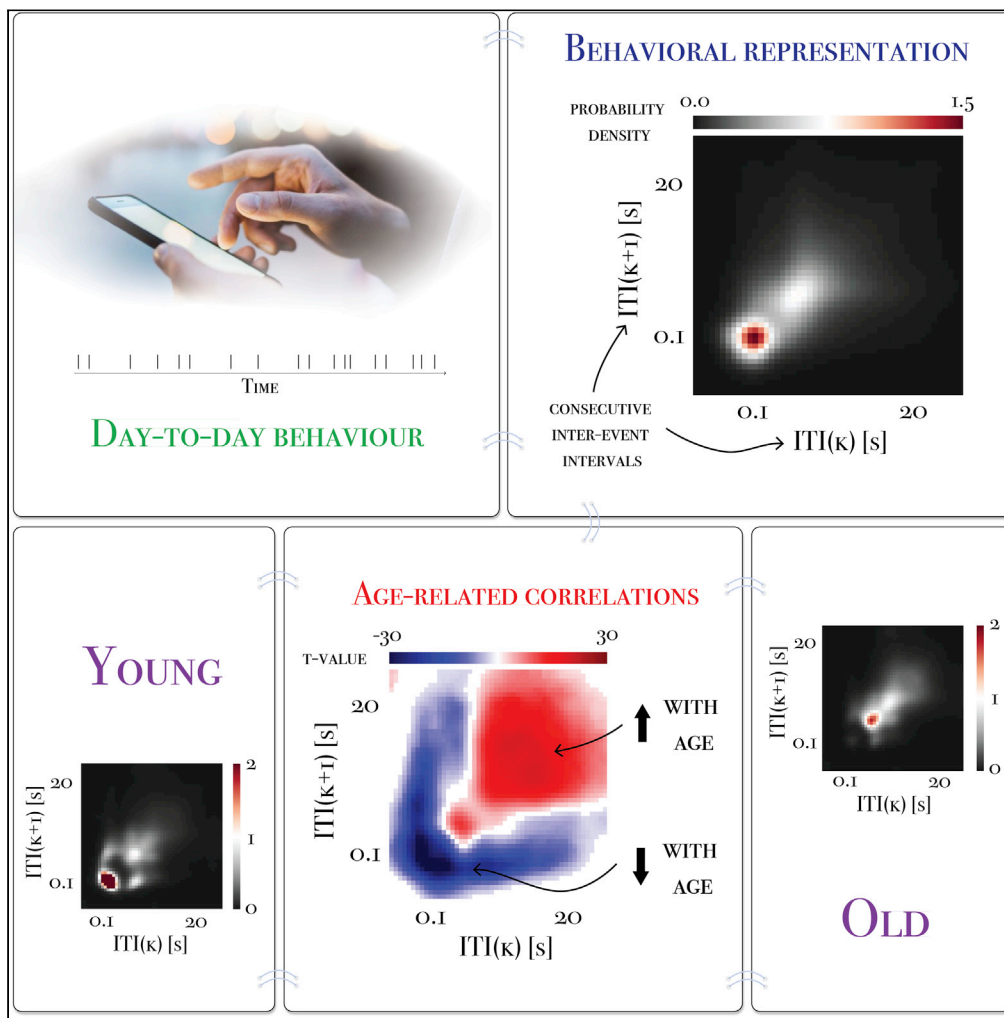# iScience

Article

Temporal clusters of age-related behavioral alterations captured in smartphone touchscreen interactions

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Guido P.H. Band,
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Arko Ghosh

a.ghosh@fsw.leidenuniv.nl

Highlights

The timing of smartphone touchscreen interactions varies from one person to the next

A diverse range of interactions was studied by quantifying the next interval dynamics

The smartphone dynamics reflected the performance in cognitive tests and age

The way aging shapes behavior may depend on its underlying temporal dynamics

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Temporal clusters of age-related behavioral alterations captured in smartphone touchscreen interactions

Enea Ceolini,[1] Ruchella Kock,[1] Guido P.H. Band,[1] Gijsbert Stoet,[2] and Arko Ghosh[1,3,*]

SUMMARY

Smartphones touchscreen interactions may help resolve if and how real-world behavioral dynamics are shaped by aging. Here, in a sample spanning the adult life span (16 to 86 years, N = 598, accumulating 355 million interactions), we clustered the smartphone interactions according to their next inter-touch interval dynamics. There were age-related behavioral losses at the clusters occupying short intervals ($\sim$100 ms, $R^2 \sim 0.8$) but gains at the long intervals ($\sim$4 s, $R^2 \sim 0.4$). Our approach revealed a sophisticated form of behavioral aging where individuals simultaneously demonstrated accelerated aging in one behavioral cluster versus a deceleration in another. Contrary to the common notion of a simple behavioral decline with age based on conventional cognitive tests, we show that the nature of aging systematically varies according to the underlying dynamics. Of all the imaginable factors determining smartphone interactions, age-sensitive cognitive and behavioral processes may dominatingly shape smartphone dynamics.

INTRODUCTION

Quantifying real-world behavior across the adult life span may help unravel the impactful nature of aging and is key to discovering the underlying mechanisms. The gross impact of aging on behavior is widely studied by using self-reports and physical-activity sensors, and they reveal difficulties in the execution of daily behavior and mobility in the elderly (Burns, 1999; Chen et al., 2019; Gale et al., 2015; Lawton, 1971; Taraldsen et al., 2012). Real-world behavioral outputs may contain surprisingly informative indicators of aging, such as specific linguistic skills expressed in personal diaries early in life that are correlated to healthy cognition later in life (Iacono et al., 2009). Detailed behavioral measurements in the real world may be particularly useful in understanding the interactions between distinct cognitive processes. Indeed, in the naturalistic behavior of typing, the compensatory interplay between hand and eye movements has been observed with aging and this interplay is thought to help maintain typing speed through an otherwise declining motor system (Salthouse, 1984). Such observations raise the possibility that the impact of aging on real-world behavior may be systematically coordinated—where some types of performance decline while others remain unaffected or even improve, whether this happens under the influence of changing ability or motivation (Heckhausen et al., 2019; Korniotis and Kumar, 2011; Veríssimo et al., 2021). However, addressing this possibility in the real world is challenging due to its complex and unclear behavioral structures.

There is emerging evidence that the time series of smartphone touchscreen interactions (tappigraphy) can be used to proxy specific cognitive processes in the real world despite the various ways in which people opt to use their devices—from the distinct body and finger postures to the underlying differences in the motivation for phone use. Tappigraphy contains information on circadian processes, sensorimotor processes, and reward pathways (Balerna and Ghosh, 2018; Borger et al., 2019; Gindrat et al., 2015; Huber and Ghosh, 2021; Westbrook et al., 2021). The speed of keystrokes on the smartphone declines with age (Vesel et al., 2020). In these recent efforts using tappigraphy, smartphone interaction intervals are simply accumulated and highly reduced before correlating with variables of interest such as age. For instance, the tapping speed may be estimated by using the 25th percentile of the accumulated inter-touch intervals. Still, such approaches do not leverage the rich behavioral diversity of the smartphone.

How can the rich smartphone behaviors be separately considered to study aging? One analytical approach—borrowing from ethology—entails capturing the diversity using a detailed categorization of

[1]Cognitive Psychology Unit, Institute of Psychology, Leiden University, Wassenaarseweg 52, Leiden 2333 AK, the Netherlands

[2]Department of Psychology, University of Essex, Colchester, UK

[3]Lead contact

*Correspondence:
a.ghosh@fsw.leidenuniv.nl

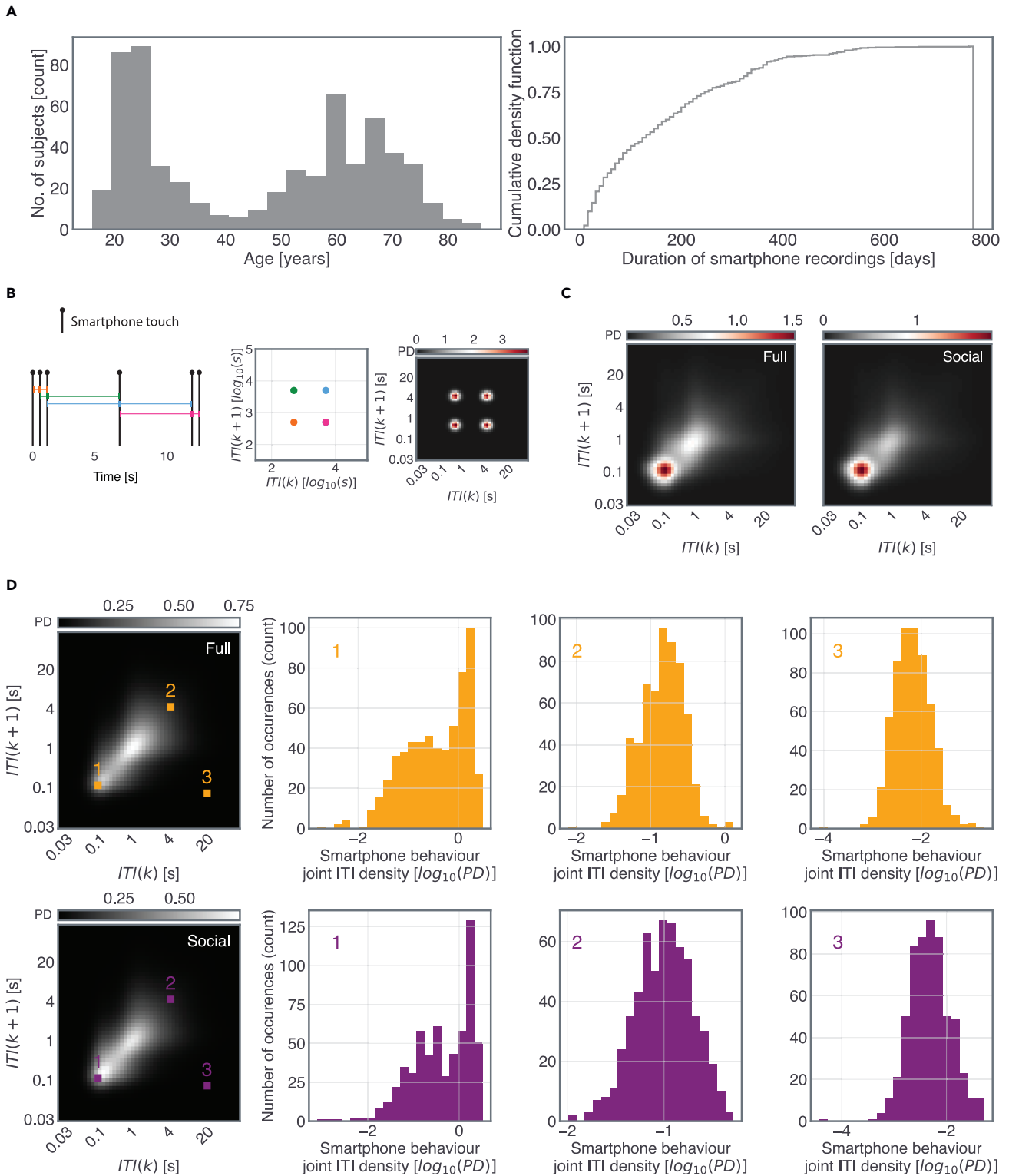https://doi.org/10.1016/j.isci.2022.104791

Figure 1. Heterogeneous behavioral dynamics captured using the distribution of inter-touch intervals (ITIs) on the smartphone touchscreen

(A) The sample studied here spanned between 16 to 86 years of age. The smartphone recording durations spanned between 7 to 775 days.

(B) We quantified smartphone behavior using the probability density of joint-interval distribution in two-dimensional bins. An example of the probability density resulting from a series of 6 simulated interactions.

Figure 1. _Continued_

(C) Example joint-interval distributions based on all smartphone interactions (Full), and social networking and browser apps only (Social) accumulated within smartphone usage sessions spanning 166 days in one individual.

(D) The population-based mean probability densities and for chosen joint-interval bins (yellow and magenta markers) the corresponding inter-individual differences are shown in histograms.

actions. However, despite its appeal, there are several barriers to applying this approach to smartphone behavior. Firstly, how the categories should be formed is not clear. In ethology, the categories are driven by their biological significance such as courtship vs. aggression in insects (Anderson and Perona, 2014). In the absence of such biological relevance, smartphone interactions may be only categorized using intuitive classes such as typing on the keyboard vs. swiping on the browser. Furthermore, such arbitrary classes may unwittingly discard age-informative features. Secondly, the intuitive smartphone behavioral categories may be broad—as in smartphone touchscreen interaction—or narrow—as in typing with spelling errors on a particular social app, and the level of detail needed to study aging is not clear. Thirdly, the data necessary for the detailed categorization may be simply unavailable. For instance, the users may not be willing to share the details of all of their activities and even if they did there may be substantial observation-induced measurement biases. The emerging study of human dynamics offers an alternative approach that is less reliant on detailed categorized behaviors and instead leverages the timing of discrete behavioral events. For instance, the distribution of inter-event times of email correspondences (rather than the email length or content) derived from the servers can be used to model the underlying behavioral processes (Barabási, 2005; Malmgren et al., 2008). Such focus on event timings has been deployed to capture and model the dynamics in mail correspondences, phone calls, printing, library loans, and the broad number of activities conducted online (Pfister and Ghosh, 2020; Vázquez et al., 2006)[for example, in animals see dwelling intervals in rodents (Proekt et al., 2012)]. This approach focused on the behavioral event timings may be used to unravel fundamental patterns of smartphone interactions and isolate the temporal features that alter with age.

For dynamical data containing discrete events (such as a smartphone interaction), the distribution of subsequent intervals is commonly used. The analysis of next-interval dynamics—where any interval say k is quantified in conjunction with the next interval $k+1$—is well established to quantify cardiac and neural properties (Brennan et al., 2001; Rodieck et al., 1962). In cardiac data analysis for instance, "Poincare plots" containing next interval dynamics are used in combination with linear data reductions such as in an elliptical fit linking k and $k+1$ and the corresponding standard deviations (Brennan et al., 2001). However, such a linear reduction of the next-interval dynamics is unreasonable for smartphone behavior given its well-established non-linearities (Pfister and Ghosh, 2020). Furthermore, in smartphone behavior, there may be age-informative activities outside of Poincare diagonal—for instance when transitioning from a slow to a fast behavior. Therefore, we recently introduced the use of joint-interval distribution (JID, Figure 1) to quantify the time series of smartphone touchscreen events such that the diverse behaviors are clustered according to the next-interval temporal dynamics (Duckrow et al., 2021). These distributions only consider the intervals accumulated within a usage session (so while the screen is on, and do not consider the long intervals stemming from inter-session intervals). Here, the distributions are further binned in 50 logarithmic steps spanning 30 ms to 2 min, resulting in a probability density estimation of the smartphone behavior across the time range. The result is a 2500 large feature space where each two-dimensional bin or "pixel" (feature) contains the probability density of the corresponding next-interval dynamics accumulated over the recording period. In theory, this probably density distribution is not trivially impacted by the amount of smartphone usage, i.e., any two individuals with a very different number of interactions may arrive at the same JID reflecting the similarity in the underlying behavioral dynamics. This then allows us to compare the dynamics between individuals regardless of the amount of smartphone usage, as it may be that in advanced age the smartphone is used less. Moreover, this analytical framework avoids the forced linear reduction of the complex data as commonly used in the analysis using Poincare plots, and still maintains the interpretability of the features. For instance, the short inter-touch intervals preceded by similarly short intervals—indicating rapid actions—can be separately considered from the short intervals preceded by long intervals—indicating switching between behaviors with distinct temporal dynamics. It is likely that the rapid behaviors are driven by fundamentally different cognitive processes than the slow behaviors, and a distinct set of processes underlies switching between behaviors (Kahneman, 2011; Uddin, 2021).

Given that the behavioral dynamics on the smartphone can be captured at the level of each individual using the JID, next we shall consider how to link the inter-individual differences in the JID to chronological age.

We anticipate inter-individual differences in the JID accumulated over the entire recording period. Each two-dimensional bin (pixel) of the JID may be distinctly correlated to chronological age, and there is no *a priori* reason to consider only one of the 2500 pixels. This is akin to the neuroimaging parametric statistical analysis where each brain location (or other features such as signal latency or signal frequency) of an fMRI dataset (or EEG) may be distinctly related to a parameter of interest evoking the need for multiple comparison corrections following the mass univariate regressions. The common and theoretically well-established general linear modeling can be followed by multiple comparisons correction by using two-dimensional clustering and bootstraps (Pernet et al., 2011; Poline et al., 1997). An assumption underlying the statistical clustering is that the neighboring times, frequencies, or spatial locations are similar due to the underlying fundamental structures. Extending this assumption to the behavioral JID allows us to directly adapt the statistical tools common to neuroimaging toward the touchscreen interaction dynamics. Therefore, by combining event-based approaches from human dynamics, the analysis of next-interval dynamics and parametric general linear modeling, it is possible to systematically address the nature of age-related behavioral correlates captured in the rich time-series of smartphone interactions.

Capturing the human dynamics via smartphone interactions may provide a better understanding of aging than currently possible using conventional cognitive tests. Cognitive tests such as reaction time tests seek to evaluate specific cognitive processes and are routinely deployed to capture age-related decline but they only offer limited insights into real-world behavior. First, the tests may be too detached from how cognitive processes are deployed in real-world behavior (Kliegel et al., 2007; Slegers et al., 2009). For instance, age-related performance decline in the Tower-of-London planning task does not translate to the more ecological Plan-a-Day task (Phillips et al., 2006). Second, many tests—in particular those focused on processing speed—are evaluated in terms of the time taken to perform the task but such emphasis on speed may be present only in a small fraction of real-world behavior. It is notable that in the designed tasks the elderly may be intrinsically inclined to emphasize accuracy at the cost of speed (Band and Kok, 2000). In the context of our analytical framework based on the next intervals on the smartphone, these tasks examine a very narrow temporal segment as in tasks that typically take <1 s to complete. Here, we seek to address: what are the real-world behavioral correlates of cognitive tests? Do behaviors with distinct dynamics—occupying distinct time scales—differently reflect the cognitive tests? Does age similarly impact behaviors with distinct temporal dynamics or does the nature of the behavioral change depend on the underlying dynamics?

To address the above questions, we focused on the inter-individual differences in smartphone touchscreen interactions. We captured the timestamps of all smartphone touchscreen events—as in when it was touched by the user in a screen-unlocked state. We clustered the interactions of each individual according to their next-interval temporal dynamics in two-dimensional bins as described above. Toward addressing the implications of the processes captured in cognitive tests for real-world behavior, we correlated the inter-individual differences of the JID to cognitive tasks specifically sensitive to sensorimotor processes (visual reaction time), executive functions (task switching), and working memory (Corsi block and 2-back tasks) using mass univariate regressions (Pernet et al., 2011). Notably, the age-related decline of these tasks—albeit at varying degrees—has been previously documented with outstanding declines in the choice reaction time and task switching (Beigneux et al., 2007; Deary and Der, 2005; Der and Deary, 2006; Salthouse et al., 2003; Wasylyshyn et al., 2011). Next, by correlating the interindividual differences in JID to chronological age, we find temporal clusters of age-related smartphone behavioral correlates such that the correlation strength varies according to the underlying behavioral dynamics. Additionally, the residuals stemming from such regressions can be used to infer accelerated or decelerated aging (Beydoun et al., 2020; Wolf et al., 2018). Using this approach, we establish that the same individuals who show accelerated aging in one behavioral cluster can show decelerated aging in another cluster. In our analysis, we considered all smartphone touchscreen interactions and also two sub-categories of the behavior—when engaged in social networking & browser apps available on the Google play store (henceforth referred to as "Social") and by focusing on the interactions accumulated when transitioning from one app to the next (henceforth referred to as "Transition"). The latter sub-categories helped us address if the patterns were also visible in more selective smartphone behavioral data.

RESULTS

Overview of the sampled population

This study involved 598 smartphone users. Here, we shall provide a brief overview of the study sample (for graphical representation Figure S1). The sample was bimodally distributed with modes at 25 and 63 years
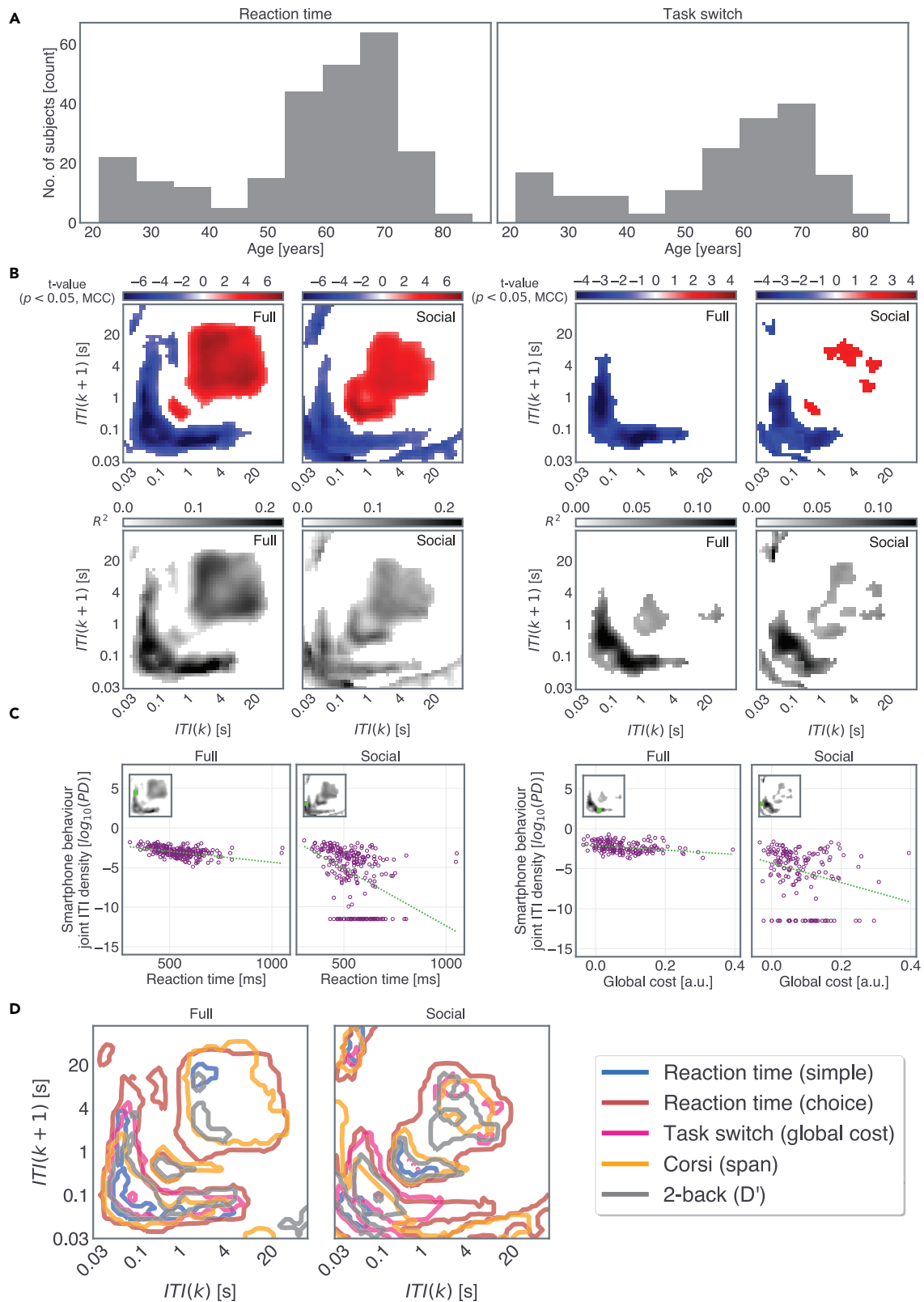
Figure 2. Cognitive tests reflect on specific behavioral dynamics

(A) The distribution of age of the participants who performed the choice reaction time and task-switching tests (for the distribution of age corresponding to the other tasks see Figure S3).

(B) We performed iterative least-square linear regressions at each two-dimensional bin with cognitive test performance and gender as explanatory variables. The *t*-statistics corresponding to the two tests (left, choice reaction time, and right, global cost estimate on the task switch) are shown in the blue-red color scale when using all smartphone interactions (*Full*) and when using the interactions on social networking apps & browsers (*Social*). The corresponding R^2 of the full regression model.

(C) Adjusted response plots to visualize the linear relationships composing the *t*-value representations, with the variables gathered from a single two-dimensional bin.

(D) Contours of the joint inter-touch interval distributions show significant relationships to the different cognitive tests. The contour lines were thresholded at *f* = 4 for the statistically significant clusters that survived multiple comparison corrections. Note that the task-switch local costs did not show any significant correlations. All statistics were corrected for multiple comparisons using two-dimensional clustering (1000 bootstraps, α = 0.05).

of age. The sample was biased toward females (62.5% females). The exact geographical coordinates of the users were not recorded for this study, but based on the recruitment strategy and payment requirements it is safe to assume that almost all of the participants were located in The Netherlands. The participants showed substantial variation in their smartphone descriptors, as in the years of usage, numbers of interactions per day, fingers used on the screen, and the size of the screen itself (Figure S1).

Distribution of smartphone intervals and the behavioral correlates of cognitive tests

We used joint-interval distributions (JIDs) to quantify the probability densities of smartphone behavior at distinct time scales based on all interactions that accumulate within smartphone usage sessions (*Full*, Figure 1). In addition, we separately considered the interactions on apps used for social networking and the browser (*Social*, Figure 1). For JID based on intervals involving a switch from one app to the next, see Figure S2 (indicated as *Transition*). According to grand averages of the "*Full*" and "*Social*" distributions, the behavior was dominated by short consecutive intervals and by intervals with similar consecutive durations as indicated by the higher probabilities at the corner and the diagonal of the JIDs, respectively (the inter-transition intervals were distinctly dominated by long followed by short intervals). Notably, even in the two-dimensional bins with high probabilities, there was substantial inter-individual difference allowing us to relate these variances to the performance in cognitive tests conducted on a PC.

Mass univariate regressions between the cognitive test and each of the two-dimensional bins of the JID were performed to reveal the real-world behavioral correlates of the cognitive tests (Figure 2, see Figure S3 for the age distribution of the participants who were tested on the 2-back and Corsi block tests). The JID smartphone behavior accumulated within ±10 days of the test being used. For the *Full* JID, the choice reaction time was moderately correlated to a range of smartphone behaviors involving short intervals consecutive to the longer intervals. The slower the reaction time, the lower the probability densities at the short intervals and the higher were densities at the long intervals. A similar pattern was visible for the *Social* JID (and *Transition* JID, see Figure S4). The behavioral correlates for the simple reaction time were weak and mostly constrained in the JID locations occupied by short intervals irrespective of the temporal context, such that the slower the reaction time, the lower the probability densities at the edges of the JID (Figure S5). In addition, we found weak correlations for the global cost on the task-switching task for the *Full* and *Social* JIDs (Figure 2, for Transition JID, see Figure S6). No correlations were found for the local cost determined by using the same task. Clusters of behavioral correlates were found for the 2-back tasks such that the higher the sensitivity (*d'*), the higher the probability densities of consecutive short intervals and the lower the densities at the longer intervals (Figure S7). Stronger correlates were captured for the span of the Corsi block memory task (Figure S8). Overlaying the JID correlation contours of the cognitive tests revealed the differences in the behavioral clusters dominated by the distinct correlates of cognitive tests (Figure 2).

In sum, all cognitive test outcomes but the local costs on the task-switching test were reflected in the smartphone behavioral distributions. The pattern of the correlations was similar across the distinct forms of JID, but the transition JID showed a weaker spread of correlations. Relative to the other tests, choice reaction time distinctly reflected on a broad range of intervals—spanning from consecutive short intervals to consecutive long intervals and in terms of correlation strength. While multiple tests reflected on the probability densities of consecutive short intervals, only choice reaction time and Corsi block span consistently dominated the long intervals.

Age-related smartphone behavioral distributions

We addressed the links between age and the highly reduced measures of smartphone behavior—usage and entropy based on the JIDs from the entire recording duration; before we describe the correlations against the JIDs' two dimensional bins. The amount of smartphone usage, quantified as median number of touchscreen interactions decreased with age (β_{age} = −0.009; $t(595)$ = −14.07; p = 4.89 × 10^{-39}, $\beta_{gender\ (1==male,\ 2\ ==\ female)}$ = 0.137; $t(595)$ = 5.12; p = 4.14 × 10^{-07}, full model R^2 = 0.28; $F(2, 595)$ = 113.98; p = 1.24 × 10^{-42}, based on robust multiple regression including gender, Figure S9).

We quantified the behavioral diversity using the entropy of the JIDs (i.e., the higher the entropy, the more diverse the behavior). Intuitively, the entropy measures the organizational structure of the JID. For instance, if a user were to exclusively generate fast-consecutive intervals then the entropy would be lower than for a user who occupies a broad range of intervals (say generating slow and fast consecutive intervals, see Figure S10 for exampled JIDs at various levels of entropy). Interestingly, the entropy of the JID marginally declined with age (*Full JID*, β_{age} = −0.001; $t(595)$ = −2.45; p = 0.014, full model R^2 = 0.08; $F(2,595)$; p = 7.41 × 10^{-12}, based on robust multiple regression including gender, Figure S10). Interestingly, this measure showed strong gender differences with males showing more diverse behaviors than females ($\beta_{gender(1==male,\ 2\ ==\ female)}$ = - 0.11; $t(595)$ = −5.98; p = 3.78 × 10^{-9}).

A broad range of the two-dimensional bins of both the *Full* and *Social* JIDs was strongly correlated to age according to the mass univariate analysis linking each JID bin to chronological age and gender (Figure 3, for *Transition* JIDs, see Figure S11). The probability densities of the short inter-touch intervals were diminished with age whereas longer intervals showed higher probability densities. The correlations were the strongest for the consecutive short intervals and there was a gradual decline in the strength of the correlations as the surrounding intervals became longer (correlation at the bin with max R^2 on *Full* JID, β_{age} = −0.038; $t(595)$ = −35.71; p ≈ 0, full model R^2 = 0.77; $F(2, 595)$ = 639.3; p ≈ 0, based on robust multiple regression including gender, at a cluster, surviving 2D multiple comparisons correction, scattered in Figure 3). The *Full* and *Social* JIDs also showed relatively marginal gender differences such that the consecutive short-interval probability densities were higher in females whereas the longer intervals showed higher probability densities in males (Figure S12, albeit such patterns, were not present for the *Transition* JID).

We next addressed whether the pattern of correlations observed in the JIDs was related to the amount of smartphone usage—given that older individuals showed lower amounts of usage. Toward this, we included the amount of usage as a variable in the regression model in addition to age and gender and the overall pattern of age-related correlates remained unchanged due to this inclusion (Figure S13). Interestingly, the correlates associated with increased usage were largely confined to the slower intervals. Finally, according to anecdotal observations, older smartphone users may use other digits than the thumb or may be constrained to using only one thumb at a time. We addressed this in a subset of the sample (N = 250) who reported their finger preference on the screen and years of the smartphone experience. Indeed, according to these self-reports, the higher the age, the lower the reliance on the thumb ($\beta_{Thumb\ pref.}$ = −0.0012, $t(247)$ = −3.55; p = 0.00046, full model R^2 = 0.087; $F(2, 247)$ = 11.7; p = 1.38 × 10^{-5}, based on robust multiple regression including gender) and the lower the simultaneous use of both thumbs ($\beta_{Dual\ thumb\ use}$ = −0.0032, $t(247)$ = −3.75; p = 0.00022, full model R^2 = 0.063; $F(2, 247)$ = 8.2; p = 0.00035, based on robust multiple regression including gender). Including these finger usage variables, the years of the smartphone experience, and the screen size in the regression model linking smartphone JID and age did not alter the pattern of age-related behavioral correlates (Figure S14). Interestingly, the behavior was weakly correlated to the screen size, such that the larger the screen, the higher the probability densities when transitioning from fast to slow intervals.

In sum, chronological age explained a substantial extent of the inter-individual differences in smartphone behavior captured using the JIDs. The probability of short consecutive intervals was particularly depleted with advanced age whereas the probability of longer intervals was higher with increased age. These correlates were independent of how much people used their devices, the number of years spent on the smartphone, the screen size, and the choice of fingers used on the touchscreen.

Chronological age is reflected in cognitive tests but weaker than in smartphone behavior

We next addressed the extent to which chronological age reflected in cognitive tests (Figure S15). The simple reaction time was only weakly correlated with age (β_{age} = 0.65; $F(2,256)$ = 8.77; p = 0.0033, R^2 = 0.034,
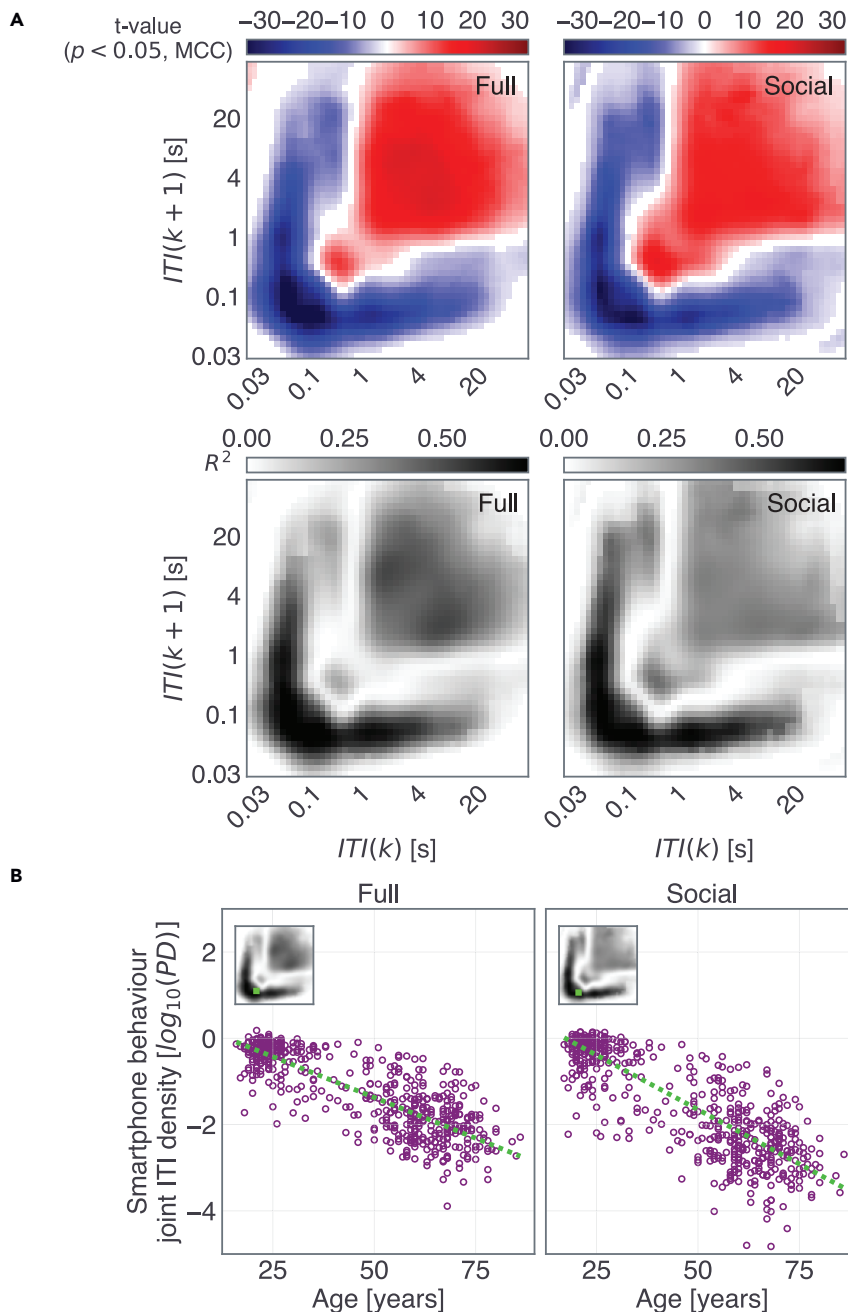
Figure 3. Smartphone behavioral dynamics at certain time scales are highly correlated to age

(A) We correlated the probability densities at each two-dimensional smartphone behavioral bin with age and gender as explanatory variables. The *t*-statistics (red-blue images) for the variable age reveal substantial behavioral differences across time scales for both types of interval distributions (JID based on all smartphone interactions: "Full" and interactions on social apps and browsers: "Social"). The corresponding R^2 of the full regression model is shown in grayscale images.

(B) Adjusted response plots of the linear relationships from a select two-dimensional bin (selection noted in the inserted R^2 plots). All statistics were corrected for multiple comparisons using two-dimensional clustering (1000 bootstraps, $\alpha = 0.05$). ITI, inter-touch interval, *k*, a given interval, and *k+1* the subsequent interval.

Robust simple regression corrected for gender). The choice reaction time showed a stronger relationship than simple reaction time, albeit still moderate in terms of correlational strength, such that the higher the age, the slower the reaction time ($\beta_{age} = 3.42$; $F(2,257) = 101.54$; $p \approx 0$; $R^2 = 0.28$, Robust simple regression
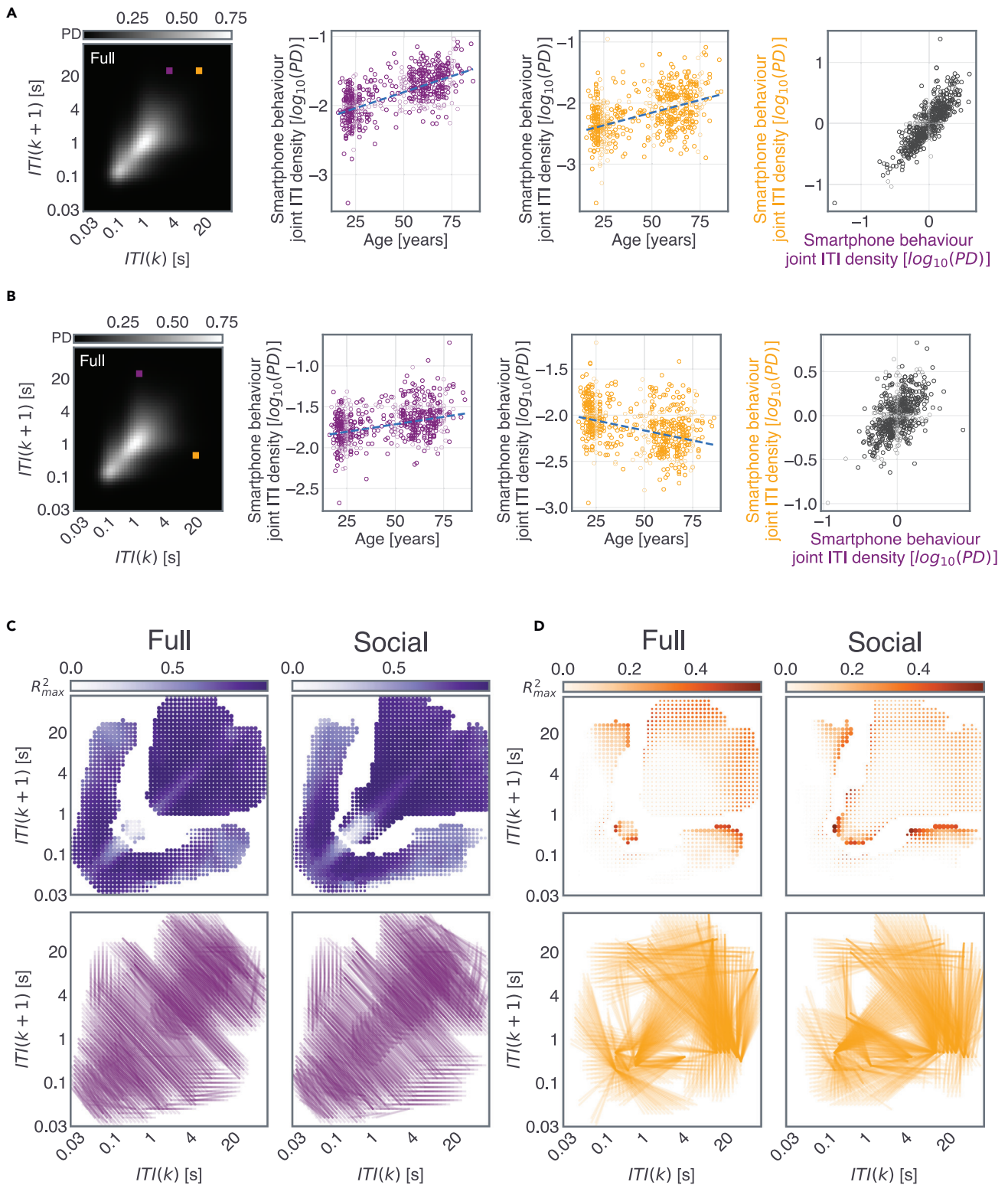
Figure 4. Locating consistency of aging across different temporal segments of smartphone behavior

We used pairwise regressions relating the age-residuals across smartphone behavioral bins.

(A) In this example pair, the age-residuals of the two-dimensional bins are correlated to each other revealing a consistency—so individuals who show accelerated aging in the first two-dimensional bin (magenta) also show accelerated aging in the second bin (yellow).

Figure 4. *Continued*

(B) In this example pair, the age-residuals of the two marked bins are correlated to each other revealing an inconsistency. Here, in the first two-dimensional bin (magenta), individuals who had lower behavioral probability density than the fitted line were considered better performers (as this behavioral density increases with age, positive slope). In the second two-dimensional bin (yellow), individuals who had a higher behavioral probability density than the fitted line are considered better performers (as this behavioral density reduces with age, negative slope). The regression between the residuals shows a positive correlation—so individuals with accelerated aging in one bin show decelerated aging in another.

(C) All two-dimensional bins with significant age-related correlations were selected for the residual analysis. Here, we show the max R^2 for the *consistent* pairs observed at a given two-dimensional bin. The corresponding line plots (each line depicting a significant correlation) show the location of the *consistent* correlational pattern linking the residuals, where the bins were separated by a bin distance of >5 bins.

(D) Same as "C" but for *inconsistent* pairs.

corrected for gender). The global cost (but not local cost) on the task-switching task was marginally correlated with age (β_{age} = 0.001; $F_{(2,166)}$ = 10.19; p = 0.0017; R^2 = 0.058, Robust simple regression corrected for gender). The Corsi span too declined with age (β_{age} = −0.0305; $F_{(2,239)}$ = 54.56; p = 5.21 × 10^{-12}; R^2 = 0.18, Robust simple regression corrected for gender). There was a tendency of age-related decline for the 2-back D' (β_{age} = - 0.018; $F_{(2,189)}$ = 2.94; p = 0.09; R^2 = 0.017, Robust simple regression corrected for gender).

The best performing cognitive test in terms of capturing age-related decline was the choice reaction time (R^2 = 0.28). Next, we contrasted this regression to the age-related decline captured on JID. Toward this, we focused on the subset of the participants who performed the choice reaction time task and re-estimated the smartphone correlates of age (adjusted for gender). In this subset, the best related two-dimensional bin (in terms of R^2 on the *Full* JID) was superior to that of the regression capturing choice reaction time (β_{age} = - 0.046; $F_{(2,257)}$ = 353.57; p ≈ 0; R^2 = 0.58, Robust simple regression corrected for gender, at a cluster surviving 2D multiple comparisons correction).

The distinct pace of aging in the different behaviors captured on the smartphone

The nature of the age-related correlations varied from one type of smartphone temporal dynamics to another. The resulting linear models were further leveraged to gain insights into the pace of aging. Considering that the regression fitted age vs. probability density at a two-dimensional bin as an indication of typical aging, we used the deviations from this fit (residuals) to quantify accelerated or decelerated aging (for *Full* and *Social* JIDs see Figure 4, for Transition JID see Figure S16). To elaborate, at a temporal bin showing an age-related reduction in probability densities, positive residuals indicate decelerated aging whereas negative residuals indicate accelerated aging. We performed mass cross-correlations between the age-related residuals between pairs of the two-dimensional bins of the JIDs to identify two forms of relationships: consistent age-related relationships, as in where accelerated aging in one two-dimensional bin also indicated accelerated aging in another bin, and inconsistent relationships, as in where accelerated aging in one bin indicated decelerated aging in another bin. For both *Full* and *Social* JIDs, consistent relationships dominated the symmetrically opposite (say short followed by long intervals and long followed by short intervals) two-dimensional bins. However, the inconsistent relationships revealed links between behaviors with rather distinct next-interval temporal dynamics (such as along the diagonal of the JID).

DISCUSSION

We captured the dynamics present in real-world behavior by using smartphone touchscreen interactions. Chronological age dominated the behavioral dynamics over and above the other examined factors spanning gender to the finger preferences on the touchscreen. How exactly age reflected on the behavior depended on the underlying dynamics such that the fast behaviors became more elusive with advanced age whereas the slower dynamics became more dominant (see Figure 5 for a summary of our findings). The nature of aging was far more heterogeneous than we had anticipated, such that the same individual could show accelerated aging in one part of the behavioral dynamic whereas decelerated aging in another. The divergent impact of aging on smartphone behavior may be attributed to the status of the underlying cognitive functions and shifting behavioral strategies.

The amount of smartphone usage and fingers used were weakly related to the chronological age confirming anecdotal observations that older individuals may use their phones less and differently. Nevertheless, including these factors in the regression model along with chronological age did not alter the pattern of age-related correlations in the smartphone behavioral JIDs. This suggests that the age-related correlates discovered here may be attributed to other factors beyond experience and postural choices. The limitation
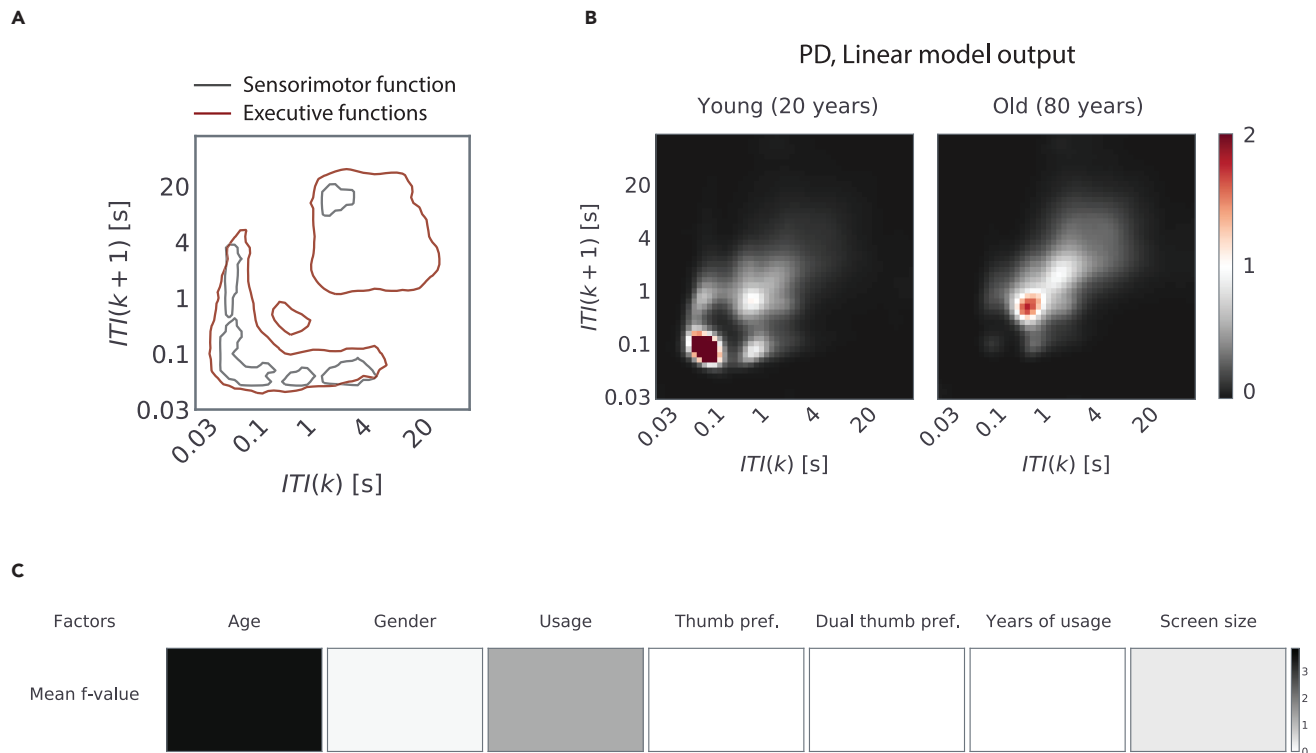
Figure 5. Summary of key findings

(A) We captured real-world behavioral dynamics using a joint-interval distribution of next intervals derived from smartphone touchscreen interactions. The cognitive test focused on sensorimotor processing correlated with distinct parts of the dynamics in contrast to the tests focused on executive functions.

(B) We used parametric modeling to link the chronological age with the smartphone behavioral dynamics, and according to this model young vs. old adults generate distinct dynamics. While youthful behavior was characterized by higher behavioral probability densities at the shorter intervals, the elderly showed a higher density at the longer intervals.

(C) Of all the examined factors, chronological age best explained the inter-individual differences in the smartphone behavioral dynamics.

of experience and finger choices was also evident in the form of near absent correlations of these factors across the dynamics captured in the JID.

The weak or marginal correlations linking chronological age and overall smartphone usage is in line with prior observations (Montag et al., 2015). In contrast to the links to usage, we found strong correlations when considering the probability densities clustered according to the next interval dynamics. This underscores the importance of capturing the temporal dynamics underlying real-world behavior for aging research. Moreover, the overall pattern of relations was visible in the JIDs using only a subset of the data—that is when using the data from social networking & browser apps (*Social* JID), or when considering only those interactions made when switching between apps (*Transition* JID). Notably, the shortest intervals in the *Transition* JID were in the range of ∼1 s whereas for the *Full* and *Social* JIDs the shortest intervals were in the range of ∼100 ms. Despite this temporal difference between these JID types, the overall pattern of age-related correlates remained consistent such that the short intervals in the respective JIDs declined with age whereas the longer intervals were enhanced. This suggests that the relative instead of the absolute temporal dynamics have a putative role in how the behavior is shaped by aging. This raises an interesting possibility that the reduction of fast consecutive behavioral outputs is a fundamental feature and is independent of the task type—such that even the time-consuming tasks are performed with more leisure in advanced age.

The idea that there may be fundamental changes in behavioral structures or strategies is further supported by the age-related decline in the JID entropy. This loss of behavioral complexity may parallel the age-related loss of physiological complexity as captured using time-series measures such as in fluctuations of the heart rate (Lipsitz and Goldberger, 1992; Vaillancourt and Newell, 2002). Intriguingly, both the *Full*

and *Social* distributions were dominated by behaviors involving similar consecutive intervals across time scales (to occupy regions around the diagonal of the JID). This pattern may be an outcome of behavioral states reliant on similar consecutive outputs such as in reading a webpage by using consecutive swipes of similar intervals. Under the assumption that shorter intervals reflect texting or rapid browsing without absorbing information, and longer intervals reflect browsing or reading, perhaps with age individuals engage on the smartphone to absorb more information rather than generate rapid outputs.

The regressions between the cognitive tests and smartphone behavior provide insights into how the intrinsic cognitive properties may shape daily behavior. Simple reaction time has been associated with measures from daily life such as falls in the elderly and questionnaires that probe daily action outcomes (Lord and Clark, 1996; Steinborn et al., 2016). In our analysis, we found that simple reaction time was mostly reflected in the probability of behavior with short inter-touch touch intervals—irrespective of their neigh-boring temporal context. This suggests that the cognitive processes reflected in simple reaction time spe-cifically impact those daily behavioral outputs that depend on rapid cognitive processing. This was in contrast to the smartphone behavioral correlates of choice reaction time which included both the short and long intervals. These distinct patterns provide real-world behavioral support to the long-standing idea that cognitive processes underlying simple reaction time are more constrained than the processes un-derlying choice reaction times (Donders, 1969).

The behavioral correlates of the Corsi span broadly occupied short and long intervals, and the correlates were more widespread than for the 2-back D'. This indicates that visual-spatial memory has a more prom-inent role in smartphone behavior than verbal memory. There was also a sharp contrast between the pattern of results for local vs. global switch costs. Local costs were unrelated to smartphone behavior whereas global costs were linked to the short intervals (and long intervals on the *Transition* JID). The later findings based on global costs underscore the real-world relevance of maintaining multiple task configu-rations. The former findings raise the possibility that processes captured by the local switch costs may be task-specific and do not play a dominant role in real-world behavior. The two-dimensional bins at the short consecutive intervals were commonly correlated to these diverse tests. Perhaps, multiple cognitive pro-cesses culminate to enable the generation of sustained rapid actions in daily life.

According to our analysis, the short consecutive inter-touch intervals were particularly vulnerable to aging. The variance in age explained by this segment of smartphone behavior was superior to the variance ex-plained by any of the cognitive tests aimed at specific cognitive processes. We speculate that the putative reliance on multiple cognitive processes to generate actions with short consecutive intervals also makes the same behavioral outputs more vulnerable to age than other actions. According to previous reports, elderly typists engage in compensatory strategies—such as faster eye movements—to protect typing speed against age-related decline (Salthouse, 1984). Our data suggest that such compensatory strategies are limited.

We considered the residuals stemming from the smartphone JID correlations with age as a behavioral mea-sure of accelerated or decelerated aging. Accelerated aging at certain temporal scales of the JID was correlated to decelerated aging at others and such inconsistent links were present across the time scales. Essentially, the same individuals could show divergent forms of aging at the different temporal bins. This helps further extend the idea that the nature of aging varies according to the underlying temporal dy-namics. Taken together with the correlations of cognitive tests suggesting that distinct temporal locations of the JID are driven by distinct cognitive processes, our findings are in line with the emerging evidence showing different forms of aging in the distinct cognitive processes (Veríssimo et al., 2021).

The pattern of results solely based on the cognitive tests mimicked previous reports on the age-related decline. As observed before, the simple reaction time was less sensitive to aging in comparison to the choice reaction time (Deary et al., 2011; Deary and Der, 2005; Der and Deary, 2006). Similarly, the local cost of the task-switching test was less sensitive to aging than the global cost (Wasylyshyn et al., 2011). Here, as in previous reports, chronological age and gender explained only a small part of the inter-individ-ual variance in the cognitive tests (Bauermeister and Bunce, 2016; Woods et al., 2015). While it is well es-tablished that cognitive test performance contains information on the aging status, our results indicate that specific aspects of smartphone behavioral output may contain even stronger indicators of age. Real-world behavioral data may be as informative (if not more) on aging as the cognitive tests.

Our study demonstrates that smartphone interactions offer unique insights into how daily life is shaped by aging across the adult life span. Our study helps upgrade the accounts of age-related decline based on narrow and artificial tasks with accounts of systematic age-related behavioral organization in daily life occupying a broad range of behavioral dynamics captured on the smartphone. These findings pave the way for longitudinal studies to track the status of aging at the level of each individual and across a broad range of behavioral dynamics. Inter-individual differences in real-world smartphone behavior—that is intuitively under diverse, long, and difficult to quantify influences such as body posture, prior experience, goals, decision making, impulsivity, habits, and information content on the screen, to list a few—maybe instead dominated by hidden cognitive and behavioral processes under the influence of aging.

Limitations of this study

This correlational study based on inter-individual differences warrants longitudinal measures to establish how real-world behavior alters with age. Furthermore, the age of the sample used here was bimodally distributed—while this still allows for parametric regression modeling as used here there is scope for improvement by including more information from middle-aged adults (Schmidt and Finan, 2018). The sample—due to its focus on The Netherlands—was constrained in its ethnic, linguistic, and cultural diversity. The linear regressions used here were highly interpretable, but this came at the cost of missing out on the more complex relationship. Follow-up studies can leverage machine learning models such as using decision tree regressions to include the more complex forms of associations between aging and real-world behavior. While the smartphone behavior itself was directly quantifiable, some of the other smartphone-related factors explored here such as the finger used on the smartphone or the number of years of smartphone usage were assessed by using questionnaires. In general, self-reports may be poor approximations of behavior and this may explain the near-absent correlations to the self-reported behavioral features in this study.

STAR★METHODS

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104791.

AUTHOR CONTRIBUTIONS

A.G. conceptualized and designed the study including the analytical approach. E.C. analyzed the data aided by A.G. R.K. constructed the customized data collection platform supervised by A.G. A.G. drafted the report and further edited by G.B., G.S., and E.C. G.S. implemented the cognitive tasks used here. G.B. edited the information displayed on the data collection platform and helped verify the usability of the cognitive tasks.

DECLARATION OF INTERESTS

A.G. is a co-founder of QuantActions Ltd., Lausanne, Switzerland, and E.C. is a founding team member. This company focuses on converting smartphone taps to mental health indicators. Software and data collection services from QuantActions were used to monitor smartphone activity. Authors R.K., G.B., and G.S. have no competing interests to report.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
PsyToolkit	Gijsbert Stoet	https://www.psytoolkit.org/
Python version 3.8	Python Software Foundation	https://www.python.org
MATLAB	MathWorks	https://www.mathworks.com/
LIMO EEG Toolbox	Pernet et al. (2011)	https://github.com/LIMO-EEG-Toolbox/limo_tools
KernelDensity from sklearn v0.24.1	Pedregosa et al., (2011)	https://scikit-learn.org/stable/
Data processing, model definition and statistical analysis	This paper	https://github.com/codelableidenvelux/TemporalCluster_Codes_2022
Agestudy.nl data collection platform	This paper	https://github.com/codelableidenvelux/agestudy

RESOURCE AVAILABILITY

Lead contact

Further information and requests for code and data should be directed to and will be fulfilled by the lead contact Arko Ghosh (a.ghosh@fsw.leidenuniv.nl).

Materials availability

This study did not generate any materials.

Data and code availability

- The analyzed data from the level of the JID and the associated cognitive test results, age, and gender information is made available on dataverse.nl (unlocked upon publication).

- The codes used to analyze the links between JID, age, and cognitive tests are deposited on the CODELAB git repository https://github.com/codelableidenvelux/TemporalCluster_Codes_2022. Furthermore, the codes used for cognitive tests are available on request without reason from the lead contact via psytoolkit.org. The platform agestudy.nl was built using codes shared in https://github.com/codelableidenvelux/agestudy.

- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Participants

We recruited 720 volunteers older than 16 years of age through on-campus flyers and emails, and via the agestudy.nl data collection platform aimed at the general population in The Netherlands. The recruitment to the online platform was facilitated by hersenonderzoek.nl which contains a list of willing research participants in The Netherlands (Zwan et al., 2021). The data from volunteers based on the on-campus recruitment have been used in previous reports (Borger et al., 2019; Huber and Ghosh, 2021). Only self-reported healthy participants in terms of neurological and psychological health (at the time of recruitment) were considered. Additional exclusion criteria included individuals who shared their smartphones with others, had dysfunctional or missing digits of the hand, people without access to email, and a desktop or laptop (for cognitive tests). All participants gave informed consent either via paper signatures or by using a digital form. The experimental procedures were approved by The Psychology Research Ethics Committee at Leiden University. The participants recruited via agestudy.nl were required to provide a Dutch citizenship number and bank account number for remuneration, while the remaining participants were paid cash in person.

Of the 720 recruits, 642 successfully installed the smartphone data logging app and reported their age in terms of the month and year of birth (235 males, 396 females, 11 unreported or unclear gender reports, 16

to 86 years of age). From this cohort, we analyzed 598 participants based on a cut-off of 7 days of smartphone recordings and a minimum of 100 smartphone interactions in that period.

METHOD DETAILS

Online data collection platform

We constructed a cloud-based (IBM Cloud, IBM, Armonk) data collection platform (agestudy.nl) to anonymously link the data – self-reported age and gender, cognitive tests, and smartphone data. They were linked through unique personal identification numbers to each participant upon sign-up. The platform presented the study information, enabled users to sign-up for the study using an online form, and recorded the age and gender self-reports, smartphone usage, and finger use questionnaire, in addition to other questionnaires as a part of larger data collection efforts (not considered here). The sign-up process was supported via email and phone consultations on demand. The platform enabled users to access the cognitive tests implemented on psytoolkit.org (Stoet, 2010, 2017).

Finger configuration preference estimation

Participants reported on their smartphone behavior using a questionnaire. The question of interest was: 'How many years have you used a smartphone?'. The users ranked their finger preference by sorting 8 images from most used to least used. The images represented: left thumb, right thumb, left&right thumb in portrait mode, left&right thumb in landscape mode, left index finger, right index finger, left middle finger, and right middle finger. These ranks were converted into two scales ranging from 0 to 1. With the first scale capturing the preference for the thumb, with 1 indicating the thumb was most preferred, and the second scale capturing the preference for simultaneous use of both thumbs, with 1 indicating dual use was most preferred.

Cognitive tests

Participants performed the cognitive tests online via agestudy.nl and psytoolkit.org, and these tests were activated when seated in front of a laptop or personal computer with a keyboard (self-reported). The tests were administered in English or Dutch. When logged in participants could choose between Deary-Liewald reaction time tasks, cued task-switching, Corsi block tapping, and 2-back tasks, apart from questionnaire-based tasks. The participants were instructed to perform at least one task per month.

The Deary-Liewald reaction time tasks were used to measure simple and choice visual reaction times (Deary et al., 2011). Towards simple reaction time, participants were instructed to respond to the presence of a checked square using a keypress (key K) with the right index finger as fast as possible. An instruction video and a practice block of 8 trials proceeded with the main task consisting of 25 trials. In the choice reaction task, we used a 4-choice paradigm. The participants were instructed to respond to the presence of a checked mark (in one of the 4 squares) using the middle or index fingers of the left or right hands corresponding to the location (keys S, D, K, and L). A practice block of 8 trials proceeded with the main task consisting of 50 trials. In both tasks, participants were informed if they were too slow (>3 s) or if they used incorrect keys on a given trial. The inter-trial interval was set within the range of 1 s and 3 s.

We used the Corsi Block tapping task to evaluate short-term spatial memory (Corsi, 1972). Briefly, nine spatially distributed locations on the screen were highlighted in certain sequential patterns and the participants were instructed to report the presented sequence by recreating the same order. The number of locations was progressively increased to determine the Corsi span until two consecutive errors were made or when all the 9 positions were correctly ordered. Participants were presented with an instruction video and performed a practice set before the main test.

We used a 2-back task to evaluate working memory. A train of letters was presented and the participant responded with a keypress (key M) when the same letter was shown two trials back. The practice set was customized such that the previously shown letters were still visible to the user in a lighter shade. A video tutorial was followed by a practice set containing 15 trials leading to the main task in three blocks of 30 trials. The gap between stimuli presentation was set at 2 s and each stimulus was presented for 760 ms. Correct responses triggered visual feedback.

A cued task-switching shape-color task was used. In the shape task, participants distinguished between circles and squares, and in the color task, participants distinguished between yellow and blue (using the keys D and K). A measurement session consisted of (in order) an optional video tutorial, a block of color tasks, a shape task, two mixed blocks, followed by a shape and color block again. The first blocks of each type were preceded by a set of 8 training trials. The color or shape blocks consisted of 20 trials each, and the mixed blocks consisted of 50 trials. The type of the task was indicated with a text cue as in 'Shape' vs. 'Color'. The cue was displayed for 400 ms and cue to item delay was set at 500 ms. Subsequent trials were triggered after waiting for 5 s for a response.

For inclusion in the data analysis a minimum number of trials had to be successfully executed per task: 12 trials, simple reaction time; 24 trials, choice reaction time; 12 trials, task switching task; two trials, Corsi; 30 trials, 2-back. Individuals who did not fulfill one or more tasks were retained for the analysis involving the other tasks. Median reaction times were used to quantify the simple reaction time, choice reaction time, and global and local cost. The global cost was normalized using the median reaction time of the shape and color blocks. The local cost was normalized using the median reaction time of the non-switch trials. Corsi span was used to quantify the performance on the Corsi block tapping task. Sensitivity (D') was used to quantify the 2-back performance.

Smartphone data collection

We use a background App and a cloud-based data collection service to record any smartphone touchscreen event generated by the user while the screen was in an unlocked state (TapCounter, QuantActions Ltd, Lausanne). Briefly, the app was downloaded and installed from the Google Playstore (Google, Mountain View). The participant entered a unique ID into the App to link with the other data. During the data collection period, the incoming data was monitored via a web-based management tool (Taps.ai, QuantActions Ltd, Lausanne). The raw smartphone data was downloaded along with the unique ID and parsed using MATLAB (Mathworks, Natick). The parsed data included the timestamps of the touchscreen interactions, the labels of the foreground apps in use, and the timestamps of the screen on and off events. We quantified the amount of usage (log_{10} count) as the median number of touchscreen interactions accumulated per day, with the days (24-h periods) where no touches were recorded excluded from the median.

The joint interval distribution (JID)

The inter-touch intervals were quantified in terms of joint-interval distributions to quantify the next interval dynamics of smartphone interactions as introduced before (Duckrow et al., 2021). Only those intervals gathered with the screen on were considered, i.e., intervals between one usage session (period from the screen turning on to being switched off) to the next were not considered here. The JID was based on subsequent inter-touch intervals (ITI). Any ITI (say k) was related against the subsequent interval (say $k + 1$). By using kernel density estimation over the accumulated ITIs we estimated the joint probabilities on log_{10} transformed data. A Gaussian kernel with a bandwidth of 0.1 was used for the two-dimensional probability density estimation (Pedregosa et al., 2011). The output of the kernel density estimation was then discretized using 50 bins per dimension in the range of $10^{0.5}$ ms and 10^5 ms. The range was determined based on the 99th percentile of all the ITIs across all the subjects. The entropy of JID was estimated using the information theory entropy formula in 2D.

We estimated three different forms of JID. In the first form, we used all accumulated intervals ('Full'). In the second form ('Social'), we only used those intervals accumulated while on social networking and browser apps as defined according to the Google Play (Google, Mountainview) 'Communication' category (such as WhatsApp, Facebook, Chome, available through Taps.ai, QuantActions, Lausanne). In the third form ('Transition') we considered the intervals based on the interactions accumulated while transitioning from one app to another. For the regression models linking the JIDs with age and gender, the data from the entire recording period was used. For the regression models linking JIDs with the cognitive test, the smartphone data from the $\pm$ 10 days from the day of the test was used, and subjects who did not have data in this period were eliminated.

QUANTIFICATION AND STATISTICAL ANALYSIS
Mass univariate regression analysis

We used the linear modeling toolbox LIMO EEG for regression analyses and multiple comparison corrections (Pernet et al., 2011). To link the JID to cognitive tests we performed robust linear regressions (iterative

least squares) linking each two-dimensional JID bin to the test output and gender (dummy variable). The probability densities were $\log_{10}$ transformed, with the minimum value encountered in the population replacing any zero. For instance, when relating to the simple reaction time task (R), a parametric regression (slope, β) was used at the level of each two-dimensional bin (probability density x_i, where i ranges from 1 to 2500), and the regression included the participant's gender as dummy variable (D):

$$x_i = R\beta_{ir} + D\beta_{id} + c_i$$

The resulting statistics were corrected for multiple comparisons using 2D clustering implemented in LIMO EEG ($\alpha = 0.05$, 1000 bootstraps). The same approach was used when linking to chronological age (A), along with gender:

$$x_i = A\beta_{ia} + D\beta_{id} + c_i$$

An additional parametric model was raised with other smartphone use related variables. The parametric regression model includes all quantified factors, chronological age (A), smartphone usage (U), thumb preference (T), years of usage (Y), dual-use of the thumb preference (Q), the screen size (S):

$$x_i = A\beta_{ia} + U\beta_{iu} + T\beta_{it} + Y\beta_{iy} + Q\beta_{iq} + D\beta_{id} + S\beta_{is} + c_i$$

To study the age-related residuals, we isolated the residuals in a two-step manner with the first step involving a linear regression using the gender dummy variables, and a subsequent linear regression against age. In the study of consistency of age-related residuals within the JID we performed pairwise correlations across all bins at a distance greater than 5 bins, $R^2 > 0.1$, and survived 2D multiple comparison correction, in the second regression. The resulting analysis was corrected for multiple comparisons using the false discovery rate implemented in LIMO EEG ($\alpha = 0.001$).