{Time \text{ from lab measure} - 203.6}{36.3}\right)^2})$$

390

391 Time-dependent neuronal variability dynamics of the correlates were qualitatively
392 similar to what we observed for motor time variability. Overall, these results indicated that
393 social touches are distinctly integrated to reconfigure the cortical circuits associated with the
394 thumb and both rapid and slow forms of use-dependent plasticity are employed towards this
395 putative reconfiguration.

396

397

398

399

400

401

402 **Discussion**

403

404 One striking finding of this report was that the individuals who generated a larger number of
405 social touches on the touchscreen were more variable in their response times when performing
406 a simple task with the thumb. The somatosensory cortical activity also exhibited more
407 variability associated with social touches. The dense digitization of behavior on the smartphone
408 allowed us to quantify and contrast these relationships with the history of non-social touches.
409 The results based on social touches data were contrary to the simplistic view of use-dependent
410 plasticity, which predicted more stable sensorimotor computations corresponding to an
411 increased touchscreen use. Even when placed outwith the framework of use-dependent
412 plasticity, these results suggested that the understanding of inter-individual differences in
413 elementary sensorimotor control is deeply inter-connected with the details of behavior
414 expressed in the real world.

415 We interpret these results as indicative that social activities on the touchscreen lead to
416 increased sensorimotor variability. However, the correlational nature of our findings precludes
417 us from discarding an alternative possibility that a higher sensorimotor variability leads to more
418 social touches, or that a common factor determines both these variables. Based on the current
419 knowledge, a reasonable case for the former cannot be made but the latter must be seriously
420 considered. Extraverted individuals are characterized by higher usage of Social Apps than
421 introverts and extraversion is associated with diminished somatosensory cortical activity
422 evoked by the fingertips (44, 45). The extraversion-based relationship is specific to the left hand
423 and is absent for the right hand (45). In contrast, our study focused on the right hand. Moreover,
424 the extraversion-based relationship is not specific to particular fingertips, in contrast to the
425 thumb-specific correlates of touchscreen use uncovered here and in our previous study (16). In
426 addition to the personality factor, cognitive states that lead to enhanced attention or arousal may
427 influence both the touchscreen behavior and neuronal measures in the laboratory (46). This

428 state-dependent view does not account for the observation that touchscreen-based correlates
429 were largely restricted to the thumb. It also does not account for how the 1-2 weeks old
430 touchscreen data could strongly correlate with the laboratory measurements. Given these
431 evidences, the framework of use-dependent plasticity may be the most appropriate for
432 considering our findings.

433 Neuronal correlates uncovered here suggest that low-level sensorimotor processing, at
434 the primary somatosensory cortex, encodes the history of social touches on the touchscreen.
435 This observation is consistent with the notion that the primary sensory areas do not exclusively
436 represent the incoming sensory inputs but integrate these inputs into behavioral context (47).
437 For the somatosensory cortex, this is supported by laboratory observations that the cortex
438 participates in multi-sensory integration and that factors, such as attention, modulate its activity
439 and plasticity (4, 48, 49). Our findings provide a real-world example that the behavioral context
440 of an experience is a key factor in configuring the cortex.

441 The temporal dynamics of the associations uncovered herein provide some insights into
442 the nature of processes engaged in the putative use-dependent plasticity. For both, trial-to-trial
443 movement time variability and neuronal variability, we observed a complex fall and then rise
444 in the relationships strength with older data from the Social Apps. This pattern suggests that
445 social touches trigger both rapid and slow mechanisms of plasticity. Rapid mechanisms may
446 include such processes as alteration in excitatory-inhibitory balance or the unmasking of pre-
447 existing circuits (8, 50). Slow mechanisms may include the formation of entirely new pathways,
448 comprising changes of the underlying white matter that may take weeks to complete (5, 51).
449 The relationship with older data from the Non-social Apps simply decayed, suggesting
450 exclusive deployment of rapid mechanisms.

451 It is not clear how the sensorimotor cortex sorts the touches on Social Apps separately
452 from Non-social Apps. One possibility is that the social touches are sorted based on top-down
453 information flow via neuromodulators or feedback from high-level neuronal networks engaged

454 in social behavior (14, 52). Another possibility is that the touches are sorted in a bottom-up
455 manner based on distinct sensory features that accompany the social touches. We tested this
456 possibility by restricting our analysis to pop-keypad touches, only to discover that even when
457 the gestures were apparently matched, the social touches showed a distinct sensorimotor
458 correlate. Other relevant but unexplored differences in the input statistics of Social vs. Non-
459 social Apps may exist in terms of the length of the words typed or the complexity of language
460 used. Nevertheless, a previous study on typing skills suggested that greater experience was
461 associated with smaller sensorimotor variability (23). Therefore, the increased variability
462 associated with social touches cannot be easily explained using the widely held notions on use-
463 dependent plasticity.

464 Why does sensorimotor variability increase with social touches on the touchscreen? We
465 propose that the increased variability is an inevitable consequence of repeated engagement of
466 the thumb in social cognition. Essentially, social touches on the touchscreen are accompanied
467 by an array of neuronal processes associated with language, anticipation, and social status (13).
468 Presumably, using Hebbian-like mechanisms of plasticity, the thumb becomes increasingly
469 connected with this broad array of processes. It is this enhanced embedding of sensorimotor
470 processing in a broad array of neuronal processes that may lead to increased noise in low-level
471 circuits (53).

472 In the population of young adults sampled here, the median number of touchscreen
473 touches generated per day was 2.7×10^3 and the most active individual generated 1.1×10^4
474 touches per day. These numbers reflect the dominance of touchscreen events in modern human
475 actions, comparable in magnitude with the number of steps (1×10^4) or eye blinks per day (1.2
476 $\times 10^4$) (54, 55). Therefore, it should not be surprising that the neuronal sensorimotor processing
477 is reconfigured by touchscreen behavior (16). The nature of the touchscreen behavior-neuronal
478 relationships uncovered by leveraging seamless quantifications on the smartphone warrants a
479 more in-depth examination on how social activities on the touchscreen reconfigure the brain.

480 These links also highlight the complex nature of neurobehavioral relationships in elementary
481 sensorimotor control, such that the history of social and non-social touches, the rate of
482 touchscreen activity, and number of different Apps used are all independently encoded to
483 impact future computations. Addressing how the quantitative history of touchscreen behavior
484 relates to elementary neuronal functions will help bridge the large gap between inherently
485 artificial laboratory experiments and the behavior expressed in the real world.

486

487

488

489

490

491

492

493

494

495

496 **Materials and Methods**

497

498 *Subjects*

499

500 Volunteers (n = 57) were recruited using campus-wide announcements at the University of
501 Zurich and ETH Zurich between December 2014 and August 2015. The sample consisted of
502 subjects within a narrow age group [26 females; 23 (20th percentile) to 28 (80th percentile)
503 years old]. The age at which the volunteers reportedly began using the phone was also narrowly
504 distributed [19 (20th percentile) to 25 (80th percentile) years old]. Previous reports on inter-
505 individual variability in cortical somatosensory signal-to-noise ratio, touchscreen use-
506 dependent plasticity and use-dependent reduction in sensorimotor variability employed a
507 sample size between 15 – 28 (16, 18, 23, 56). We anticipated a weaker impact of the social
508 touches on the touchscreen than the explanatory variables studied before, i.e., deliberate
509 laboratory practice, touchscreen use in general and the presence of autism spectrum disorder.
510 Therefore, we doubled the sample size and employed more regression parameters than the
511 previous studies to increase the sensitivity of our analysis. All experimental procedures were
512 conducted according to the Swiss Human Research Act approved by the cantons of Zurich and
513 Vaud. The procedures also conformed to the Declaration of Helsinki. The volunteers provided
514 written and informed consent before participating in the study. Reasonable health, right-
515 handedness, and ownership of a non-shared touchscreen smartphone were pre-requisites for
516 participation. The handedness was further verified by a questionnaire (57). The fingers used on
517 the touchscreen were analyzed using a pictorial survey where the volunteers ranked each finger
518 on a scale 1–10 (1, least preferred; 10, most preferred).

519

520

521

522 *Smartphone data collection and analysis*

523

524 A custom-designed background App was installed on the volunteers' smartphones to quantify
525 the touchscreen behavior (see the Supplementary Methods for in-depth description of the design
526 and performance specifications of the App). Briefly, the App recorded the timestamps of
527 touchscreen events and the label of the App on the foreground. The App recorded the
528 touchscreen events with an interquartile error range of 5 ms. Data were stored locally and
529 transmitted by the user at the end of the observation period via secure email. Smartphone data
530 were processed using custom written scripts on MATLAB (MathWorks, Natick, USA). In
531 smartphones with more relaxed permission settings (built-in), the pop-up keypad touches were
532 additionally labeled. The number of touches on each App category ("Social", "Non-social", or
533 "Uncategorized") was divided by the length of the recording period to determine the number of
534 touches per day. Apps that functioned to enable social interactions between a circle of friends
535 or acquaintances were labeled as "Social" and Apps that clearly did not feature this functionality
536 were labeled as "Non-social". Apps whose label was poorly registered by the operating system,
537 untraceable on Google Play, or that contained both social and non-social properties, e.g.,
538 gaming Apps with social messaging, were labeled as "Uncategorized". The touches that were
539 separated by less than 50 ms were eliminated from further analysis. The rate of touchscreen
540 events was determined as $\frac{1}{\text{Median inter-touch interval}}$. A recording period of up to 21 d was used
541 for the main regression analysis. The number of Apps that were used over the recording period
542 was counted.

543

544

545 *Simple reaction time task and analysis*

546

547 Volunteers responded to a brief (10 ms) tactile pulse by depressing and releasing a button
548 mounted on a micro switch. The tactile pulse was presented by using a computer-controlled
549 solenoid tactile stimulator (Heijo Research Electronics, London, UK). The stimulating
550 magnetic rod (2 mm in diameter) generated a supra-threshold 2-mN contact. The thumb or the
551 middle finger was stimulated. The micro switch (extracted from RX-300 optical mouse,
552 Logitech, Lausanne, Switzerland) was operated by press-downwards and release-upwards
553 movements of the thumb or the middle finger. All volunteers performed the task with the thumb
554 ($n = 57$) and a subset of randomly chosen volunteers performed the task with the middle finger
555 in addition to the thumb ($n = 17$). The mechanical parts for the release-upwards movement
556 malfunctioned in two volunteers and in one of the two the parts for press-downwards
557 malfunctioned as well, and the corresponding data was eliminated from further analysis.

558 The task was repeated 500 times (for each fingertip) within an experimental session,
559 with 2 min break in the middle of the session. The pulses were delivered with 3 ± 1 s gap and
560 the button presses generated analogue signals that were digitized at 1 kHz. The reaction time
561 and movement time (the time taken to execute button depression) were fitted with three ex-
562 Gaussian parameters. This form of fitting separates skewed reaction time data into a Gaussian
563 region and an exponential region. Mean of the Gaussian region was captured by parameter μ ,
564 and variability of the Gaussian region by parameter σ . The exponent τ captured unusually slow
565 responses. The parameters were estimated using previously described MATLAB scripts (36).

566

567

568 *EEG data acquisition and analysis*

569

570 A subset of volunteers (randomly chosen, $n = 43$) participated in EEG experiments. The

571 volunteers were seated upright for the EEG and the right, stimulated, hand was concealed by a
572 baffle. Computer-controlled solenoid tactile stimulator (see above) was attached to the right
573 thumb tip and to the right index and middle finger tips. To ease the tedium of the hours-long
574 measurements required for gathering the tactile evoked potentials data (SSEPs), volunteers
575 were allowed to view a movie (David Attenborough's Africa series); white noise, played to
576 mask the sound generated by the stimulator, was mixed with the movie soundtrack and
577 delivered through headphones. Due to technical malfunction during the measurements, one
578 volunteer was eliminated from further analysis. The number of trials was set to 1000 for each
579 fingertip, randomized for the tips, and the stimuli were separated for each fingertip by 2–4 s. A
580 non-alcoholic and caffeine-free drink break was offered every 10 min, for a maximum of 10
581 min. To record the EEG signals, 64 electrodes were used (62 equidistant scalp electrodes and
582 two ocular ones), against a vertex reference (EasyCap, Herrsching, Germany), as previously
583 reported (16). The electrode locations were digitized in a 3D nasion-ear coordinate frame (ANT
584 Neuro and Xensor software, Netherlands) for a representative volunteer. The signals were
585 recorded and digitized by BrainAmp (Brain Products GmbH, Gilching, Germany) at 1 kHz.
586 Offline data processing was accomplished using EEGLAB, a toolbox designed for EEG
587 analysis on MATLAB (58). The data were referenced to the average of all scalp electrodes and
588 band-pass filtered between 1 and 80 Hz. "Epoched" trials over 80 μ V were eliminated to remove
589 large signal fluctuations, e.g., from eye blinks. The data were further processed using
590 independent component analysis. Components dominated by eye movements and other
591 measurement artifacts were eliminated by using the EEGLAB plug-in SASICA (59). The
592 signal-to-noise ratio was estimated using the linear modeling toolbox LIMO EEG (EEGLAB
593 plug-in) (60). In this toolbox, R^2 values were estimated for each volunteer based on single trials,
594 as a sum of squares of the putative signal divided by the sum of squares of the residuals.
595 Essentially, the predominant notion in the sensory evoked potential research field is that the
596 average over multiple trials extracts a signal that is otherwise hidden in the measurement noise

597 and background neuronal processes (39). The signal-to-noise ratio in this case captures how
598 well the estimated mean (putative signal) represents the data. To normalize the data across the
599 sampled population, the square root of the putative signal-to-noise ratio was used for subsequent
600 analyses using multiple linear regression.

601 The trial-to-trial variations in EEG responses were estimated based on the rectified
602 event-related waveforms of 25 randomly sampled samples. The resampling was reiterated 10^5
603 times for each individual. The first local maxima above 50 and 85 ms were estimated for each
604 iteration. The maxima were estimated using a MATLAB add-on function (“EXTREMA”). This
605 form of bootstrapping was used to recover the distribution of signal timings and amplitudes,
606 and these distributions were subsequently used to derive the coefficient of dispersion for each
607 individual ($\frac{\text{Inter quartile range}}{\text{Median}}$) at marked time points.

608

609 *Correlational statistics*

610

611 All analyses involving the reaction and movement times were conducted by robust–bi-square–
612 multiple linear regression analysis (implemented in MATLAB). The fitted model was evaluated
613 using ANOVA with a level of significance set at $p = 0.05$. The following main regression
614 equation was used:

615

$$\begin{aligned} 616 \quad Y = & \beta_0 + \beta_1 X_{\text{Touches on Non-social Apps}} + \beta_2 X_{\text{Touches on Social Apps}} \\ 617 & + \beta_3 X_{\text{Touches on Uncategorized Apps}} + \beta_4 X_{\text{Rate of touchscreen touches}} \\ 618 & + \beta_5 X_{\text{Number of Apps on the touchscreen}} + \beta_6 X_{\text{Gender (female=1)}} \end{aligned}$$

619

620 Where Y took the form of $Y_{\text{Movement time variability}}$ or $Y_{\text{Reaction time variability}}$, or
621 $Y_{\text{Somatosensory putative signal-to-noise ratio}}$. For $Y_{\text{Coefficient of dispersion in peak latency}}$ and

622 $Y_{Coefficient\ of\ dispersion\ in\ peak\ amplitude}$, the explanatory variable $\beta_7 X_{Movement\ time\ variability}$
623 was added to the original equation. $\beta_{1\ to\ n}$ comprised regression coefficients estimated by robust
624 regression, and β_0 the intercept. The explanatory variables quantifying the touchscreen behavior
625 were based on 21 d of recording made prior to the laboratory measures.

626 To analyze the time-dependent structure of regression parameters associated with the
627 number of touchscreen touches, we used the following approach. The parameters
628 $X_{Touches\ on\ Non-social\ Apps}$, $X_{Touches\ on\ Social\ Apps}$, and $X_{Touches\ on\ Uncategorized\ Apps}$ were re-
629 estimated over the span of 21 d with 12-h steps and 72-h windows. Other parameters were
630 unchanged and, as in the main regression equation, were based on the data spanning the entire
631 21-d period. To describe the time-dependent fluctuation of F-values, the relationship was
632 iteratively fitted by comparing linear, exponential, and Gaussian equations with a maximum of
633 three terms. The fit with the highest R^2 was used to describe the relationships.

634 Similarly, to assess the temporal structure of the variable typical rate of touchscreen use
635 or the number of Apps used, the variables X_{Rate} or $X_{Number\ of\ Apps\ on\ the\ touchscreen}$ were re-
636 estimated with 12-h steps and 72-h windows while other parameters remained unchanged.

637 As a control, we repeated the analysis with shuffled App categories. Essentially, for the
638 original analysis, the Apps were labeled as “Social”, “Non-social”, and “Uncategorized”
639 according to a fixed criterion, i.e., Social Apps were those that enabled the communication of
640 a message or an opinion to a circle of friends or acquaintances. The list of all Apps in the
641 database and their classifications were randomly shuffled (10^5 iterations). These shuffled lists
642 were then used to estimate the number of touches in each of the action categories. Note that the
643 total number of Apps in each category was constant during shuffling.

644 Plots for displaying multiple linear regression results in two dimensions (adjusted
645 response plots) were generated using a built-in MATLAB function (`plotAdjustedResponse`).
646 Formulation of this plotting method and its advantages are described elsewhere (61).

647 The EEG data were correlated with touchscreen parameters using robust regression, the

648 iterative least squares method (implemented in LIMO EEG). The correlation coefficients were
649 estimated across all electrodes and for the time period from -30 to 200 ms relative to the
650 stimulation onset. When focusing the analysis on keypad use, due to the smaller number of
651 samples, the variables were restricted to parameters X_{Rate} , $X_{Number\ of\ touches\ on\ Social\ Apps}$, and
652 $X_{Number\ of\ touches\ on\ Non-social\ Apps}$. The regression statistics were corrected for multiple
653 comparisons by using 1000 bootstraps and spatiotemporal clustering, as implemented in LIMO
654 EEG.
655

656 **Acknowledgements**

657

658 The data collection was made possible by the assistance of Ciara Shortiss and Magali Chytiris.

659 We thank Enea Ceolini for helping in the design and implementation of the behavioral tracking

660 software. This research was funded by Holcim Stiftung and the Society in Science Branco

661 Weiss Fellowship. The authors would like to thank Eric Rouillier, Anne-Dominique Gindrat,

662 Kevan Martin for discussions. We are grateful to Valerio Mante for making the crucial

663 suggestion of randomizing the App categories. The authors thank Joanna Mackie for help in

664 editing this manuscript.

665 **References**

666

- 667 1. Hourcade JP, Mascher SL, Wu D, Pantoja L (2015) Look, My Baby Is Using an iPad! An Analysis of
668 YouTube Videos of Infants and Toddlers Using Tablets. *Proceedings of the 33rd Annual ACM Conference*
669 *on Human Factors in Computing Systems*, CHI '15. (ACM, New York, NY, USA), pp 1915–1924.
- 670 2. Herholz SC, Zatorre RJ (2012) Musical Training as a Framework for Brain Plasticity: Behavior, Function,
671 and Structure. *Neuron* 76(3):486–502.
- 672 3. Byl NN, Merzenich MM, Jenkins WM (1996) A primate genesis model of focal dystonia and repetitive
673 strain injury I. Learning-induced dedifferentiation of the representation of the hand in the primary
674 somatosensory cortex in adult monkeys. *Neurology* 47(2):508–520.
- 675 4. Jenkins WM, Merzenich MM, Ochs MT, Allard T, Guic-Robles E (1990) Functional reorganization of
676 primary somatosensory cortex in adult owl monkeys after behaviorally controlled tactile stimulation. *J*
677 *Neurophysiol* 63(1):82–104.
- 678 5. Zatorre RJ, Fields RD, Johansen-Berg H (2012) Plasticity in gray and white: neuroimaging changes in
679 brain structure during learning. *Nat Neurosci* 15(4):528–536.
- 680 6. Elbert T, Pantev C, Wienbruch C, Rockstroh B, Taub E (1995) Increased cortical representation of the
681 fingers of the left hand in string players. *Science* 270(5234):305–307.
- 682 7. Hamilton RH, Pascual-Leone A (1998) Cortical plasticity associated with Braille learning. *Trends Cogn*
683 *Sci* 2(5):168–174.
- 684 8. Donoghue JP (1995) Plasticity of adult sensorimotor representations. *Curr Opin Neurobiol* 5(6):749–754.
- 685 9. Pascual-Leone A, Amedi A, Fregni F, Merabet LB (2005) The plastic human brain cortex. *Annu Rev*
686 *Neurosci* 28:377–401.
- 687 10. Kleber B, Veit R, Birbaumer N, Gruzeliier J, Lotze M (2010) The Brain of Opera Singers: Experience-
688 Dependent Changes in Functional Activation. *Cereb Cortex* 20(5):1144–1152.
- 689 11. Münte TF, Altenmüller E, Jäncke L (2002) The musician's brain as a model of neuroplasticity. *Nat Rev*
690 *Neurosci* 3(6):473–478.
- 691 12. Moucha R, Kilgard MP (2006) Cortical plasticity and rehabilitation. *Prog Brain Res* 157:111–389.
- 692 13. Adolphs R (1999) Social cognition and the human brain. *Trends Cogn Sci* 3(12):469–479.
- 693 14. Crockett MJ, Fehr E (2014) Social brains on drugs: tools for neuromodulation in social neuroscience. *Soc*
694 *Cogn Affect Neurosci* 9(2):250–254.
- 695 15. Smith A (2015) *US Smartphone Use in 2015*. *Pew Research Center*.
- 696 16. Gindrat A-D, Chytiris M, Balerna M, Rouiller EM, Ghosh A (2015) Use-Dependent Cortical Processing
697 from Fingertips in Touchscreen Phone Users. *Curr Biol* 25(1):109–116.
- 698 17. Krakauer JW, Mazzoni P (2011) Human sensorimotor learning: adaptation, skill, and beyond. *Curr Opin*
699 *Neurobiol* 21:1–9.
- 700 18. Cohen RG, Sternad D (2009) Variability In Motor Learning: Relocating, Channeling and Reducing Noise.
701 *Exp Brain Res Exp Hirnforsch Exp Cerebrale* 193(1):69–83.
- 702 19. Slifkin AB, Newell KM (1998) Is Variability in Human Performance a Reflection of System Noise? *Curr*
703 *Dir Psychol Sci* 7(6):170–177.

- 704 20. Schmidt RA, Zelaznik H, Hawkins B, Frank JS, Quinn Jr. JT (1979) Motor-output variability: A theory for
705 the accuracy of rapid motor acts. *Psychol Rev* 86(5):415–451.
- 706 21. Davids K, Bennett S, Newell KM (2006) *Movement System Variability* (Human Kinetics).
- 707 22. Herzfeld DJ, Shadmehr R (2014) Motor variability is not noise, but grist for the learning mill. *Nat*
708 *Neurosci* 17(2):149–150.
- 709 23. Gentner DR (1983) The acquisition of typewriting skill. *Acta Psychol (Amst)* 54(1–3):233–248.
- 710 24. Wöllner C, Cañal-Bruland R (2010) Keeping an eye on the violinist: motor experts show superior timing
711 consistency in a visual perception task. *Psychol Res* 74(6):579–585.
- 712 25. McMorris T, Keen P (1994) Effect of exercise on simple reaction times of recreational athletes. *Percept*
713 *Mot Skills* 78(1):123–130.
- 714 26. Sosnoff JJ, Newell KM (2011) Aging and Motor Variability: A Test of the Neural Noise Hypothesis. *Exp*
715 *Aging Res* 37(4):377–397.
- 716 27. Dykiert D, Der G, Starr JM, Deary IJ (2012) Sex differences in reaction time mean and intraindividual
717 variability across the life span. *Dev Psychol* 48(5):1262–1276.
- 718 28. Peters RM, Hackeman E, Goldreich D (2009) Diminutive Digits Discern Delicate Details: Fingertip Size
719 and the Sex Difference in Tactile Spatial Acuity. *J Neurosci* 29(50):15756–15761.
- 720 29. Ivry RB (1996) The representation of temporal information in perception and motor control. *Curr Opin*
721 *Neurobiol* 6(6):851–857.
- 722 30. Schmidt RA, Bjork RA (1992) Paradigms Suggest New Concepts for Training. *Psychol Sci* 3(4):207–217.
- 723 31. Xiong J, Muraki S (2014) An ergonomics study of thumb movements on smartphone touch screen.
724 *Ergonomics* 57(6):943–955.
- 725 32. Henry FM (1961) Reaction time-movement time correlations. *Percept Mot Skills* 12:63–66.
- 726 33. Fitts PM, Peterson JR (1964) Information capacity of discrete motor responses. *J Exp Psychol* 67(2):103–
727 112.
- 728 34. Houlihan M, Campbell K, Stelmack RM (1994) Reaction time and movement time as measures of
729 stimulus evaluation and response processes. *Intelligence* 18(3):289–307.
- 730 35. Carlson JS, Mark C (1982) Reaction time, movement time, and intelligence: A replication and extension.
731 *Intelligence* 6(3):265–274.
- 732 36. Lacouture Y, Cousineau D (2008) How to use MATLAB to fit the ex-Gaussian and other probability
733 functions to a distribution of response times. *Tutor Quant Methods Psychol* 4(1):35–45.
- 734 37. Kofler MJ, et al. (2013) Reaction time variability in ADHD: A meta-analytic review of 319 studies. *Clin*
735 *Psychol Rev* 33(6):795–811.
- 736 38. O'brien RM (2007) A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Qual Quant*
737 41(5):673–690.
- 738 39. Makeig S, Debener S, Onton J, Delorme A (2004) Mining event-related brain dynamics. *Trends Cogn Sci*
739 8(5):204–210.
- 740 40. Huber R, et al. (2006) Arm immobilization causes cortical plastic changes and locally decreases sleep
741 slow wave activity. *Nat Neurosci* 9(9):1169–1176.

- 742 41. Allison T, McCarthy G, Wood CC (1992) The relationship between human long-latency somatosensory
743 evoked potentials recorded from the cortical surface and from the scalp. *Electroencephalogr Clin*
744 *Neurophysiol Potentials Sect* 84(4):301–314.
- 745 42. Onishi H, et al. (2010) Neuromagnetic activation of primary and secondary somatosensory cortex
746 following tactile-on and tactile-off stimulation. *Clin Neurophysiol Off J Int Fed Clin Neurophysiol*
747 121(4):588–593.
- 748 43. Nicoletis MAL, et al. (1998) Simultaneous encoding of tactile information by three primate cortical areas.
749 *Nat Neurosci* 1(7):621–630.
- 750 44. Montag C, et al. (2015) Smartphone usage in the 21st century: who is active on WhatsApp? *BMC Res*
751 *Notes* 8:331.
- 752 45. Schaefer M, Heinze H-J, Rotte M (2012) Touch and personality: extraversion predicts somatosensory
753 brain response. *NeuroImage* 62(1):432–438.
- 754 46. Coull JT (1998) Neural correlates of attention and arousal: insights from electrophysiology, functional
755 neuroimaging and psychopharmacology. *Prog Neurobiol* 55(4):343–361.
- 756 47. Gilbert CD, Sigman M (2007) Brain States: Top-Down Influences in Sensory Processing. *Neuron*
757 54(5):677–696.
- 758 48. Cardini F, Longo MR, Haggard P (2011) Vision of the Body Modulates Somatosensory Intracortical
759 Inhibition. *Cereb Cortex* 21(9):2014–2022.
- 760 49. Mima T, Nagamine T, Nakamura K, Shibasaki H (1998) Attention Modulates Both Primary and Second
761 Somatosensory Cortical Activities in Humans: A Magnetoencephalographic Study. *J Neurophysiol*
762 80(4):2215–2221.
- 763 50. Dayan E, Cohen LG (2011) Neuroplasticity Subservicing Motor Skill Learning. *Neuron* 72(3):443–454.
- 764 51. Scholz J, Klein MC, Behrens TEJ, Johansen-Berg H (2009) Training induces changes in white matter
765 architecture. *Nat Neurosci* 12(11):1370–1371.
- 766 52. Carmichael ST, Price JL (1995) Sensory and premotor connections of the orbital and medial prefrontal
767 cortex of macaque monkeys. *J Comp Neurol* 363(4):642–664.
- 768 53. Shadlen MN, Newsome WT (1998) The Variable Discharge of Cortical Neurons: Implications for
769 Connectivity, Computation, and Information Coding. *J Neurosci* 18(10):3870–3896.
- 770 54. Bohannon RW (2007) Number of pedometer-assessed steps taken per day by adults: a descriptive meta-
771 analysis. *Phys Ther* 87(12):1642–1650.
- 772 55. Barbato G, et al. (2000) Diurnal variation in spontaneous eye-blink rate. *Psychiatry Res* 93:145151.
- 773 56. Dinstein I, et al. (2012) Unreliable Evoked Responses in Autism. *Neuron* 75(6):981–991.
- 774 57. Oldfield RC (1971) The assessment and analysis of handedness: The Edinburgh inventory.
775 *Neuropsychologia* 9(1):97–113.
- 776 58. Delorme A, Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics
777 including independent component analysis. *J Neurosci Methods* 134(1):9–21.
- 778 59. Chaumon M, Bishop DVM, Busch NA (2015) A practical guide to the selection of independent
779 components of the electroencephalogram for artifact correction. *J Neurosci Methods* 250:47–63.
- 780 60. Pernet CR, Chauveau N, Gaspar C, Rousselet GA (2011) LIMO EEG: A Toolbox for Hierarchical Linear
781 MOdeling of ElectroEncephaloGraphic Data. *Comput Intell Neurosci* 2011:e831409.

782 61. DuMouchel W (1988) Graphical representation of main effects and interaction effects in a polynomial
783 regression on several predictors. *Proc. 20th Symp. on the Interface: Computer Science and Statistics*, pp
784 127–134.

785

786 **Figure Legends**

787

788 **Figure 1.** The history of unconstrained touchscreen behavior reflects on the performance of a
789 simple task. (a) Touchscreen activity was recorded for 21 d and followed by laboratory
790 measurements of sensorimotor variability. (b) The task required responding to tactile stimuli
791 by pressing and releasing a micro switch, as fast as possible, with the thumb. (c-d) Adjusted
792 response plots. (c) Movement time variability (σ) was directly proportional to the number of
793 touches generated on the Social Apps (social touches). (d) The movement time variability was
794 inversely proportional to the number of touches generated on the Non-social Apps (non-social
795 touches). (e) The distribution of relationships for randomly categorized Apps (10^4 iterations)
796 in comparison to the relationship uncovered for social touches. (f) Parsing the touchscreen
797 recordings in 12 h steps (72 h bin) revealed that the relationship involving non-social touches
798 simply decayed as a function of time, whereas the relationship involving social touches showed
799 a more complex pattern. The statistical tests and the details of the fits are reported in the main
800 text.

801 **Figure 1 - Supplement 1.** The social touches do not reflect on movement time variability when
802 the task is performed with the middle finger. (a) Adjusted response plot showing the link
803 between the number of social touches generated on the touchscreen and the movement-time
804 variability when the task was performed by using the thumb. Specifically, higher the number
805 of social touches the higher the movement time variability (b) When the same volunteers
806 performed the task with the middle finger the relationship was absent.

807 **Figure 1 - Supplement 2.** Analysis of explanatory variables other than the number of social
808 and non-social touches. (a-b) Adjusted response plots. (a) The link between the typical rate of

809 touchscreen usage and movement time variability and (b) the number of Apps used and the
810 variability. (c) The analysis of the relationships to movement time variability after parsing the
811 touchscreen recordings in 12 h steps (72 h bin).

812 **Figure 2.** Early cortical somatosensory processing reflects the history of Social App usage. (a)
813 We estimated the signal-to-noise ratio in the cortical responses upon a brief tactile stimulus
814 presented to the right thumb tip, the hand was in a resting position during the recording. The
815 head plot shows the electrode location with the best response (red) (b) Putative signal-to-noise
816 ratio (SNR) at the electrode (SS, sum of squares). Individual volunteers (gray lines) and
817 population mean (black). (c) Event related coefficients with the SNR as dependent variable and
818 touchscreen parameters based on the entire 21 d recordings as explanatory variables.
819 Statistically significant coefficients (thickened lines, $p < 0.05$, corrected for multiple
820 comparisons, ANOVA). (d) Head plot of the population mean of the SNR at a latency of 80
821 ms. (e,f) The event related coefficients and the corresponding statistics at 80 ms. (g) At the
822 chosen electrode and at 80 ms, the distribution of the relationship strength based on randomly
823 categorized Apps (10^4 iterations) in comparison to the relationship uncovered for social
824 touches. (h) The relationship with social touches was the strongest for the thumb, followed by
825 the index finger, and, finally, the middle finger. (i) Parsing the touchscreen recordings in 12 h
826 steps (72 h bin) revealed that the relationship between social touches and the signal-to-noise
827 ratio evoked from the thumb at 80 ms latency fluctuated in a complex manner through the
828 recording period. The details of the fit is reported in the main text.

829 **Figure 2 – Supplement 1.** The links between somatosensory cortical signal-to-noise ratio and
830 the touchscreen-based explanatory variables. (a) Multiple regression analysis was conducted to
831 explain the inter-individual variability in response to tactile stimulation at the thumb. The
832 regression coefficients for the signal-to-noise ratio measured at the electrode with the strongest
833 response. The sold lines depict $p < 0.05$ (corrected for multiple comparisons, ANOVA). (b-e)
834 Head plot of the regression coefficients and the corresponding statistics. (f-g) The relationships

835 for the number of non-social touches and the typical rate on the touchscreen were the strongest
836 for the thumb followed by the index and then the middle finger.

837

838 **Figure 3.** The trial-to-trial variability in the degree of cortical responses is proportional to
839 Social App usage. **(a–c)** Depiction of the analysis method to separately estimate the trial-to-
840 trial variability in the cortical signal latency and the amplitude. **(a)** Rectified event related
841 potentials based on a random sample of 25 trials was generated 10^5 times. The rectified potential
842 based on all the trials in one volunteer is drawn in grey. The first local maxima encountered on
843 10^3 iterated potentials after the set temporal landmarks of 50 and 85 ms are indicated (colored
844 dots). The distribution of latencies **(b)** and amplitudes **(c)** of the first maxima in the same
845 volunteer based on which the corresponding coefficient of dispersion (CD) was estimated. **(d-**
846 **e)** Adjusted response plots. **(d)** The greater the number of social touches in the 21-d recording
847 period, the larger the variability in signal amplitudes at the 85 ms landmark (measured in terms
848 of CD). **(e)** The relationship between the number of non-social touches and the variability was
849 not significant. **(f)** Parsing the touchscreen recordings in 12 h steps (72 h bin) revealed that the
850 relationship for non-social touches simply decayed with older touchscreen data and a more
851 complex pattern was apparent for the social touches.

852

853 **Supplementary Information Index**

854

855 Supplementary Methods: Description of the App used to track touchscreen behavior.

856

857 Supplementary List: A sample of all the Apps in the database to illustrate the App categorization
858 used in this study in Social and Non-social Apps.

859

860 Supplementary Figure 1: The plot matrix of the explanatory variables and the corresponding
861 variation inflation factors.

862

863 Supplementary Figure 2: Social touches on the keypad is related to movement time variability.
864 (a-b) Adjusted response plots. (a) Higher the number of social touches on the touchscreen pop-
865 up keypad the higher the movement time variability. (b) The non-social touches on the keypad
866 were not related to the variability.

867

868 Supplementary Figure 3: The reaction time variability is related to the number of social touches.
869 (a) Adjusted response plot displaying that higher the number of social touches the larger was
870 the reaction time variability. (b) The non-social touches were unrelated to the reaction time
871 variability. (c) The relationship discovered for the social touches was well apart from the
872 distribution of relationships obtained by using randomly shuffled categories.

873

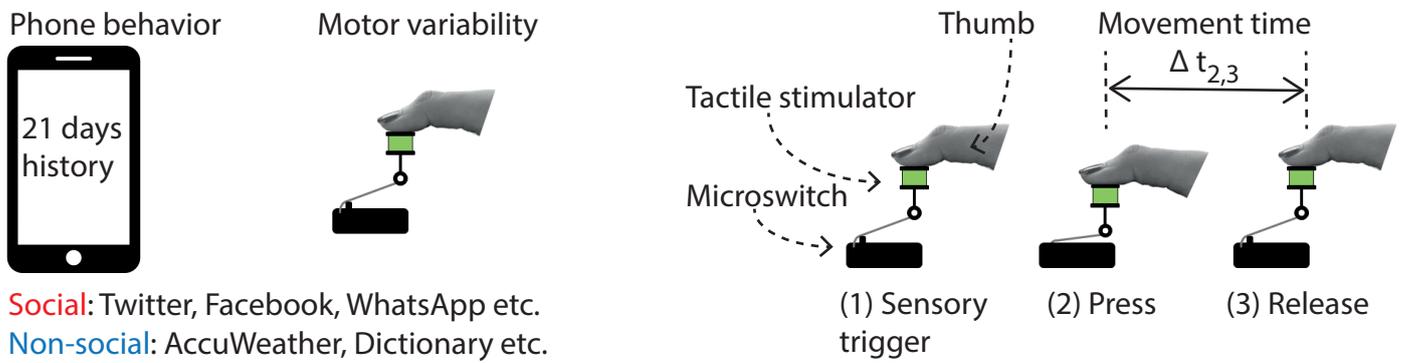
874 Supplementary Figure 4: The neuronal correlates of the number of social touches on the
875 touchscreen keypad. When we restricted our analysis to the pop-up keypad touches, we found
876 that higher the number of social touches on the keypad smaller the signal-to-noise ratio as in
877 the original analysis including all types of touchscreen events. The legend is identical to Figure
878 2 panels a-f.

879

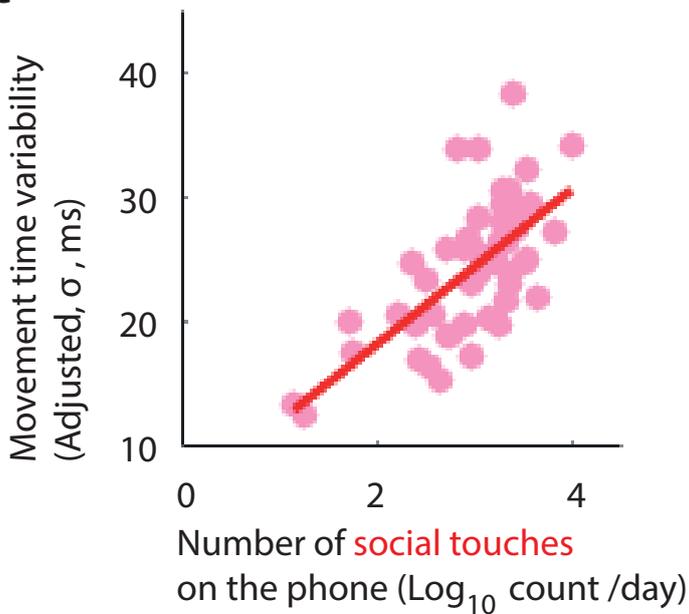
880 Supplementary Figure 5: The neuronal variability determined from the early temporal landmark
881 set at 50 ms was unrelated to the number of touches. (a-d) Data by using the 50 ms temporal
882 landmark. Adjusted response plots showing the non-significant regressions between social or
883 non-social touches and neuronal variability in terms of amplitude or latency. (e,f) Latency data
884 by using the 85 ms temporal landmark shows a weak relationship between social touches (and
885 not for non-social touches) and trial-to-trial temporal variability.

886

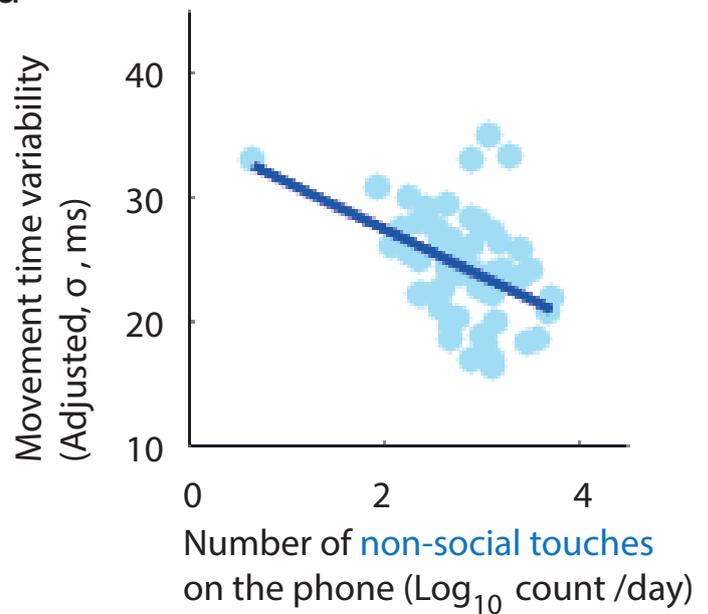
a



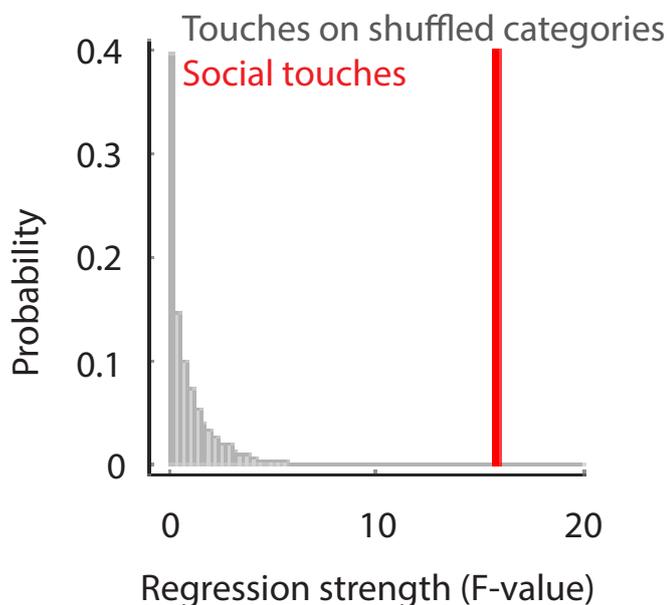
c



d



e



f

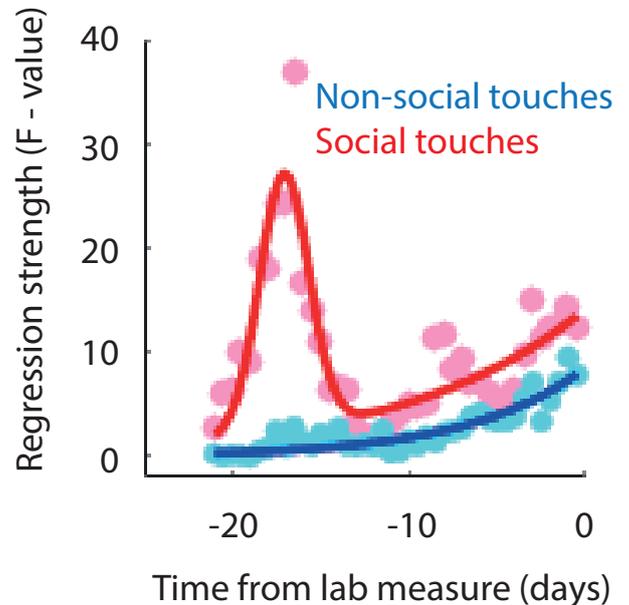


Figure 1. The history of unconstrained touchscreen behavior reflects on the performance of a simple task. (a) Touchscreen activity was recorded for 21 d and followed by laboratory measurements of sensorimotor variability. (b) The task required responding to tactile stimuli by pressing and releasing a micro switch, as fast as possible, with the thumb. (c-d) Adjusted response plots. (c) Movement time variability (σ) was directly proportional to the number of touches generated on the Social Apps (social touches). (d) The movement time variability was inversely proportional to the number of touches generated on the Non-social Apps (non-social touches). (e) The distribution of relationships for randomly categorized Apps (10^4 iterations) in comparison to the relationship uncovered for social touches. (f) Parsing the touchscreen recordings in 12 h steps (72 h bin) revealed that the relationship involving non-social touches simply decayed as a function of time, whereas the relationship involving social touches showed a more complex pattern. The statistical tests and the details of the fits are reported in the main text. Also see **Figure 1 - Supplement 1** and **Figure 1 - Supplement 2**, for related analysis.

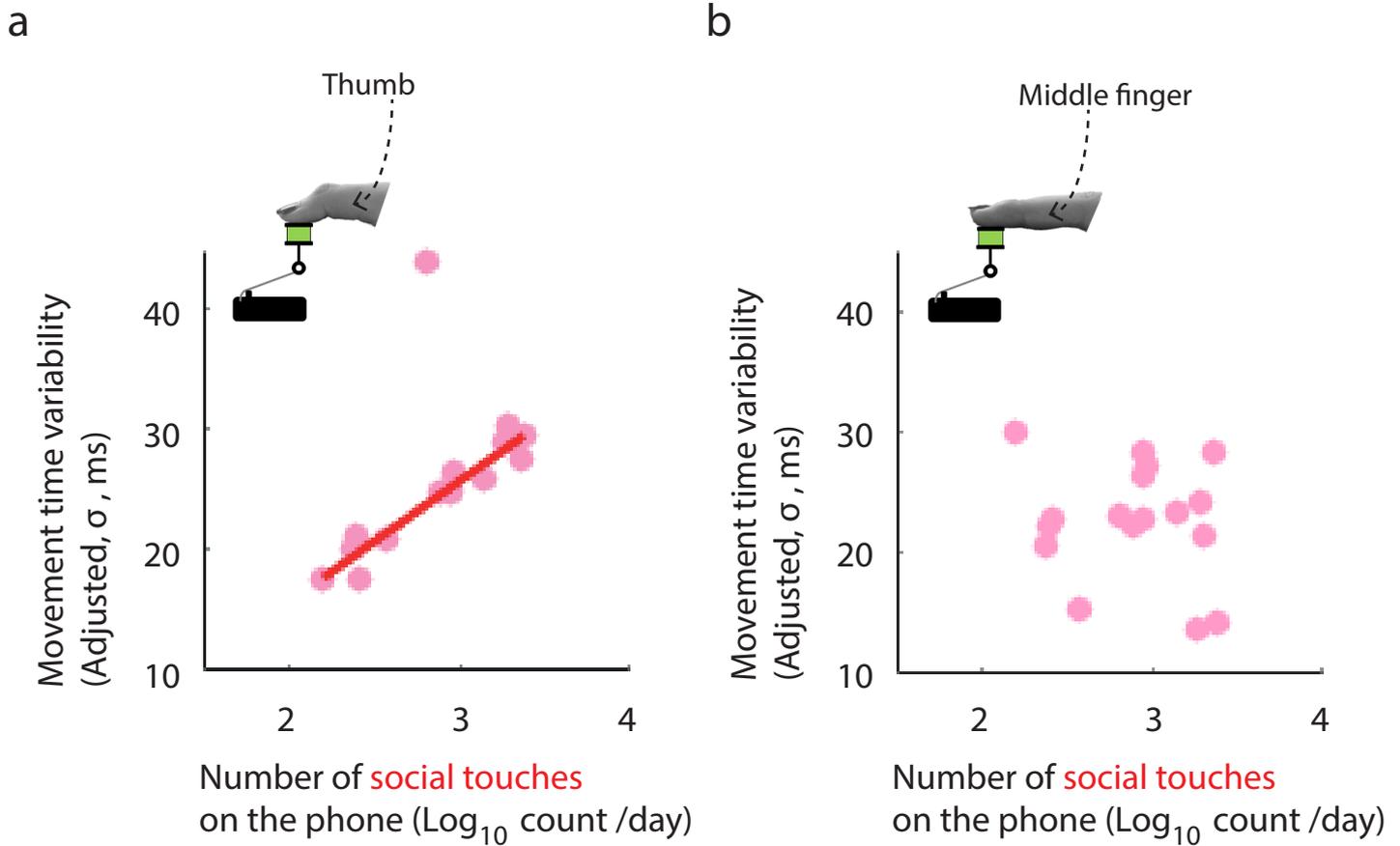
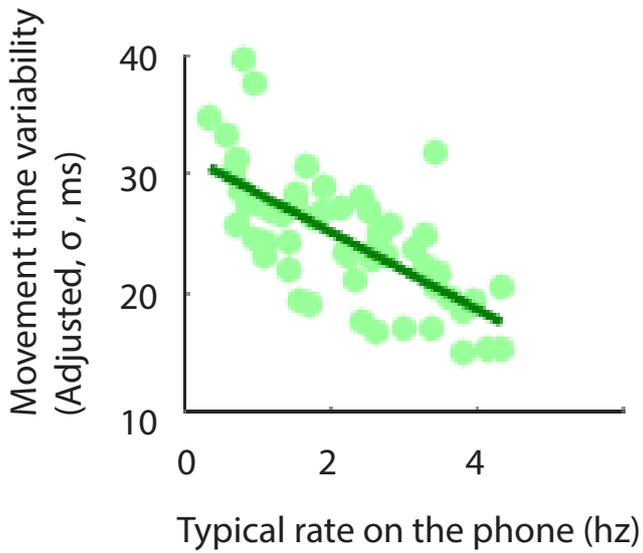
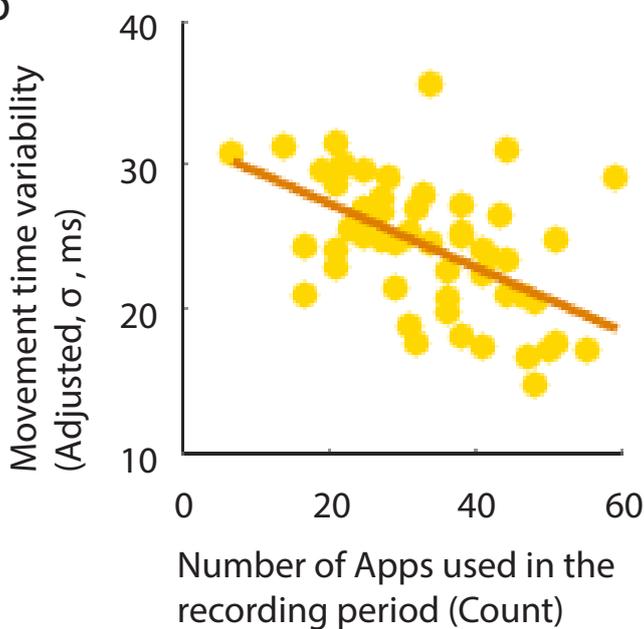


Figure 1 - Supplement 1. The social touches do not reflect on movement time variability when the task is performed with the middle finger. (a) Adjusted response plot showing the link between the number of social touches generated on the touchscreen and the movement-time variability when the task was performed by using the thumb. Specifically, higher the number of social touches the higher the movement time variability (b) When the same volunteers performed the task with the middle finger the relationship was absent.

a



b



c

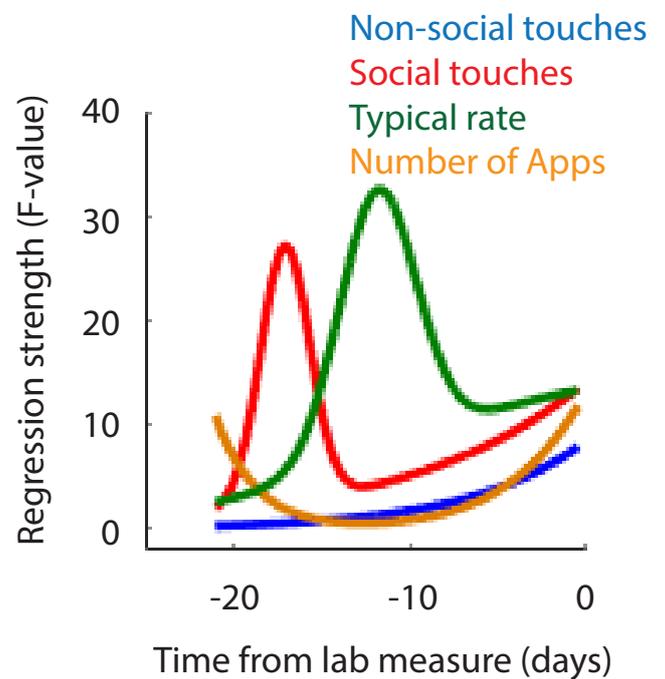
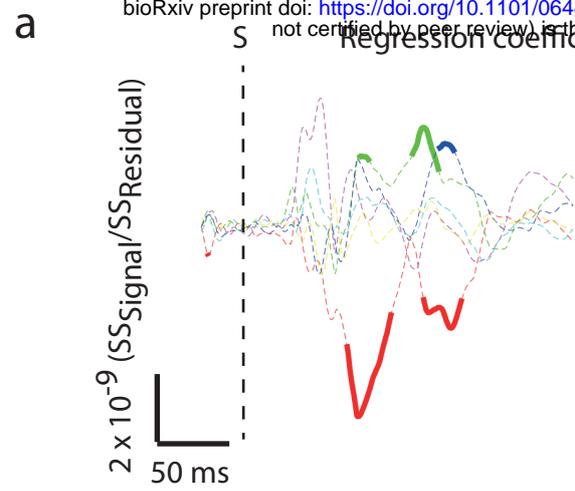


Figure 1 - Supplement 2. Analysis of explanatory variables other than the number of social and non-social touches. (a-b) Adjusted response plots. (a) The link between the typical rate of touchscreen usage and movement time variability and (b) the number of Apps used and the variability. (c) The analysis of the relationships to movement time variability after parsing the touchscreen recordings in 12 h steps (72 h bin).



β Social touches
 β Non-social touches
 β Typical rate
 β Gender
 β Uncategorised touches
 β Number of Apps

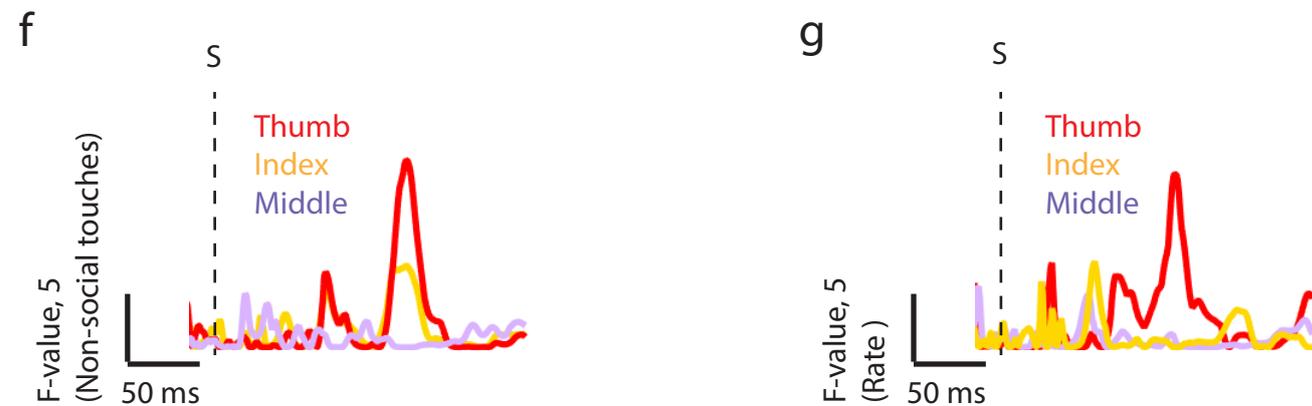
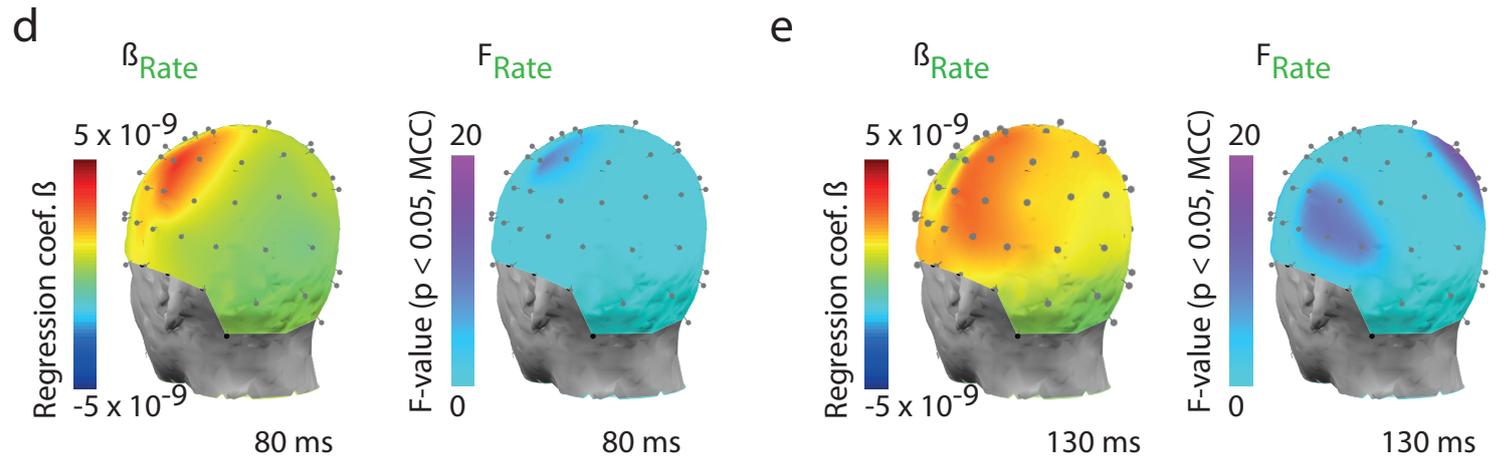
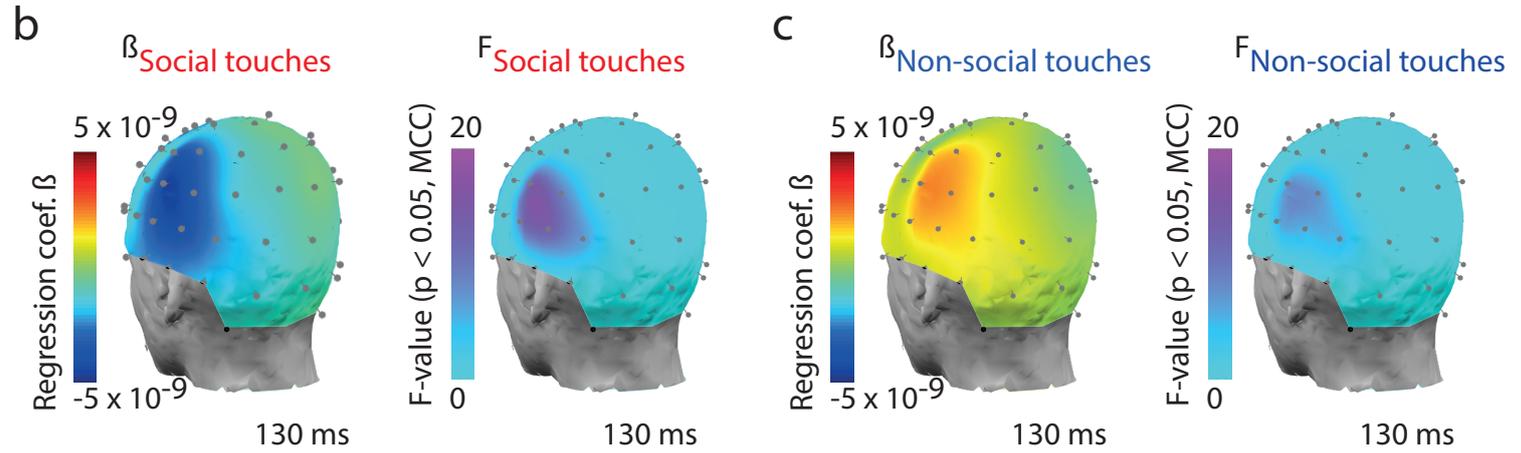


Figure 2 - Supplement 1. The links between somatosensory cortical signal-to-noise ratio and the touchscreen-based explanatory variables. (a) Multiple regression analysis was conducted to explain the inter-individual variability in response to tactile stimulation at the thumb. The regression coefficients for the signal-to-noise ratio measured at the electrode with the strongest response. The solid lines depict $p < 0.05$ (corrected for multiple comparisons, ANOVA). (b-e) Head plot of the regression coefficients and the corresponding statistics. (f-g) The relationships for the number of non-social touches (f) and the typical rate (g) on the touchscreen were the strongest for the thumb followed by the index and then the middle finger.

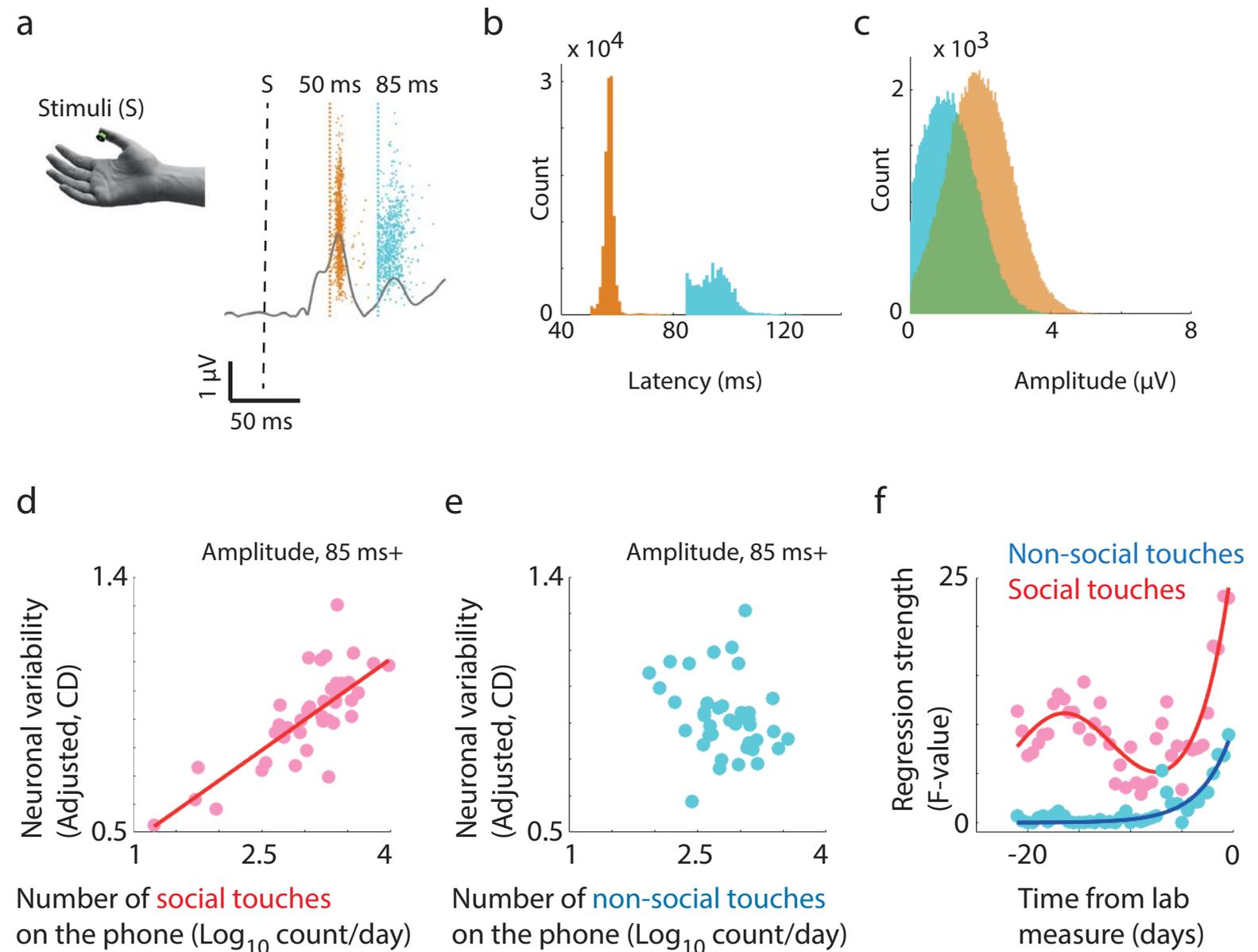


Figure 3. The trial-to-trial variability in the degree of cortical responses is proportional to Social App usage. (a–c) Depiction of the analysis method to separately estimate the trial-to-trial variability in the cortical signal latency and the amplitude. (a) Rectified event related potentials based on a random sample of 25 trials was generated 10^5 times. The rectified potential based on all the trials in one volunteer is drawn in grey. The first local maxima encountered on 10^3 iterated potentials after the set temporal landmarks of 50 and 85 ms are indicated (colored dots). The distribution of latencies (b) and amplitudes (c) of the first maxima in the same volunteer based on which the corresponding coefficient of dispersion (CD) was estimated. (d–e) Adjusted response plots. (d) The greater the number of social touches in the 21-d recording period, the larger the variability in signal amplitudes at the 85 ms landmark (measured in terms of CD). (e) The relationship between the number of non-social touches and the variability was not significant. (f) Parsing the touchscreen recordings in 12 h steps (72 h bin) revealed that the relationship for non-social touches simply decayed with older touchscreen data and a more complex pattern was apparent for the social touches.