

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

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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.

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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 conclude that smartphone use affects elementary computations  
35 even in tasks not involving a phone and suggest that social activities uniquely reconfigure the  
36 thumb to touchscreen use.

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## 41 **Introduction**

42

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

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

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

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

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

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

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102

103 **Results**

104

105 *Basic features of touchscreen use*

106

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

123

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

126

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

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

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

156 To what extent does the social behavior-movement time variability relationship (*Figure*  
157 *1c*) depend on App classification? We addressed this by repeating our analysis  $10^5$  times using  
158 randomly shuffled categories. The relationship uncovered for social touches was well separated  
159 from the distribution of relationships obtained by quantifying random category touches (*Figure*  
160 *1e*). This result further supported the notion that the type of touchscreen behavior determines  
161 how neuronal processes responsible for the thumb are configured.

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

175  
176 *Social keypad touches distinctly impact on motor variability*  
177

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



183 touches for Social Apps are the same as the ones for Non-social Apps. The difference concerns  
184 the specific content typed. Full regression model based on the keypad touches was significantly  
185 related to motor time variability [ $R^2 = 0.60, f(6,25) = 6.36, p = 0.0004$ , robust linear regression].  
186 We noted that the higher the number of social touches on the keypad, the larger the movement  
187 time variability [ $t(1,25) = 3.76, p = 0.0009$ , **Supplementary Figure 3**]. This suggested that  
188 gestures cannot simply account for the distinct imprint of social activities on motor time  
189 variability.

190

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

192

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

201

$$\begin{aligned} 202 \quad Y_{\text{Non-social touches vs. motor variability relationship strength}} \\ 203 \quad = 8.6 \times e^{\text{Number of non-social touches} \times 0.15} \end{aligned}$$

204

205 The relationship for social touches was more complicated, consisting of both an initial decay  
206 and a strong relationship with older data. This dynamic was well described ( $R^2 = 0.81$ , **Figure**  
207 **1f**) by:

208

209  $Y_{\text{Social touches vs. motor variability relationship strength}}$

$$210 = [24.53 \times e^{-\left(\frac{\text{Number of social touches} + 17.06}{1.97}\right)^2}] + [2.06 \times 10^{15} \times e^{-\left(\frac{\text{Number of social touches} - 655.2}{114.7}\right)^2}]$$

211

212

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

215 We also revealed the dynamics of other explanatory variables that were significantly  
216 related to touchscreen use recorded over the 21-d period. In brief, as anticipated, variability was  
217 smaller with a higher typical rate of touchscreen touches [ $t(1,48) = -5.10$ ,  $p = 5.73 \times 10^{-6}$ ,  
218 *Supplementary Figure 4*] and with a larger number of Apps used [ $t(1,48) = -3.29$ ,  $p = 0.002$ ,  
219 *Supplementary Figure 4*]. Time-dependent dynamics for the typical rate of touchscreen  
220 touches indicated slow plasticity but the “number of Apps” variable dynamics indicated both  
221 rapid and slow plasticity (*Supplementary Figure 4*). The gender of the user was not  
222 significantly associated with the motor time variability [ $t(1,48) = -0.90$ ,  $p = 0.37$ ].

223

224 *Social touches distinctly affect the reaction time variability*

225

226 We opportunistically explored the variability of higher cognitive levels captured by the reaction  
227 time. For the reaction time variability, the full regression model was significant but weak [ $R^2 =$   
228  $0.26$ ,  $f(6,49) = 2.86$ ,  $p = 0.02$ , robust linear regression]. Similarly to the results for movement  
229 time variability, we observed that a higher number of social touches was associated with greater  
230 reaction time variability [ $t(1,49) = 2.72$ ,  $p = 0.009$ , *Supplementary Figure 5*]. The only other  
231 explanatory variable that significantly contributed to the regression model was the participant  
232 gender, such that the females showed less variability [ $t(1,49) = -3.25$ ,  $p = 0.0002$ ] than the  
233 males. Since the reaction and movement times measure different aspects of cognition, taken

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

236

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

239

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

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

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

260 noise ratio (*Figure 2c–f*). Our analysis revealed that the number of social touches was  
261 correlated with the thumb-associated signal-to-noise ratio at time points between 70 and 100  
262 ms, and then again between 125 and 150 ms (*Figure 2c*). Notably and contrary to the simplistic  
263 prediction, the direction of the correlation was such that the higher the number of social touches,  
264 the lower the signal-to-noise ratio (*Figure 2c*). In contrast, the history of non-social touches  
265 was significantly related to the cortical signals in a narrow window between 135 and 150 ms,  
266 so that the higher the number of touches, the larger the signal-to-noise ratio (the relationships  
267 with other explanatory variables are presented in *Supplementary Figure 6*). These results  
268 suggested that social touches were tracked by the somatosensory cortex separately from non-  
269 social touches, and that the social touches were encoded at multiple stages of somatosensory  
270 processing.

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

283

284

285

286 *Neuronal correlates of social touches on the keypad*

287

288 The neuronal correlates of social touches described above were based on all touchscreen  
289 gestures, leaving open the possibility that the correlates reflected the underlying differences in  
290 the gestures used on Social vs. Non-social Apps. We matched the gesture type by restricting  
291 the analysis to pop-up keypads. A near-identical pattern of correlates was observed as in the  
292 original analysis that included all gestures. Briefly, with an increasing number of social touches  
293 on the keypad, the signal-to-noise ratio associated with the thumb between 70 and 100 ms  
294 decreased (*Supplementary Figure 7*).

295

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

297

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

309

310

311

312  $Y_{\text{Social touches vs. signal-to-noise ratio relationship strength}}$

$$\begin{aligned} 313 &= (24.1 \times e^{-\left(\frac{\text{Number of social touches} + 6.68}{1.1}\right)^2}) \\ 314 &+ (21.3 \times e^{-\left(\frac{\text{Number of social touches} + 2.01}{3.3}\right)^2}) \\ 315 &+ (22.5 \times e^{-\left(\frac{\text{Number of social touches} + 24.76}{12.1}\right)^2}) \end{aligned}$$

316

317

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

320

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

323

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

337 at the center of the correlated range of 70–100 ms). We repeated this with a different subset of  
338 25 trials,  $10^5$  times for each volunteer, to estimate the trial-to-trial variability of the  
339 corresponding latencies and amplitudes (**Figure 3b,c**).

340 The variability of cortical signal amplitudes detected by the 50 ms landmark was  
341 unrelated to the explanatory variables that included movement time variability in addition to  
342 the original set of variables derived from the touchscreen and gender [ $R^2 = 0.31, f(7,33) = 2.11,$   
343  $p = 0.07$ , robust linear regression]. In particular, amplitude variability was clearly unrelated to  
344 the number of social touches [ $t(1,33) = 0.68, p = 0.5$ ] and non-social touches [ $t(1,33) = -0.02,$   
345  $p = 0.98$ , **Supplementary Figure 8**]. The variability of signal latencies at this temporal landmark  
346 was also unrelated to the social touches [ $t(1,33) = 0.60, p = 0.6$ ] and non-social touches [ $t(1,33)$   
347  $= -0.23, p = 0.8$ , **Supplementary Figure 8**]. In contrast, the variability of signal amplitudes  
348 detected by the 85 ms landmark was strongly related to the explanatory variables [ $R^2 = 0.45, f$   
349  $(7,33) = 3.9, p = 0.003$ , robust linear regression]. We observed that the higher the number of  
350 social touches, the larger the variability [ $t(1,33) = 4.62, p = 5.6 \times 10^{-5}$ , **Figure 3d**]. There was  
351 a weak trend linking the number of non-social touches and neuronal variability, such that the  
352 higher the number, the lower the variability [ $t(1,33) = -1.9, p = 0.07$ , **Figure 3e**]. In terms of  
353 variability of signal latencies at this landmark, a weak relationship with the explanatory  
354 variables was observed [ $R^2 = 0.34, f(7,33) = 2.5, p = 0.04$ , robust linear regression], and the  
355 higher the number of social touches, the larger the neuronal temporal variability [ $t(1,33) = 2.3,$   
356  $p = 0.03$ , **Supplementary Figure 8**]. Finally, we did not find any significant links between  
357 movement time variability and neuronal response variability [latency dispersion at 85 ms:  $t(33)$   
358  $= -1.8, p = 0.08$ ; amplitude dispersion at 85 ms:  $t(33) = -1.91, p = 0.06$ ]. This raised the  
359 possibility that although both movement time variability and neuronal variability increased with  
360 social touches, the two measures themselves reflected largely separate neuronal process.

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

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

365

366 *Time-dependent structure of the relationships between touchscreen use and neuronal*  
367 *variability*

368

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

376

$$377 \quad Y_{\text{Non-social touches vs. variability relationship strength}} = 9.9 \times e^{\text{Number of non-social touches} \times 0.34}$$

378

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

383

$$384 \quad Y_{\text{Social touches vs. variability relationship strength}}$$

385

$$386 \quad = (11.04 \times e^{-\left(\frac{\text{Number of social touches} + 16.6}{7.47}\right)^2}) + (1.2 \times 10^{15}$$

$$387 \quad \times e^{-\left(\frac{\text{Number of social touches} - 203.6}{36.3}\right)^2})$$



388

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

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399

## 400 **Discussion**

401

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

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

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

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

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

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

452 in social behavior (14, 51). Another possibility is that the touches are sorted in a bottom-up  
453 manner based on distinct sensory features that accompany the social touches. We tested this  
454 possibility by restricting our analysis to pop-keypad touches, only to discover that even when  
455 the gestures were apparently matched, the social touches showed a distinct sensorimotor  
456 correlate. Other relevant but unexplored differences in the input statistics of Social vs. Non-  
457 social Apps may exist in terms of the length of the words typed or the complexity of language  
458 used. Nevertheless, a previous study on typing skills suggested that greater experience was  
459 associated with smaller sensorimotor variability (23). Therefore, the increased variability  
460 associated with social touches cannot be easily explained using the widely held notions on use-  
461 dependent plasticity.

462         Why does sensorimotor variability increase with social touches on the touchscreen? We  
463 propose that the increased variability is an inevitable consequence of repeated engagement of  
464 the thumb in social cognition. Essentially, social touches on the touchscreen are accompanied  
465 by an array of neuronal processes associated with language, anticipation, and social status (13).  
466 Presumably, using Hebbian-like mechanisms of plasticity, the thumb becomes increasingly  
467 connected with this broad array of processes. It is this enhanced embedding of sensorimotor  
468 processing in a broad array of neuronal processes that may lead to increased noise in low-level  
469 circuits (52).

470         In the population of young adults sampled here, the median number of touchscreen  
471 touches generated per day was  $2.7 \times 10^3$  and the most active individual generated  $1.1 \times 10^4$   
472 touches per day. These numbers reflect the dominance of touchscreen events in modern human  
473 actions, comparable in magnitude with the number of steps ( $1 \times 10^4$ ) or eye blinks per day ( $1.2$   
474  $\times 10^4$ ) (53, 54). Therefore, it should not be surprising that the neuronal sensorimotor processing  
475 is reconfigured by touchscreen behavior (16). The nature of the touchscreen behavior-neuronal  
476 relationships uncovered by leveraging seamless quantifications on the smartphone warrants a  
477 more in-depth examination on how social activities on the touchscreen reconfigure the brain.

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

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494 **Materials and Methods**

495

496 *Subjects*

497

498 Volunteers (n = 57) were recruited using campus-wide announcements at the University of  
499 Zurich and ETH Zurich between December 2014 and August 2015. The sample consisted of  
500 subjects within a narrow age group [26 females; 23 (20th percentile) to 28 (80th percentile)  
501 years old]. The age at which the volunteers reportedly began using the phone was also narrowly  
502 distributed [19 (20th percentile) to 25 (80th percentile) years old]. Previous reports on inter-  
503 individual variability in cortical somatosensory signal-to-noise ratio, touchscreen use-  
504 dependent plasticity and use-dependent reduction in sensorimotor variability employed a  
505 sample size between 15 – 28 (16, 18, 23, 55). Essentially we anticipated a weaker impact of the  
506 social touches on the touchscreen than the explanatory variables studied before, i.e., deliberate  
507 laboratory practice, touchscreen use in general and the presence of autism spectrum disorder.  
508 Therefore, we doubled the sample size and employed more regression parameters than the  
509 previous studies to increase the sensitivity of our analysis. All experimental procedures were  
510 conducted according to the Swiss Human Research Act approved by the cantons of Zurich and  
511 Vaud. The procedures also conformed to the Declaration of Helsinki. The volunteers provided  
512 written and informed consent before participating in the study. Reasonable health, right-  
513 handedness, and ownership of a non-shared touchscreen smartphone were pre-requisites for  
514 participation. The handedness was further verified by a questionnaire (55). The fingers used on  
515 the touchscreen were analyzed using a pictorial survey where the volunteers ranked each finger  
516 on a scale 1–10 (1, least preferred; 10, most preferred).

517

518 *Smartphone data collection and analysis*

519

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

539

540

541 *Simple reaction time task and analysis*

542

543 Volunteers responded to a brief (10 ms) tactile pulse by depressing and releasing a button  
544 mounted on a micro switch. The tactile pulse was presented by using a computer-controlled  
545 solenoid tactile stimulator (Heijo Research Electronics, London, UK). The stimulating  
546 magnetic rod (2 mm in diameter) generated a supra-threshold 2-mN contact. The thumb or the  
547 middle finger was stimulated. The micro switch (extracted from RX-300 optical mouse,  
548 Logitech, Lausanne, Switzerland) was operated by press-downwards and release-upwards  
549 movements of the thumb or the middle finger. All volunteers performed the task with the thumb  
550 (n = 57) and a subset of randomly chosen volunteers performed the task with the middle finger  
551 in addition to the thumb (n = 17).

552         The task was repeated 500 times (for each fingertip) within an experimental session,  
553 with 2 min break in the middle of the session. The pulses were delivered with  $3 \pm 1$  s gap and  
554 the button presses generated analogue signals that were digitized at 1 kHz. In two volunteers,  
555 the micro switch off-state measurements malfunctioned; in one other volunteer, the on-state  
556 measurements malfunctioned. The corresponding measurements were subsequently eliminated  
557 from further analysis. The reaction time and movement time (the time taken to execute button  
558 depression) were fitted with three ex-Gaussian parameters. This form of fitting separates  
559 skewed reaction time data into a Gaussian region and an exponential region. Mean of the  
560 Gaussian region was captured by parameter  $\mu$ , and variability of the Gaussian region by  
561 parameter  $\sigma$ . The exponent  $\tau$  captured unusually slow responses. The parameters were estimated  
562 using previously described MATLAB scripts (36).

563

564 *EEG data acquisition and analysis*

565

566 A subset of volunteers (n = 43) participated in EEG experiments. The volunteers were seated



567 upright for the EEG and the right, stimulated, hand was concealed by a baffle. Computer-  
568 controlled solenoid tactile stimulator (see above) was attached to the right thumb tip and to the  
569 right index and middle finger tips. To ease the tedium of the hours-long measurements required  
570 for gathering the tactile evoked potentials data (SSEPs), volunteers were allowed to view a  
571 movie (David Attenborough's Africa series); white noise, played to mask the sound generated  
572 by the stimulator, was mixed with the movie soundtrack and delivered through headphones.  
573 The number of trials was set to 1000 for each fingertip, randomized for the tips, and the stimuli  
574 were separated for each fingertip by 2–4 s. A non-alcoholic and caffeine-free drink break was  
575 offered every 10 min, for a maximum of 10 min. To record the EEG signals, 64 electrodes were  
576 used (62 equidistant scalp electrodes and two ocular ones), against a vertex reference (EasyCap,  
577 Herrsching, Germany), as previously reported (16). The electrode locations were digitized in a  
578 3D nasion-ear coordinate frame (ANT Neuro and Xensor software, Netherlands) for a  
579 representative volunteer. The signals were recorded and digitized by BrainAmp (Brain Products  
580 GmbH, Gilching, Germany) at 1 kHz. Offline data processing was accomplished using  
581 EEGLAB, a toolbox designed for EEG analysis on MATLAB (56). The data were referenced  
582 to the average of all scalp electrodes and band-pass filtered between 1 and 80 Hz. "Epoched"  
583 trials over 80  $\mu$ V were eliminated to remove large signal fluctuations, e.g., from eye blinks. The  
584 data were further processed using independent component analysis. Components dominated by  
585 eye movements and other measurement artifacts were eliminated by using the EEGLAB plug-  
586 in SASICA (57). The signal-to-noise ratio was estimated using the linear modeling toolbox  
587 LIMO EEG (EEGLAB plug-in) (58). In this toolbox,  $R^2$  values were estimated for each  
588 volunteer based on single trials, as a sum of squares of the putative signal divided by the sum  
589 of squares of the residuals. Essentially, the predominant notion in the sensory evoked potential  
590 research field is that the average over multiple trials extracts a signal that is otherwise hidden  
591 in the measurement noise and background neuronal processes (39). The signal-to-noise ratio in  
592 this case captures how well the estimated mean (putative signal) represents the data. To

593 normalize the data across the sampled population, the square root of the putative signal-to-noise  
594 ratio was used for subsequent analyses using multiple linear regression.

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

602

### 603 *Correlational statistics*

604

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

609

$$\begin{aligned} 610 \quad Y = & \beta_0 + \beta_1 X_{\text{Touches on Non-social Apps}} + \beta_2 X_{\text{Touches on Social Apps}} \\ 611 & + \beta_3 X_{\text{Touches on Uncategorized Apps}} + \beta_4 X_{\text{Rate of touchscreen touches}} \\ 612 & + \beta_5 X_{\text{Number of Apps on the touchscreen}} + \beta_6 X_{\text{Gender (female=1)}} \end{aligned}$$

613

614 Where  $Y$  took the form of  $Y_{\text{Movement time variability}}$  or  $Y_{\text{Reaction time variability}}$ , or  
615  $Y_{\text{Somatosensory putative signal-to-noise ratio}}$ . For  $Y_{\text{Coefficient of dispersion in peak latency}}$  and  
616  $Y_{\text{Coefficient of dispersion in peak amplitude}}$ , the explanatory variable  $\beta_7 X_{\text{Movement time variability}}$   
617 was added to the original equation.  $\beta_{1 \text{ to } n}$  comprised regression coefficients estimated by robust

618 regression, and  $\beta_0$  the intercept. The explanatory variables quantifying the touchscreen behavior  
619 were based on 21 d of recording made prior to the laboratory measures.

620 To analyze the time-dependent structure of regression parameters associated with the  
621 number of touchscreen touches, we used the following approach. The parameters  
622  $X_{Touches\ on\ Non-social\ Apps}$ ,  $X_{Touches\ on\ Social\ Apps}$ , and  $X_{Touches\ on\ Uncategorized\ Apps}$  were re-  
623 estimated over the span of 21 d with 12-h steps and 72-h windows. Other parameters were  
624 unchanged and, as in the main regression equation, were based on the data spanning the entire  
625 21-d period. To describe the time-dependent fluctuation of F-values, the relationship was  
626 iteratively fitted by comparing linear, exponential, and Gaussian equations with a maximum of  
627 three terms. The fit with the highest  $R^2$  was used to describe the relationships.

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

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

638 Plots for displaying multiple linear regression results in two dimensions (adjusted  
639 response plots) were generated using a built-in MATLAB function (`plotAdjustedResponse`).  
640 Formulation of this plotting method and its advantages are described elsewhere (59).

641 The EEG data were correlated with touchscreen parameters using robust regression,  
642 iterative least squares method (implemented in LIMO EEG). The correlation coefficients were  
643 estimated across all electrodes and for the time period from -30 to 200 ms relative to the

644 stimulation onset. When focusing the analysis on keypad use, due to the smaller number of  
645 samples, the variables were restricted to parameters  $X_{Rate}$ ,  $X_{Number\ of\ touches\ on\ Social\ Apps}$ , and  
646  $X_{Number\ of\ touches\ on\ Non-social\ Apps}$ . The regression statistics were corrected for multiple  
647 comparisons by using 1000 bootstraps and spatiotemporal clustering, as implemented in LIMO  
648 EEG.  
649

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651

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796 **Figure Legends**

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807 recordings in 12 h steps (72 h bin) revealed that the relationship involving non-social touches  
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809 a more complex pattern. The statistical tests and the details of the fits are reported in the main  
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811

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

830 **Figure 3.** The trial-to-trial variability in the degree of cortical responses is proportional to  
831 Social App usage. **(a–c)** Depiction of the analysis method to separately estimate the trial-to-  
832 trial variability in the cortical signal latency and the amplitude. **(a)** Rectified event related  
833 potentials based on a random sample of 25 trials was generated  $10^5$  times. The rectified potential  
834 based on all the trials in one volunteer is drawn in grey. The first local maxima encountered on  
835  $10^3$  iterated potentials after the set temporal landmarks of 50 and 85 ms are indicated (colored  
836 dots). The distribution of latencies **(b)** and amplitudes **(c)** of the first maxima in the same  
837 volunteer based on which the corresponding coefficient of dispersion (CD) was estimated. **(d-**  
838 **e)** Adjusted response plots. **(d)** The greater the number of social touches in the 21-d recording  
839 period, the larger the variability in signal amplitudes at the 85 ms landmark (measured in terms  
840 of CD). **(e)** The relationship between the number of non-social touches and the variability was  
841 not significant. **(f)** Parsing the touchscreen recordings in 12 h steps (72 h bin) revealed that the  
842 relationship for non-social touches simply decayed with older touchscreen data and a more  
843 complex pattern was apparent for the social touches.

#### 844 **Supplementary Information Index**

845

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

847

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

850

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

853

854 Supplementary Figure 2: The social touches do not reflect on movement time variability when  
855 the task is performed with the middle finger. (a) Adjusted response plot showing the link

856 between the number of social touches generated on the touchscreen and the movement-time  
857 variability when the task was performed by using the thumb. Specifically, higher the number  
858 of social touches the higher the movement time variability (b) When the same volunteers  
859 performed the task with the middle finger the relationship was absent.

860

861 Supplementary Figure 3: Social touches on the keypad is related to movement time variability.  
862 (a-b) Adjusted response plots. (a) Higher the number of social touches on the touchscreen pop-  
863 up keypad the higher the movement time variability. (b) The non-social touches on the keypad  
864 were not related to the variability.

865

866 Supplementary Figure 4: Analysis of explanatory variables other than the number of social and  
867 non-social touches. (a-b) Adjusted response plots. (a) The link between the typical rate of  
868 touchscreen usage and movement time variability and (b) the number of Apps used and the  
869 variability. (c) The analysis of the relationships to movement time variability after parsing the  
870 touchscreen recordings in 12 h steps (72 h bin).

871

872 Supplementary Figure 5: The reaction time variability is related to the number of social touches.  
873 (a) Adjusted response plot displaying that higher the number of social touches the larger was  
874 the reaction time variability. (b) The non-social touches were unrelated to the reaction time  
875 variability. (c) The relationship discovered for the social touches was well apart from the  
876 distribution of relationships obtained by using randomly shuffled categories.

877

878 Supplementary Figure 6: The links between somatosensory cortical signal-to-noise ratio and  
879 the touchscreen-based explanatory variables. (a) Multiple regression analysis was conducted to  
880 explain the inter-individual variability in response to tactile stimulation at the thumb. The  
881 regression coefficients for the signal-to-noise ratio measured at the electrode with the strongest

882 response. The sold lines depict  $p < 0.05$  (corrected for multiple comparisons, ANOVA). (b-e)  
883 Head plot of the regression coefficients and the corresponding statistics. (f-g) The relationships  
884 for the number of non-social touches and the typical rate on the touchscreen were the strongest  
885 for the thumb followed by the index and then the middle finger.

886

887 Supplementary Figure 7: The neuronal correlates of the number of social touches on the  
888 touchscreen keypad. When we restricted our analysis to the pop-up keypad touches, we found  
889 that higher the number of social touches on the keypad smaller the signal-to-noise ratio as in  
890 the original analysis including all types of touchscreen events. The legend is identical to Figure  
891 2 panels a-f.

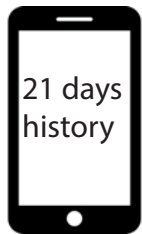
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893 Supplementary Figure 8: The neuronal variability determined from the early temporal landmark  
894 set at 50 ms was unrelated to the number of touches. (a-d) Data by using the 50 ms temporal  
895 landmark. Adjusted response plots showing the non-significant regressions between social or  
896 non-social touches and neuronal variability in terms of amplitude or latency. (e,f) Latency data  
897 by using the 85 ms temporal landmark shows a weak relationship between social touches (and  
898 not for non-social touches) and trial-to-trial temporal variability.

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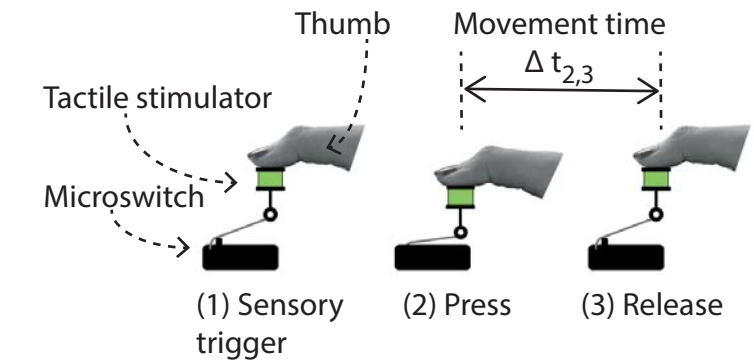
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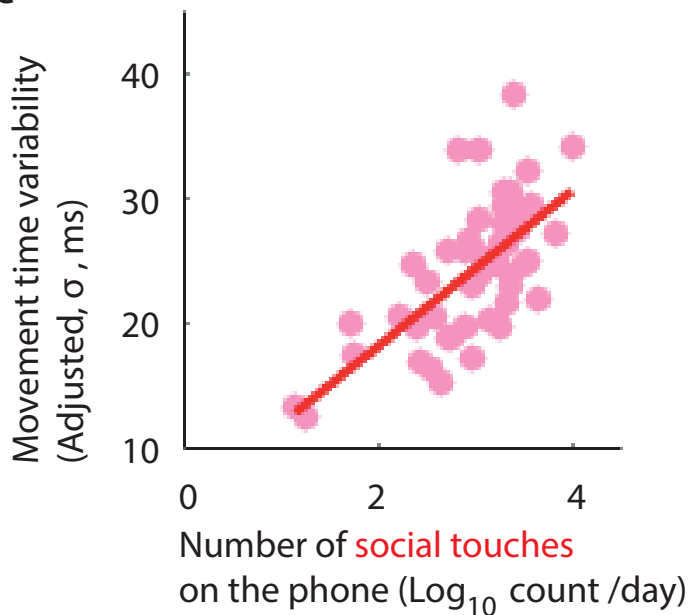
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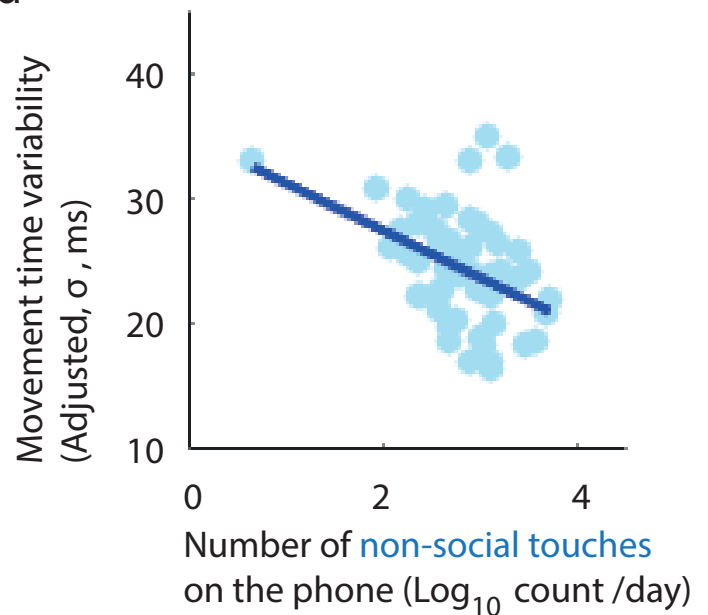
**Social:** Twitter, Facebook, WhatsApp etc.  
**Non-social:** AccuWeather, Dictionary etc.



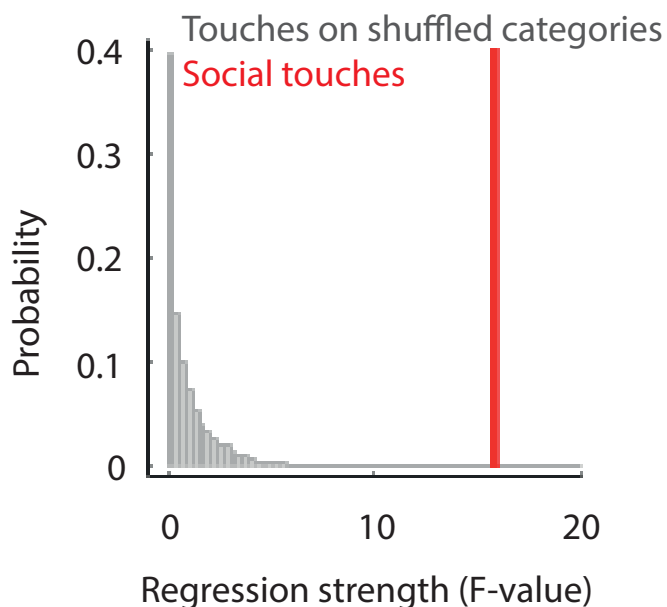
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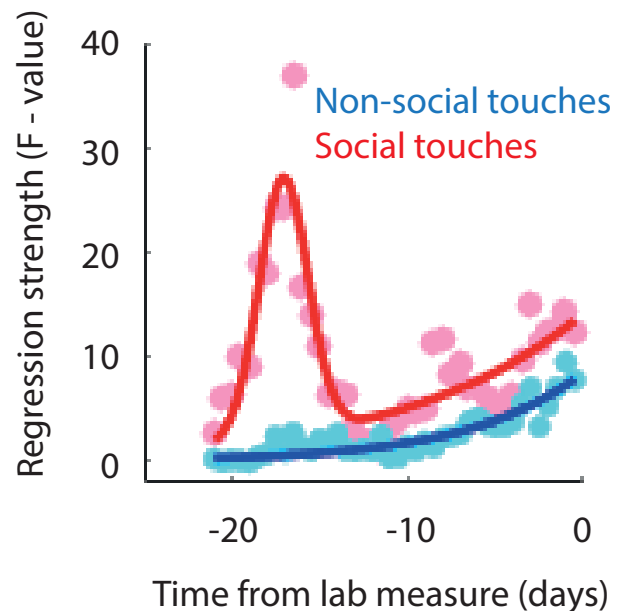
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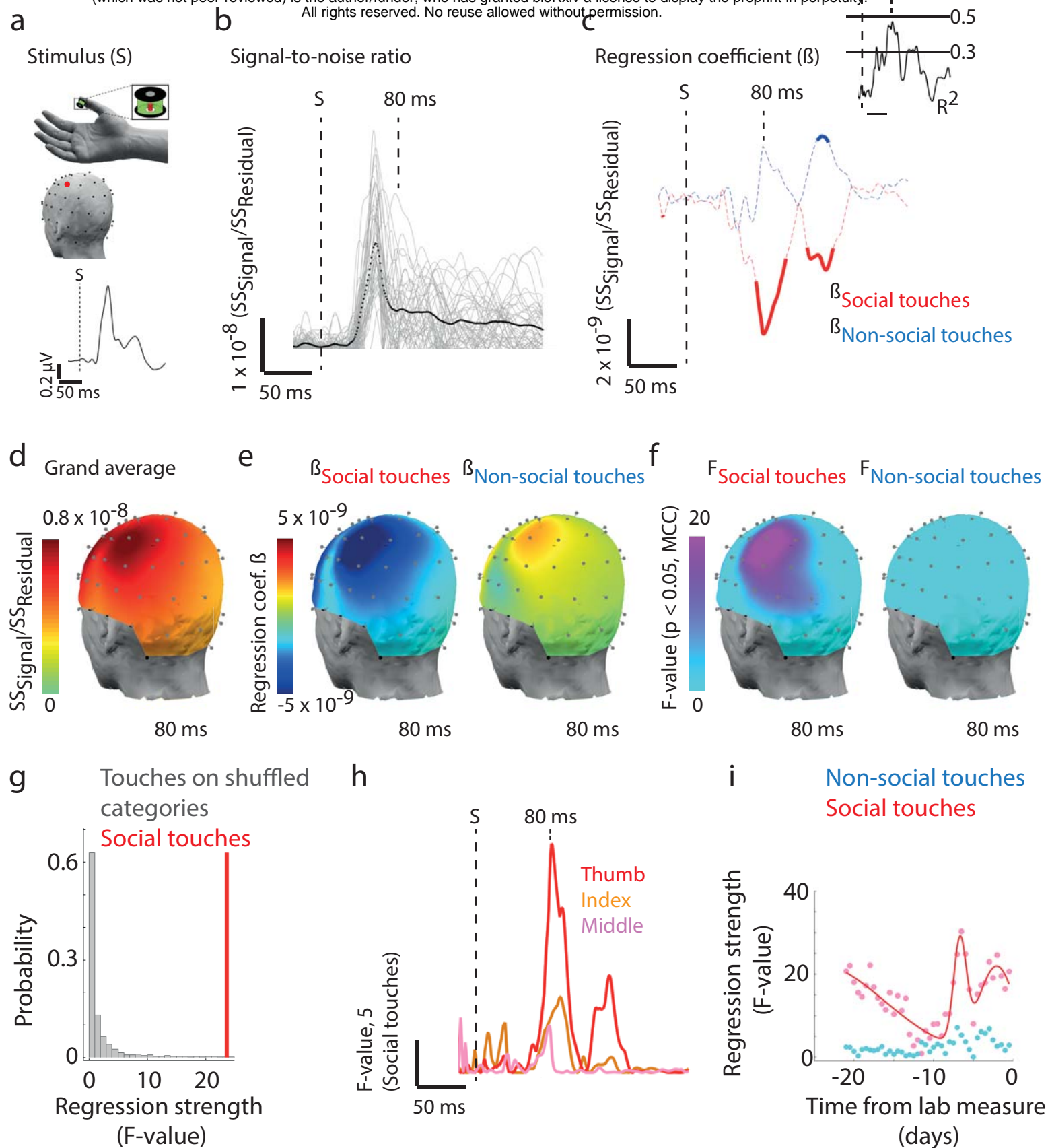
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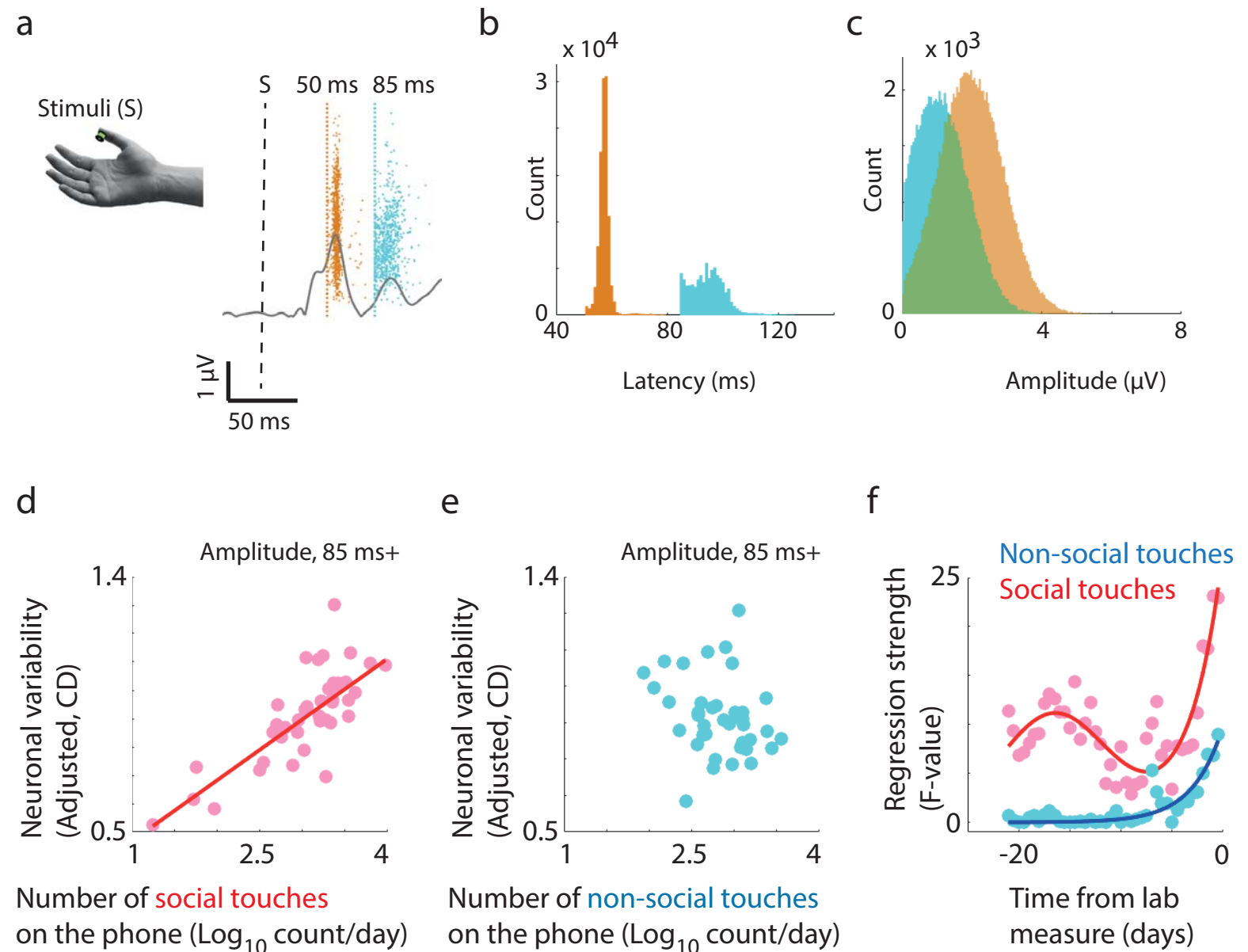
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