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Multimodal passive smartphone sensing in older adults: a guide for clinical scientists based upon an ongoing cohort study

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Abstract

Background and Objectives: Technology for Smartphone Assessment of Neurocognitive Symptoms (TechSANS) is a digital phenotyping project exploring passive smartphone sensing as a complement to infrequent clinical assessments for long-term cognitive characterization. This manuscript presents a guide for passive sensing applications, including a primer on data modalities and derived measures, initial findings on feasibility and analytic considerations, and preliminary relationships with cognitive performance from an ongoing study of older adults.

Research Design and Methods: An analytic pipeline cleaned the raw data and extracted 145 digital phenotyping features from 6 months of multimodal passive smartphone sensing data for 21 participants (aged 75.81 ± 4.86 years, 13 cisgender women; 17 cognitively normal, 4 with mild cognitive impairment/dementia), characterizing daily behaviors and smartphone interactions. Generalized linear mixed models assessed associations between these measures and baseline cognitive performance.

Results: Digital measures were extracted for 141 days per participant on average (74.4% of the data inclusion period), suggesting good study adherence. Statistical analyses identified relationships between cognitive performance, smartphone typing, and gait. Specifically, poorer working, episodic, and semantic memory were associated with slower typing, more frequent typing errors, slower walking, higher walking asymmetry, and lower walking cadence.

Discussion and Implications: This manuscript introduced clinical scientists to the technical foundations of passive smartphone sensing. The exploratory cross-sectional analysis suggested the feasibility of this approach in older adults for scalable, long-term cognitive characterization. We also provided practical considerations to improve future research and highlighted the need for larger, more diverse cohorts to discover and validate generalizable digital biomarkers.

Keywords: Passive sensing, Digital phenotyping, Digital biomarker, Cognitive impairment, Dementia

Innovation and Translational Significance: With passive smartphone sensing emerging as a possible adjunct to in-person clinical assessments for scalable, long-term cognitive characterization, the technical complexity of data analysis remains a significant barrier for clinical scientists. This manuscript discusses the feasibility of this approach in older adults and serves as a practical guide by detailing a data analytics pipeline that transforms the raw sensing data into digital phenotyping features that reflect participants' daily routines. It also presents preliminary associations between these digital measures and cognitive performance.

Background and objectives

With the growing ubiquity of smartphones and wearable devices in daily life, digital phenotyping, defined as the "moment-by-moment quantification of the individual-level human phenotype in-situ using data from personal digital devices",[1] has gained increasing attention in research. In

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contrast to "active" smartphone approaches such as games or assessments presented in a digitized format,[2,3] passive sensing holds potential for scalable and low-burden monitoring of older adults in naturalistic settings by unobtrusively capturing real-world behavioral and physiological signals from device sensors already used by participants. While some would argue that digital approaches to measuring daily activities may be negatively impacted by the digital divide that exists with older adults, recent surveys indicate that among older adults in the United States, over 90% had internet access and nearly 80% regularly used smartphones among both cognitively normal and impaired individuals,[4] suggesting the potential feasibility of these approaches.

Building on this foundation, digital phenotyping studies have utilized passive sensing to identify potential digital biomarkers of cognitive impairment across various behavioral domains, including gait,[5,6] speech,[7] social communication,[8] keyboard typing,[9,10] sleep,[11] and mobility.[12] To illustrate, Buchman et al.[6] analyzed wearable inertial measurement unit (IMU) data from walking tasks and found that walking regularity, speed, and cadence were associated with the development of cognitive impairment over 3.6 years of follow-up. Park[10] examined keystroke dynamics from everyday smartphone touchscreen typing and reported moderate correlations of keystroke hold time (ie, time between key press and release) and flight time (ie, time between key release and subsequent press) with Montreal Cognitive Assessment (MoCA) scores. Both metrics also outperformed MoCA in cognitive screening.

Despite promising findings, understanding and approaching these sensing modalities for clinical scientists can be challenging, given both the technical complexity of the sensors and data obtained, as well as the need to consider novel analytic approaches. Further, initial technical studies tend to address cognition and functioning in older adults as primarily a unidimensional construct,[13] with less known about how passive activities relate to the broad array of cognitive phenotypes present in older adults.[14]

These issues can be confounded by study length, and to date, several studies were limited by relatively short monitoring durations.[15-17] Specifically, Chen et al.[15] acquired smartphone and wearable sensing data over 12 weeks to develop machine learning models for classifying the cognitive status of 113 participants. The RADAR-AD (Remote Assessment of Disease and Relapse – Alzheimer's Disease) study[16] employed multiple remote monitoring technologies, including wearable fitness trackers and smartphone-based functional assessments, to characterize cognitive performance over 8 weeks. While these studies demonstrated the potential of multimodal sensing, in which data were acquired from multiple sensor data streams, a longer monitoring duration is needed to capture behavioral patterns associated with cognitive decline, which can unfold over several years.[18] As the largest study ever seeking to address current research gaps, the Intuition study collected multimodal smartphone and smartwatch sensing data from over 20,000 US adults over 2 years. However, their initial analysis focused on validating interactive cognitive assessments, rather than exploring the value of passive sensing for characterizing cognitive performance.[19]

To address the gaps, we employed multimodal passive smartphone sensing in a 1-year prospective cohort study of older adults. Specifically, this manuscript leverages currently available data from this ongoing quantitative study to:

- Introduce clinical scientists to digital phenotyping features obtained through passive sensing, such as activity, location, and keyboard typing.
- Describe patterns and considerations for these features that could be enhanced in future studies.
- Explore preliminary associations between passive sensing features and cognitive domains of interest and familiarity to clinical scientists.

Together, these aims position our work as a methodological guide that connects the technical foundations of passive sensing with the domain knowledge of clinical research, while also suggesting its feasibility in older adults for scalable, long-term cognitive characterization.

Research design and methods

Study protocol

The study was approved by the University of Texas at Austin Institutional Review Board (STUDY00002933). The purpose-built TechSANS app was used to passively collect multimodal data from smartphone sensors and interaction logs as participants interact with their devices naturalistically every day. This study was observational (no intervention conducted).

Study recruitment began in May 2023 with outreach conducted in the Austin Metropolitan Area, a US metropolitan region in Texas with over 2 million residents. Outreach strategies included referrals from an urban outpatient clinical center specializing in neurodegenerative conditions, advertisements in a local newspaper targeting adults aged 55 and older, and presentations in local urban and suburban retirement communities. Participation was open to individuals across the United States.

The inclusion criteria require participants to be at least 65 years old, possess both a smartphone and basic smartphone operating skills, have Wi-Fi at home, and have a collateral aged 21 years or older to complete questionnaires about participants' conditions. The study duration was intended for 1 year. During onboarding, they provided informed consent and installed the TechSANS app for passive sensing. They also completed online questionnaires on demographics (eg, age, sex/gender, race/ethnicity, employment) and medical history, and underwent remotely administered cognitive assessments to establish the baseline cognitive performance. Throughout the study, participants and their collaterals completed surveys every 3 months, while the cognitive assessments were repeated every 6 months. These longitudinal measures provided insights into potential cognitive decline over the one-year period. All user-identifiable information was securely stored in REDCap,[20,21] a web-based research data management platform, and was only accessible to the study team. Each participant was assigned a unique numeric ID in REDCap, and all questionnaires, assessments, and sensing data were associated with the ID to protect the privacy and security of study information.

As the study is still ongoing in 2025, baseline cognitive performance is currently available for 21 participants recruited through June 2024. Their sensing data were used to develop this methodological guide and examine study adherence, and the baseline cognitive scores served as the clinical ground truth in a cross-sectional analysis exploring associations between digital phenotyping features and cognitive performance.

Cognitive assessments

The cognitive assessments incorporated clinically validated instruments from the telephone-based neuropsychological battery (Form C2T) of the National Alzheimer's Coordinating Center Uniform Data Set v3,[22] including Craft Story 21 Recall (immediate and delayed recall of a paragraph), MoCA-Blind (a measure of general cognitive status), Number Span Test (forward and backward digit span), Animal Fluency, and Auditory Naming Test (a naming to description test). Additionally, the Verbal Series Attention Test[23] was performed to evaluate participants' attention, concentration, and executive functioning. All cognitive measures were administered by a trained speech-language pathology graduate student while neuropsychologists from the study team reviewed the assessment results to categorize participants' cognitive performance into 3 levels: cognitively normal, possible mild cognitive impairment (MCI), and possible dementia.

Application development

The TechSANS app was originally created as an iOS application designed to operate continuously in the background without requiring active user interaction. The captured data modalities include motion (ie, through IMU readings), activity, gait, location, device usage, keyboard typing, communication, and ambient light. Notably, the last 4 modalities require access to Apple's SensorKit framework,[24] which is exclusively granted to approved research studies. Researchers seeking to utilize this framework should be aware that access permission requires additional review by Apple (https://www.researchandcare.org/resources/accessing-sensorkit-data/). We also built an integrated voice recorder for participants to record their cognitive assessments. Audio was not captured at any other time during the study. To conserve cellular data and battery, data were automatically uploaded to a secure study server when the smartphone was connected to Wi-Fi, but only while charging or having at least 50% of battery. Data uploading and storage were managed by HIPAA-compliant services from Amazon Web Services. An Android version was developed later based on the Beiwe platform.[1,25] For this manuscript, we focused on data collected from the iOS application.

As SensorKit access was granted exclusively for this study, the app is not available for external use. However, researchers can develop similar apps using standard iOS frameworks or by leveraging publicly available SensorKit-enabled apps, such as Avicenna (https://avicennaresearch.com/) and MindLAMP (https://docs.lamp.digital/).

Analytic pipeline

Such data collection of routine behaviors requires consideration of the broader analytic pipeline. Figure 1 illustrates our overall pipeline. Multimodal passive sensing data were collected from smartphones and uploaded to a secure remote server. Digital measures were then extracted from the raw sensing data to comprehensively characterize participants' daily behaviors. Statistical analyses examined the preliminary associations between the digital measures and baseline cognitive performance. Each stage is described in turn below, though we encourage clinical researchers to consider the entire process to facilitate eventual data analysis and ensure the privacy and security of data at rest and in transit.

Sensing data feature extraction

We developed data processing pipelines to clean raw sensing data and extract a total of 145 digital measures. Each pipeline was tailored to the sampling strategy of its corresponding data modality. To minimize bias and ensure that extracted measures objectively represented routine behaviors, we designed strategies to include only days with sufficient sensing data and to properly handle missing data. This section summarizes these measures and their established links to cognitive domains in the literature, which motivate their inclusion in the analysis. Sample raw data format and technical details for feature computation are described in Supplementary Material Section 1, and detailed descriptions of the measures are provided in Supplementary Table 10.

For this cross-sectional analysis, we only analyzed sensing data collected within 6 months of each participant's baseline cognitive assessment. This timeframe was selected to align with the interval between assessments and to reduce potential confounding effects from cognitive changes over time. A universal data cutoff date of November 26, 2024 was applied for participants enrolled for less than 6 months.

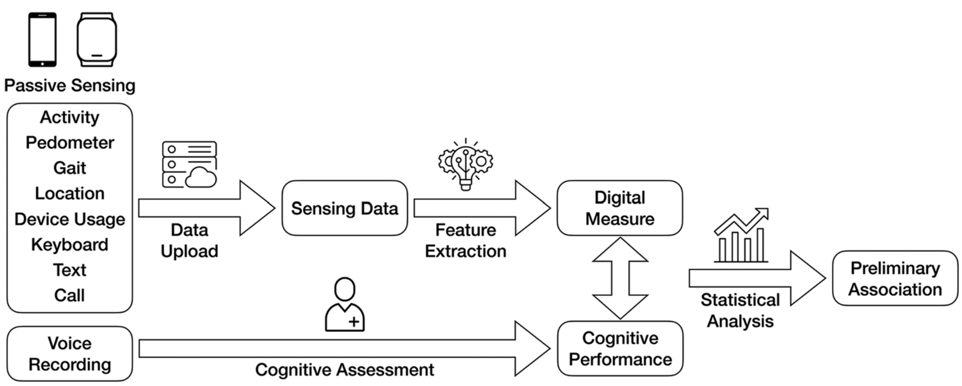

Figure 1. The pipeline of the cross-sectional analysis, including data collection, feature extraction, and statistical analysis.

Data preprocessing

An essential step in constructing digital measures of daily activities involves organizing raw data into separate data frames for each day. In our study, we used the location tracking data to determine participants' time zones and constructed data frames from samples recorded each day. Days without time zone information were discarded, and those with time zone transitions (ie, when participants were traveling) were excluded to avoid potential underestimation or overestimation of daily activities.

Activity

Existing studies have demonstrated the benefits of physical activity and exercise for improving cognitive performance, especially for executive function, potentially through underlying biological mechanisms.[26,27] Accordingly, we computed daily durations of walking, running, automotive travel, and cycling from corresponding activity instances recorded by the app.

Pedometer and gait

An analysis of 78,430 adults found that higher daily step counts were associated with lower risks of dementia, with even greater benefits at higher step intensities.[28] Chen et al.[15] also noted a delayed onset of daily walking among participants with cognitive impairment. Motivated by these findings, we used pedometer data recorded by the app from the smartphone's built-in pedometer to compute the total daily step count, walking distance, and the time of the first step. Step count and walking distance were also extracted from the Apple Health app, which incorporated steps recorded by a paired Apple Watch alongside the pedometer. The study did not provide Apple Watches to participants who did not already own one. To further assess walking intensity, we computed summary statistics of step count, distance, cadence (steps per second), and pace (seconds per meter) across continuous walking segments, capturing overall levels, variability, and percentiles. The total number of walking segments per day was also counted.

Furthermore, gait has been extensively studied in aging research, with prior work linking declines in both general cognitive performance and specific domains such as executive function and attention to gait disturbances, including reduced gait speed and instability.[6,29,30] Our app retrieved gait metrics recorded by the Apple Health app, including walking speed, walking step length, walking asymmetry, and double support time. Walking asymmetry quantifies the proportion of steps with different speeds between the left and right foot, while double support time measures the percentage of time during walking when both feet are on the ground.[31] For each metric, we summarized the daily average, minimum, and maximum.

Location

Evidence from prior studies indicates associations between human mobility and cognitive functioning across various mobility and cognitive dimensions. For example, Shoval et al.[32] found that cognitively impaired individuals exhibited reduced amount, spatial extent, and timing variability of out-of-home mobility. A systematic review reported associations between life-space mobility and cognitive function, particularly in the domains of executive function, memory, and processing speed.[33]

Inspired by these findings, we derived features to comprehensively characterize participants' mobility patterns. As a preprocessing step, we classified the location samples as stationary or moving and identified significant places visited by clustering the stationary samples. We then computed features that capture the variability, timing, and extent of participants' overall daily mobility patterns, including location variance,[34,35] total distance traveled, moving and stationary time, time of first movement, and convex hull measures. The convex hull is the smallest polygon on the map that encloses all location coordinates for each day, and we calculated its area, perimeter, and Gravelius compactness[36] to quantify the size and shape of the daily life space.

Next, we extracted measures to characterize both the time spent at significant locations and the life space covered by these clusters, including location entropy,[34,35] number of clusters, total length of stay at clusters, maximum pairwise distance,[37] and radius of gyration.[38] Finally, we determined participants' home locations as the cluster with the longest stay between midnight and 6 AM on each day, and derived features to characterize their home-related mobility. These included the total home stay time, its proportion out of the time spent across all clusters, the maximum distance between home and any other cluster, and the time when the participant was farthest from home.

Device usage

A recent meta-analysis highlighted associations between digital technology use and reduced risk of cognitive impairment.[39] To quantify daily phone usage, we extracted the total number of unlocks and the cumulative unlock duration. Additionally, we grouped application usage across 29 categories (eg, entertainment, music, utilities) recorded by the app into 6 broader classes: information, productivity, life, health, social, and other (Supplementary Table 11). For each class, we calculated its proportion of the total application usage time to characterize participants' preferences over different types of apps.

Keyboard typing

A growing body of work has linked typing dynamics to cognitive functioning.[40] Park[10] reported that longer keystroke hold and flight times were correlated with worse cognition. Chen et al.[41] further found that slower typing was associated with poorer executive function, attention, and processing speed.

We first extracted measures of overall typing activity across all typing sessions, including typing duration and the number of words, sessions, and continuous typing episodes within the sessions. We then quantified the frequencies of taps, altered words, deletions, pauses, and corrections, relative to the total word count. Together, these features captured typing continuity and accuracy.

Furthermore, we extracted keystroke-level timing and distance measures to characterize multiple dimensions of typing. Specifically, we obtained character key hold time, and we used character–character transition time to estimate typing speed, character–delete transition time to capture potential self-corrections, and deviations of character keystrokes from key centers to assess spatial typing accuracy. As with pedometer features, we computed counts and summary statistics across keystroke-level values to characterize the overall distributions.

Communication

Prior studies have examined the role of social communication in cognitive functioning. For example, Muurling et al.[8] observed more frequent phone calls to the same contacts among cognitively impaired individuals. Other studies have further associated greater social engagement, both in person and through digital communication, with better episodic memory, executive function, and processing speed.[42,43] Building on this foundation, we leveraged text messages and phone calls recorded by the app as proxies for participants' social communication. For each day, we extracted the number of incoming and outgoing messages and calls, along with call duration, to assess the overall level of communication. We also used the number of unique call and message contacts to characterize communication diversity.

Daily feature inclusion criteria

To ensure accurate representation of participants' daily behaviors, digital measures were only extracted from days with sufficient sensing data. Given the varying sampling strategies, we employed tailored approaches to estimate the daily sensing duration for each data modality. Technical details of these procedures are provided in Supplementary Material Section 2.

A minimum sensing duration of 14 hours between 6 AM and midnight was required to extract most measures characterizing daytime activities. Additionally, at least 1 hour of data from midnight to 6 AM was necessary for computing location features dependent on home identification and whole-day behavior tracking. Exceptions to this requirement included distance traveled, total moving time, time of first movement, and convex hull features, as these primarily reflected daytime mobility.

Missing data imputation

We handled missing data conservatively to preserve missingness caused by application inactivity as a potentially meaningful reflection of cognitive impairment. Rather than imputing all missing daily measures, we limited imputation to empty event-based data streams, including activities, pedometer, keyboard typing, and communication events, on days with sufficient daytime sensing duration. In these cases, missing values were treated as an absence of the corresponding activity (eg, no calls), rather than data loss.

Statistical analysis

The statistical analysis aimed to explore the associations between digital phenotyping features and cognitive performance. Considering the repeated measures of daily features over 6 months and varying feature distributions, we employed generalized linear mixed models (GLMMs) to account for within-subject correlations and between-subject differences. Each digital measure was modeled as the dependent variable by an appropriate distribution (Supplementary Material Section 3 Supplementary Table 12), and one instrument score from the cognitive assessment was included as a fixed effect.

All instrument scores, except for MoCA-Blind, were converted to demographically-adjusted z-scores based upon normative data, adjusting for relative demographic factors. We constructed separate models for each of the 6 instruments that are most sensitive to cognitive decline in older adults, including delayed Craft Story 21 Recall (verbatim scoring), forward and backward digit spans (number of correct trials), Animal Fluency, Auditory Naming Test, and Verbal Series Attention Test (completion time). In total, 870 (145 features × 6 scores) models were fitted, each trained on an average of 2542 ± 396 days of data (range: 1891-3250).

To control for demographic impacts on smartphone usage, age, sex, and years of education were included as fixed effects in all models. A random intercept was applied for each participant to capture individual variability. To ensure sufficient data for robust analyses, we only included participants with at least 30 days of non-missing values for each feature. False discovery rate correction with the Benjamini–Hochberg procedure[44] was applied separately for each cognitive score to adjust for multiple comparisons. GLMMs were fitted using the R glmmTMB package.[45]

Results

Digital measure visualization

To better understand the extracted digital phenotyping features, Figure 2 illustrates the characteristics of selected measures across different modalities. Figure 2A presents the activity durations of a participant over one week. During this period, they spent over one hour walking each day, whereas the running duration was negligible. Figure 2B shows the cumulative step count throughout one day. A significant increase in step count early in the morning suggests that the participant began their day with some exercise. Figure 2C plots the range and average of daily double support time for a week. This gait metric mostly varied between 28% and 33%, with an average of around 31% for the participant. Figure 2D visualizes the distribution of cadence from all continuous walking segments of a participant on a single day, along with summary statistics. The median cadence is approximately 1.5 steps per second, with the 5th to 95th percentile range spanning roughly 1.2 to 1.7 steps per second. Figure 2E and 2F visualize the location trajectory throughout a day from one author for illustrative purposes to avoid exposure of identifiable data from participants. The location samples were classified as stationary or moving, and the stationary samples were clustered to identify 4 significant places visited. Figure 2G illustrates the daily usage duration of different smartphone app categories over a week. The participant used apps for around 1.5 to 2.5 hours per day, with productivity apps (eg, web browser) accounting for more than half of the total usage time. Figure 2H shows the distribution and summary statistics of character–character transition time from all typing sessions of a participant collected on one day. The distribution is right-skewed, with the median, 5th percentile, and 95th percentile at about 0.17, 0.23, and 0.4 seconds, respectively. Finally, Figure 2I displays the number of incoming and outgoing text messages, as well as the number of unique contacts, for all text message records of a participant throughout a day. Each record covered a 30-minute interval. Shortly after 8 AM, the participant received the highest inflow of 11 messages, while the greatest outflow of 8 messages occurred between 1:30 PM and 2 PM. Meanwhile, 6 unique contacts were involved in text communication from 12:30 PM to 1 PM.

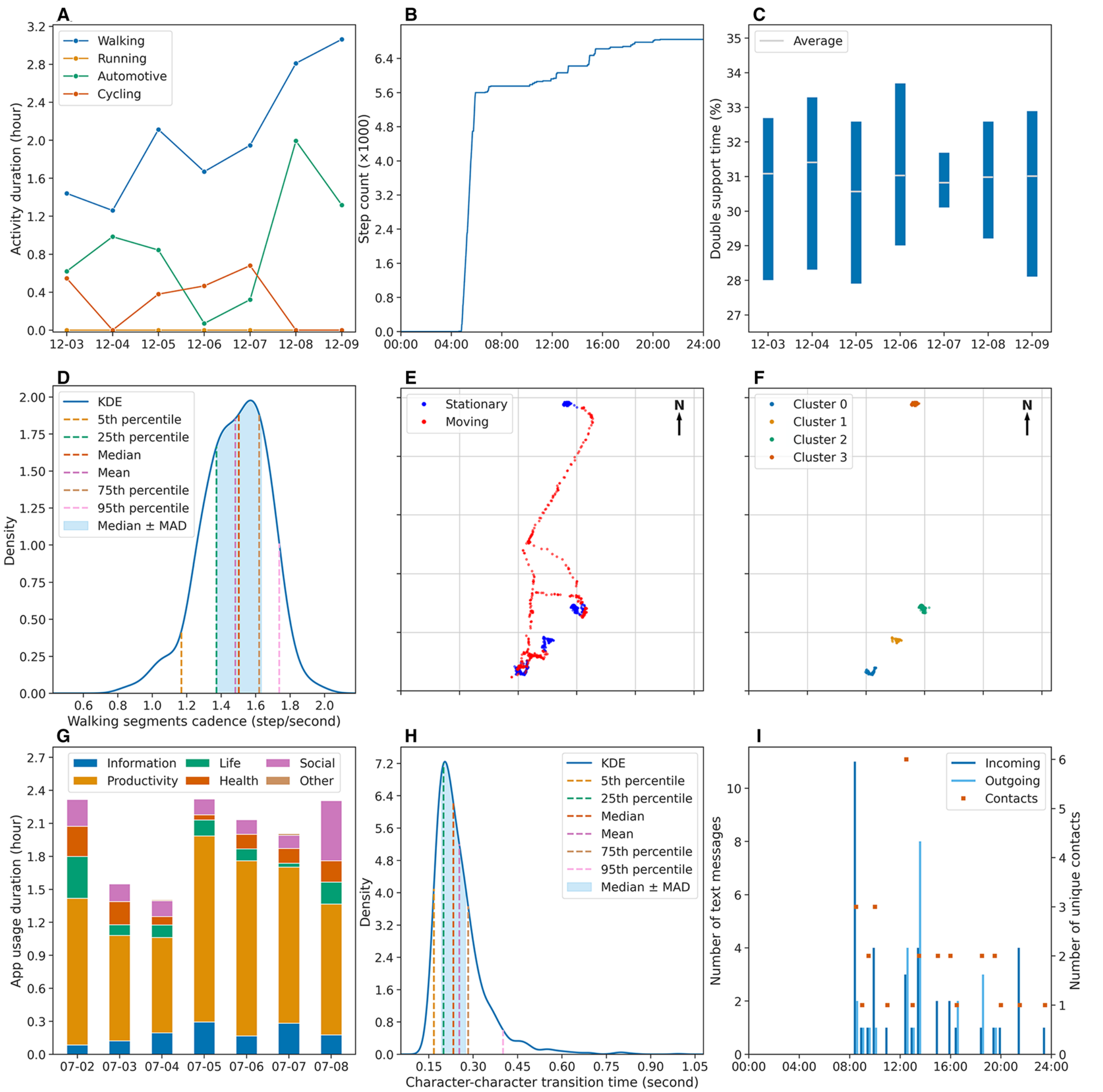

Figure 2. Visualizations of multimodal digital measures extracted from passive smartphone sensing data. Notes. (A) Daily durations of walking, running, automotive, and cycling of a participant over one week. (B) Cumulative step count of a participant throughout one day. (C) Range and average daily double support time of a participant over one week. (D) Kernel density estimate (KDE) of cadence from all continuous walking segments of a participant on one day. (E) Location trajectory with moving and stationary samples from an author on one day, for illustrative purposes. Each tick corresponds to 1 km. Participant data were not used in this plot to avoid exposure of their identifiable data. (F) Location clusters (ie, significant locations visited) identified from stationary samples of the location trajectory. (G) Daily app usage duration by category for a participant over one week. (H) KDE of character–character transition time from all typing sessions of a participant on one day. (I) Counts of incoming and outgoing text messages and the number of unique contacts from all records of a participant on one day.

Feasibility, adherence, and missing data

Figure 3 presents the absolute number and percentage of days with digital measures extracted for each modality over the data inclusion period for all participants. Exact coverage may slightly vary between measures within each modality due to differences in missing data imputation. For example, typing duration on a day without any typing activity would be imputed as 0, whereas summary statistics of character key hold time would remain missing.

On average, each participant contributed 141 days of digital measures, representing 74.4% of the data inclusion period. These results suggest passive smartphone sensing as a feasible approach in older adults. From the initial cohort of 21 participants, 3 ended participations early, with data obtained up until

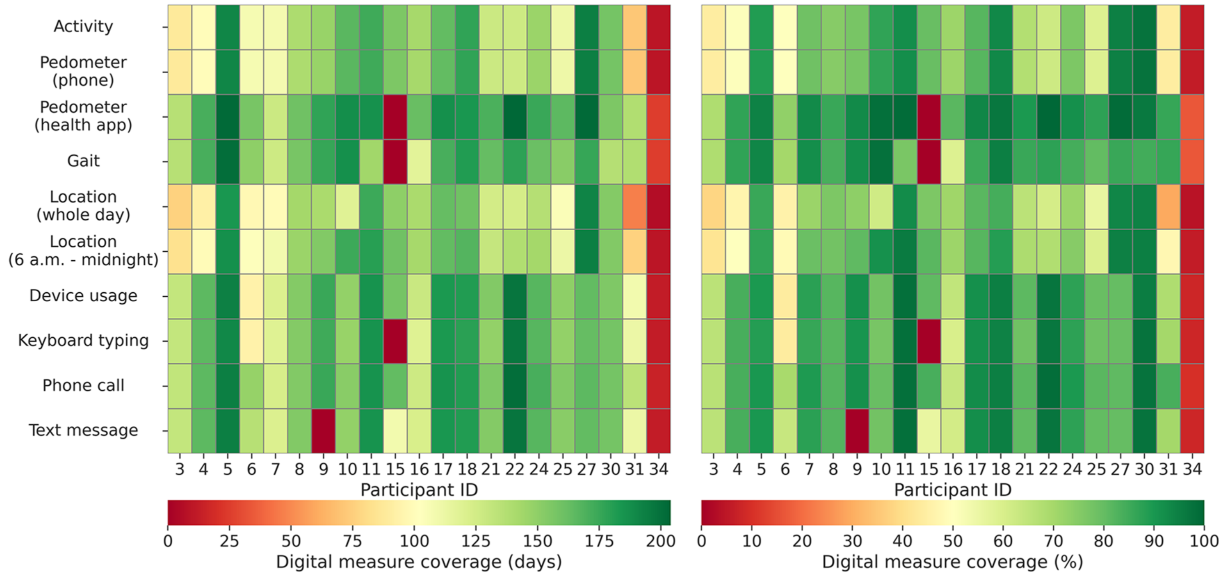

Figure 3. Absolute number and percentage of days with extracted features for each modality over the data inclusion period of all participants. Notes. The maximum number of days exceeds 6 months because the inclusion cutoff date was set at 6 months after the baseline cognitive assessment, which could occur up to one month after application installation during onboarding.

withdrawal included for analysis. Specifically, one participant withdrew 4 months after enrollment, citing a lack of perceived benefit, given that this was an observational study without intervention.

From a technical standpoint, one participant was excluded from all statistical analyses due to difficulties with the Tech-SANS app, which led to significant data loss despite multiple troubleshooting attempts by the study team. Although the app did not require active user interaction, iOS system constraints required participants to keep the app running in the background (ie, not swipe it away from the app switcher) and to reopen it after each phone restart. The withdrawals of 2 participants at the 6-month milestone were also attributed to technical issues with the app. Although the issues were resolved with a subsequent app update, both participants became frustrated and withdrew from the study.

Missing data also proved to pose a data collection challenge. This issue affected 2 participants who turned off their phones at night in particular. Consequently, location measures that required home identification and full-day behavioral tracking were not computed on those days to avoid biases. Future analyses may explore more reliable methods for inferring home locations from daytime data to reduce feature missingness. Furthermore, 2 participants did not accumulate at least 30 days of typing events, so their summary statistics for the typing timing and error distance metrics were excluded from the corresponding statistical analyses. A likely explanation is that they primarily used voice input rather than typing when interacting with their smartphones.

No text message records were collected for one participant, and no Health app data was retrieved for another. However, these errors could not be reproduced during internal testing and were attributed to iOS system malfunctions. Although this resulted in missing data streams that are difficult to resolve, examination of data from newly enrolled participants in the ongoing study indicated that such occurrences were rare and did not substantially affect overall data quality.

It is worth noting that no participants withdrew from the study due to privacy concerns. Privacy is a crucial consideration in digital phenotyping studies. To address this, we ensured transparency during onboarding by presenting sample data from collected modalities to illustrate safeguards for participant information and by demonstrating how participants could disable individual data streams. With this approach,[46] only one participant turned off a single data stream during the study.

Participant and digital measure characteristics

Out of the 21 participants, 17 were cognitively normal, 3 had possible MCI, and 1 had possible dementia at baseline. Table 1 summarizes participant demographics and the extracted digital measures. On average, participants were 75.81 ± 4.86 years old and had 17.71 ± 1.79 years of education. This cohort included 20 non-Hispanic Whites and one Hispanic participant, of whom 13 were cisgender women and 8 were cisgender men. One participant was employed part-time while others were retired. The cognitively normal group had an average age of 74.58 ± 4.51 years, 17.53 ± 1.91 years of education, and included 11 cisgender women and 6 cisgender men. The possible MCI or dementia group had an average age of 81.00 ± 2.04 years, 18.50 ± 1.00 years of education, and included 2 cisgender women and 2 cisgender men. There were no significant differences in sex, gender, or years of education between the 2 groups. However, participants with possible MCI or dementia were significantly older than cognitively normal individuals ($p = .001$, Mann–Whitney U test).

The means and *SD*s of the multimodal digital measures across all days revealed interesting aspects of participants' daily behaviors. Behavioral measures varied substantially across days and individuals, as indicated by the large *SD*s observed for many variables. This cohort appeared to be largely car-dependent. On average, participants spent around 0.9 hours per day on automotive traveling, compared to only 0.6 hours walking. Based on the pedometer and Health app data, the mean daily step count ranged from approximately 2500 to

Table 1. Participant demographics and extracted digital measures.

Category	Variables	Mean ± *SD*	%	*N*
Demographics	Age (years)	75.81 ± 4.86		
	Sex/gender (% cisgender women)		61.90	
	Education (years)	17.71 ± 1.79		
	Race/ethnicity			
	Non-Hispanic White			20
	Hispanic			1
	Employment status			
	Retired			20
	Employed part-time			1
Activity	Walking duration (h)	0.59 ± 0.70		
	Running duration (h)	0.001 ± 0.004		
	Automotive duration (h)	0.91 ± 1.00		
	Cycling duration (h)	0.05 ± 0.14		
Pedometer and gait	Pedometer step count	2651.06 ± 2491.74		
	Pedometer walking distance (km)	1.71 ± 1.57		
	Number of walking segments	31.44 ± 27.71		
	Median walking segments step count	30.56 ± 29.71		
	Median walking segments distance (m)	20.30 ± 20.35		
	Median walking segments cadence (steps/second)	1.49 ± 0.14		
	Median walking segments pace (seconds/meter)	1.04 ± 0.13		
	Time of first step (hours since midnight)	7.59 ± 2.86		
	Health app step count	3998.06 ± 2826.38		
	Health app walking distance (km)	2.72 ± 1.97		
	Average walking speed (km/h)	3.38 ± 0.43		
	Average walking step length (cm)	56.37 ± 5.09		
	Average walking asymmetry (%)	11.27 ± 13.79		
	Average double support time (%)	31.25 ± 1.72		
Location	Location variance	−9.88 ± 5.23		
	Location entropy	0.37 ± 0.32		
	Normalized location entropy	0.31 ± 0.23		
	Distance traveled (km)	49.09 ± 86.54		
	Home stay time (h)	19.81 ± 3.69		
	Number of location clusters	2.90 ± 1.62		
	Cluster stay time (h)	22.30 ± 2.05		
	Home stay proportion (% cluster stay)	88.40 ± 12.56		
	Maximum cluster pairwise distance (km)	18.32 ± 67.47		
	Maximum distance from home (km)	17.81 ± 67.33		
	Farthest from home time (hours since midnight)	13.58 ± 3.54		
	Radius of gyration (km)	6.60 ± 31.63		
	Convex hull area (km^2)	443.15 ± 4550.11		
	Convex hull perimeter (km)	42.74 ± 131.22		
	Gravelius compactness	1.38 ± 0.25		
	Time of first movement (hours since midnight)	10.32 ± 3.02		
	Stationary duration (h)	22.37 ± 2.03		
	Moving duration (h)	0.74 ± 0.85		
Device usage	Number of unlocks	28.70 ± 21.42		
	Unlock duration (h)	2.59 ± 1.98		
	Information app usage proportion (%)	12.00 ± 21.60		
	Productivity app usage proportion (%)	61.74 ± 28.52		
	Life app usage proportion (%)	13.23 ± 18.05		
	Health app usage proportion (%)	3.65 ± 8.88		
	Social app usage proportion (%)	8.50 ± 17.53		
	Other app usage proportion (%)	0.88 ± 5.12		
Keyboard typing	Number of typing sessions	6.99 ± 8.35		
	Number of words	130.64 ± 170.33		
	Total typing duration (s)	379.52 ± 461.28		
	Number of typing episodes	19.21 ± 22.60		
	Taps relative frequency	5.44 ± 0.90		
	Altered words relative frequency	0.06 ± 0.08		

(Continued)

Table 1. Continued.

Category	Variables	Mean ± *SD*	%	*N*
	Deletes relative frequency	0.30 ± 0.28		
	Auto corrections relative frequency	0.09 ± 0.10		
	Other corrections relative frequency	0.16 ± 0.14		
	Pauses relative frequency	1.09 ± 1.82		
	Number of character keystrokes	261.67 ± 339.37		
	Median character key hold time (s)	0.09 ± 0.03		
	Median character keystroke error distance (points)[a]	10.92 ± 2.12		
	Number of character–character transitions	166.26 ± 217.16		
	Median character–character transition time (s)	0.46 ± 0.20		
	Number of character–delete transitions	6.34 ± 8.99		
	Median character–delete transition time (s)	1.54 ± 1.09		
Communication	Number of incoming calls	2.85 ± 3.27		
	Number of outgoing calls	2.78 ± 3.72		
	Call duration (s)	1392.00 ± 2052.88		
	Number of unique call contacts	3.34 ± 3.44		
	Number of incoming text messages	14.40 ± 16.15		
	Number of outgoing text messages	8.13 ± 9.07		
	Median number of unique message contacts	1.16 ± 0.62		
	Maximum number of unique message contacts	3.30 ± 3.59		

Demographics variables were aggregated across all participants. Daily digital measures were aggregated across all days from all participants. For summary statistics of walking segments metrics (ie, step count, distance, cadence, pace) and keyboard typing metrics (ie, character key hold time, character keystroke error distance, character–character transition time, character–delete transition time), only the daily medians were aggregated to compute the means and *SD*s across all days. Meanwhile, daily averages of gait metrics (ie, walking speed, walking step length, walking asymmetry, double support time) were aggregated across all days. The daily median and maximum numbers of unique message contacts were summarized from text message records each spanning 30 min.
[a]Character keystroke error distances were measured by the distances between centers of the intended character keys and actual keystrokes in short words. The unit of measurement was specified in points, the internal unit used in iOS user interfaces.

4000 steps, corresponding to a walking distance of 1.7 to 2.7 km. In contrast, location tracking data indicated that participants traveled an average of 50 km per day. Additionally, participants took their first step around 7:30 AM every day on average, but the first significant movement detected by location tracking usually occurred about 3 hours later. They then reached the location farthest from their home, on average 18 km away, around 1:30 PM.

Regarding smartphone interactions, participants unlocked their phones an average of 29 times and used them for 2.6 hours daily. Productivity apps accounted for over 60% of total app usage time, followed by life apps (13%) and information apps (12%). Participants also more frequently used calls and text messages than social networking apps for communication. Specifically, social apps constituted only 8.5% of total app usage time, whereas participants made and received more than 5 calls and 22 text messages per day on average, with total daily call duration exceeding 23 minutes. Participants also spent an average of 380 seconds per day typing on their phones, with a daily median character key hold time of 0.09 seconds and a character–character transition time of 0.46 seconds.

Associations between digital measures and cognitive status

Figure 4 presents digital measures that are significantly associated with scores from 6 instruments of the cognitive assessment, as identified by the GLMMs. While no measures were associated with the performance of forward digit span, better performance on backward digit span was associated with a higher frequency of taps relative to the total number of words typed, as well as shorter and less variable transition time between character keystrokes. These findings suggest a potential relationship between better working memory and the use of more complex words and faster typing speed during smartphone use.

Similarly, better episodic memory, as reflected by the performance on the delayed Craft Story 21 Recall, was associated with shorter character–character transition time, faster walking speed, lower walking asymmetry, and higher walking cadence, suggesting more intact typing and gait patterns overall. It was also associated with a larger 95th percentile of error distances between intended and actual character keystrokes, potentially driven by faster typing speed, as well as a lower frequency of outgoing calls. One plausible explanation for the latter finding is that older adults with better memory may be more independent and therefore less likely to call others for support.

Better performance on Animal Fluency was associated with lower relative frequencies of altered words and deletions, indicating less frequent typing errors. It was also associated with higher double support time. However, in contrast to findings for working memory, better semantic memory, as reflected by this task, was associated with lower relative frequency of taps, more variable character–character transition times, and longer character–delete transition times. While this may suggest distinct manifestations of working and semantic memory in smartphone typing, future investigation is needed to understand the underlying mechanisms. Lastly, better performances on the Auditory Naming Test and Verbal Series Attention Test were associated with a shorter 95th-percentile character–delete transition time and a faster walking cadence, respectively.

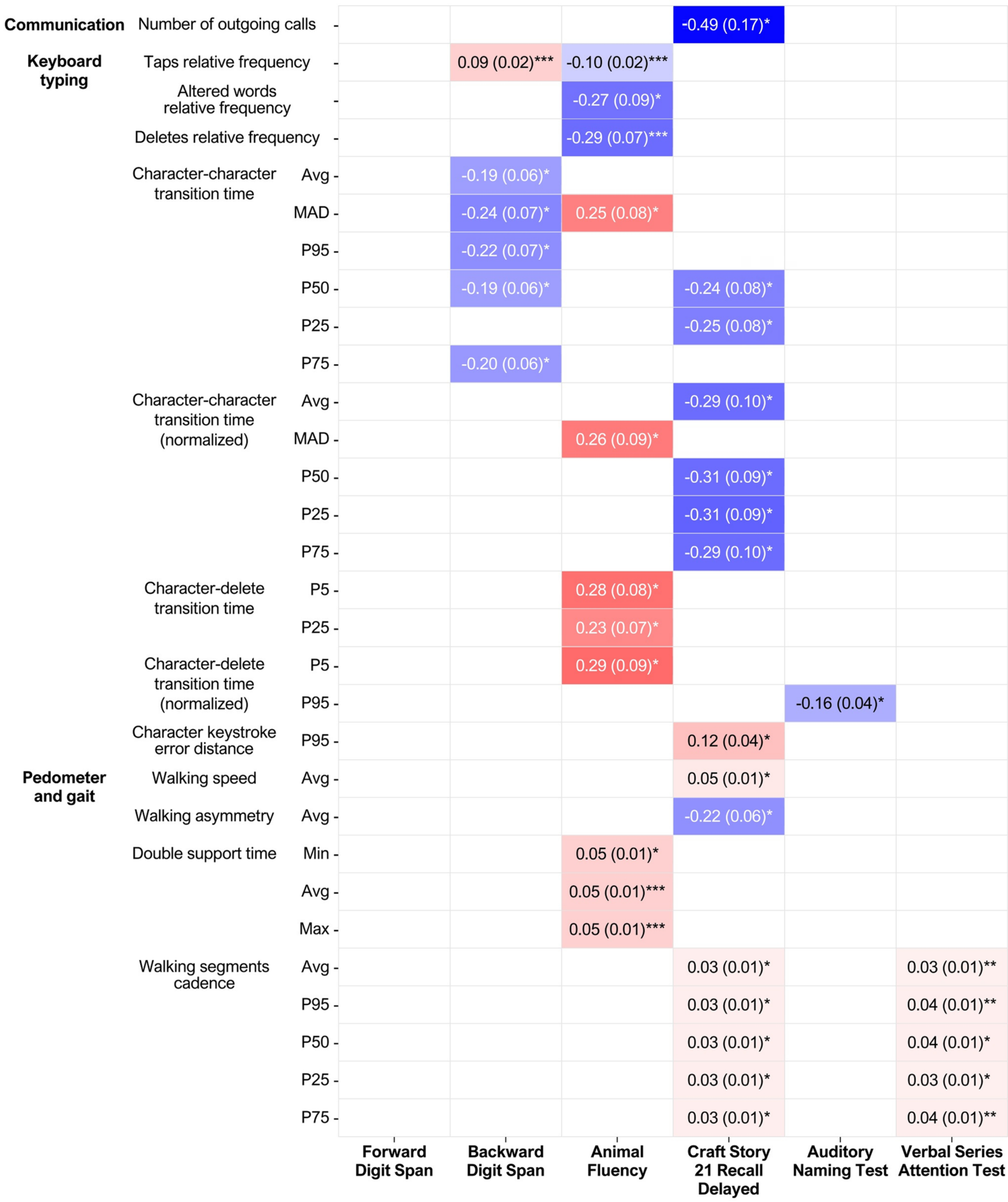

Figure 4. Statistically significant associations between the digital measures and scores from 6 instruments of the cognitive assessment: delayed Craft Story 21 Recall (verbatim scoring), forward and backward digit spans (number of correct trials), Animal Fluency, Auditory Naming Test, and Verbal Series Attention Test (completion time). Notes. Avg = average; MAD = median absolute deviation; P5 = 5th percentile, P25 = 25th percentile; P50 = median; P75 = 75th percentile; P95 = 95th percentile. Associations are shown in estimate (standard error). *$p < .05$. **$p < .01$. ***$p < .001$.

Discussion and implications

Methodological guide to multimodal passive smartphone sensing

In this manuscript, we aim to introduce clinical scientists to the multimodal passive smartphone sensing data collected by the TechSANS app. Clinical scientists and researchers may use this guide to understand the technical foundations of passive smartphone sensing for identifying potential digital biomarkers. Specifically, we detailed our data cleaning and feature extraction approaches to transform raw sensing data into interpretable digital phenotyping measures. These measures spanned multiple behavioral domains to capture participants' daily routines, including physical activities, naturalistic gaits, mobility patterns, and smartphone interactions such as device and app usage, keyboard typing, and communication via calls and text messages.

The measures provide valuable opportunities for clinical scientists to assess both aggregate levels of activity, such as step count, distance traveled, and smartphone usage time, as well as fine-grained behavioral patterns (eg, gait variability and typing speed) over extended periods. The multimodal, high-frequency, and longitudinal nature of the data further enables the examination of subtle, gradual changes across behavioral domains in older adults, such as mobility, sociability, and motor performance. Moreover, these data can support the development of machine learning models to classify participants' clinical status (eg, cognitively normal vs cognitively impaired) and predict their progression to future cognitive impairment.

Additionally, we addressed practical and analytical considerations for passive sensing studies, including protections for sensitive participant information, power-efficient sensing approaches (eg, Wi-Fi positioning), and feature extraction pipelines tailored to sampling strategies across different data modalities.

Considerations for improvement

This section further discusses the reasons for withdrawals and data loss and provides suggestions for future research. Regarding withdrawals due to lack of perceived benefits, this observational study did not provide monetary or material compensation for 2 reasons. First, the passive data collection required minimal participant interaction and imposed little burden. Second, cognitive assessment results were not disclosed to participants because they were conducted by trained graduate students rather than licensed clinicians.

Findings from this feasibility analysis suggest that, even with low-burden data collection, compensation may play an important role in reducing attrition. Incentives could include one-time financial compensation, milestone-based rewards, and non-monetary benefits such as feedback on cognitive assessments. Incorporating such strategies may enhance participant retention, engagement, and recruitment in future research.

Attrition related to technical burden may be mitigated in several ways in future studies. First, as the requirements to keep the app running in the background may be too demanding for individuals with limited technological literacy, smartphone operating skills, one of the eligibility criteria could be evaluated more systematically through practical tasks. Second, it is crucial to ensure app reliability through extensive pre-release testing to minimize participant frustration from technical burden and reduce attrition risk.

Finally, although missing data introduced by participants' privacy concerns and usage habits reduced the amount of usable data, these circumstances highlighted the strength of our study in maintaining transparency in data collection and respecting participants' existing smartphone usage habits. Such considerations are essential for building trust and sustaining engagement in long-term digital phenotyping studies.

Associations between passive sensing features and cognitive performance

The statistical analyses identified preliminary relationships between cognitive performance, smartphone typing dynamics, and naturalistic gait. Specifically, poorer working, episodic, and semantic memory were associated with slower typing speed, more frequent typing errors, slower walking speed, higher walking asymmetry, and lower walking cadence.

Prior research has reported similar associations between typing, gait, and cognitive impairment.[6,10,15,47] For example, Buchman et al.[6] found more regular and faster walking to be linked with a lower risk of future cognitive decline. Li et al.[47] demonstrated greater gait asymmetry as a potential marker for detecting Alzheimer's disease. Additionally, the observed relationship of longer keystroke flight time, and thus slower typing speed, with worse cognitive performance mirrored the findings of Park[10] and Chen et al.[15] Together, these results highlight motor function as a valuable behavioral domain for investigating its relationship with cognitive decline.

Unlike these studies that assessed motor performance using single-session structured tests or short monitoring periods, our multimodal passive sensing approach captured naturalistic human behaviors over several months in real-world settings. This enhanced the ecological validity of identified associations, as behavioral patterns may vary across different contexts and conditions.[48] Our findings underscored the potential of passive sensing to move beyond performance snapshots toward scalable, long-term, and continuous cognitive characterization.

Limitations and future work

As this work was primarily positioned as a methodological guide and feasibility demonstration, rather than a hypothesis-driven examination of digital biomarkers, the identified associations between passive sensing features and cognitive decline should be interpreted with caution. Several limitations of the cross-sectional analysis made it exploratory in nature. First, as we used only the currently available cognitive assessment ground truth from 21 participants in the ongoing study, the statistical power of the detected associations was constrained by the small cohort. Additional data loss across specific participants and modalities further reduced the sample size.

Second, the current cohort lacked demographic diversity. All but one subject was non-Hispanic white, and participants were highly educated (17.71 ± 1.79 years of education). Although demographic factors were controlled in the statistical analyses, the limited diversity may restrict the generalizability of the findings. Varying levels of acceptance of digital phenotyping for health monitoring across populations may also introduce sampling bias. For example, older adults with regular smartphone use may be more likely to participate than those with severe cognitive decline and limited smartphone use.

With these limitations in mind, this manuscript serves as a valuable resource for clinical scientists to extend passive smartphone sensing to larger and more diverse populations while accounting for potential confounding factors. Particularly, it will be important to include individuals with limited technological literacy. Although such participants may rarely use smartphones, meaningful insights can still be extracted from data modalities that do not require active device use, such as activity, location, and gait. While some participants may need to be excluded due to missing data, studies involving large and diverse cohorts can ultimately enable the discovery and validation of generalizable digital biomarkers with clinical significance in aging research.

The current analyses were conducted on the 145 digital measures, which may limit interpretability regarding their clinical relevance to specific cognitive domains. These measures also represent a common, though not exhaustive, set of features that can be derived from the multimodal sensing data. Thus, future work could explore novel behavioral signatures and apply factor analysis to consolidate the measures into a smaller set of interpretable behavioral dimensions.

Furthermore, extending beyond cross-sectional analyses to longitudinal designs would allow the identification of behavioral signatures of long-term cognitive decline. Studies may also leverage more advanced computational models and richer data sources, such as concurrent IMU signals during typing and walking, to capture subtle motor variations and provide deeper insights into the connection between motor function and cognitive impairment.

Conclusion

This manuscript suggests the feasibility of multimodal passive smartphone sensing for characterizing the cognitive performance of older adults based on data from an ongoing study. We comprehensively described our data cleaning and feature extraction approaches to derive digital phenotyping measures that reflect participants' daily behaviors. We then conducted statistical analyses to examine preliminary relationships between digital measures and cognitive performance. Our findings supported prior research and highlighted the need for future studies with larger and more diverse cohorts to enhance generalizability, identify longitudinal markers of cognitive decline, and deepen our understanding of the relationship between motor function and cognitive impairment.

Supplementary material

Supplementary data are available at *Innovation in Aging* online.

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Conflict of interest

None declared.

Data availability

As the study is still ongoing, the data and analysis code are not currently available to other researchers. The study was not preregistered.

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