









ORIGINAL RESEARCH

Associations of Demographic, Socioeconomic, and Cognitive Characteristics With Mobile Health Access: MESA (Multi-Ethnic Study of Atherosclerosis)

Reshmi J. S. Patel , BA; Jie Ding , PhD; Francoise A. Marvel , MD; Rongzi Shan , MD; Timothy B. Plante , MD; Michael J. Blaha , MD, MPH; Wendy S. Post , MD, MS*; Seth S. Martin , MD, MHS*

BACKGROUND: Mobile health (mHealth) has an emerging role in the prevention of cardiovascular disease. This study evaluated possible inequities in mHealth access in older adults.

METHODS AND RESULTS: mHealth access was assessed from 2019 to 2020 in MESA (Multi-Ethnic Study of Atherosclerosis) telephone surveys of 2796 participants aged 62 to 102 years. A multivariable logistic regression model adjusted for general health status assessed associations of mHealth access measures with relevant demographic, socioeconomic, and cognitive characteristics. There were lower odds of all access measures with older age (odds ratios [ORs], 0.37–0.59 per 10 years) and annual income <\$50 000 (versus ≥\$50 000 ORs, 0.55–0.62), and higher odds with higher Cognitive Abilities Screening Instrument Score (ORs, 1.22–1.29 per 5 points). Men (versus women) had higher odds of internet access (OR, 1.32 [95% CI, 1.05–1.66]) and computing device ownership (OR, 1.31 [95% CI, 1.05–1.63]) but lower fitness tracker ownership odds (OR, 0.70 [95% CI, 0.49–0.89]). For internet access and computing device ownership, we saw lower odds for Hispanic participants (versus White participants OR, 0.61 [95% CI, 0.44–0.85]; OR, 0.69 [95% CI, 0.50–0.95]) and less than a high school education (versus bachelor's degree or higher OR, 0.27 [95% CI, 0.18–0.40]; OR, 0.32 [95% CI, 0.28–0.62]). For internet access, lower odds were seen for Black participants (versus White participants OR, 0.64 [95% CI, 0.47–0.86]) and other health insurance (versus health maintenance organization/private OR, 0.59 [95% CI, 0.47–0.74]). Chinese participants (versus White participants) had lower internet access odds (OR, 0.63 [95% CI, 0.44–0.91]) but higher computing device ownership odds (OR, 1.87 [95% CI, 1.28–2.77]).

CONCLUSIONS: Among older-age adults, mHealth access varied by major demographic, socioeconomic, and cognitive characteristics, suggesting a digital divide. Novel mHealth interventions should consider individual access barriers.

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Key Words: cardiovascular disease ■ mHealth ■ mobile health ■ prevention

Correspondence to: Seth S. Martin, MD, MHS, Division of Cardiology, Department of Medicine, Ciccarone Center for the Prevention of Cardiovascular Disease, Johns Hopkins University School of Medicine, Johns Hopkins Hospital, Carnegie 591, 600 North Wolfe Street, Baltimore, MD 21287.
Email: smart100@jhmi.edu

*W. S. Post and S. S. Martin contributed equally.

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CLINICAL PERSPECTIVE

What Is New?

- Within a large cohort of older multiracial and multiethnic adults, demographic, socioeconomic, and cognitive characteristics were associated with mobile health access, indicating the presence of a digital divide.
- In general, participants who were older, of underrepresented racial and ethnic groups, had lower socioeconomic status, or had lower cognitive function experienced lower mobile health access.

What Are the Clinical Implications?

- Future mobile health–based interventions for the prevention or treatment of cardiovascular disease should consider individual barriers to access.
- Both patients and insurance companies may benefit from the integration of wearable fitness trackers into insurance plans.
- Directing patients to existing low-cost broadband programs or providing loaner smart devices with prepaid data plans may alleviate health insurance disparities.

Nonstandard Abbreviations and Acronyms

CASI	Cognitive Abilities Screening Instrument
MESA	Multi-Ethnic Study of Atherosclerosis
mHealth	mobile health

Mobile health (mHealth) is a growing field that can be applied to promote cardiovascular health.^{1–5} Most cardiovascular diseases are preventable by controlling modifiable risk factors such as smoking, physical inactivity, diabetes, hypertension, and hyperlipidemia.⁶ Given the burgeoning rise in mobile device usage and health-related mobile apps in the US general population, mHealth interventions have the potential to facilitate the prevention and management of cardiovascular disease (CVD) through risk factor modification.⁷

Based on a telephone and web-based survey of participants aged 18 years and older, representative of the entire US population, as of 2019 an estimated 90% of adults use the internet, 96% own a cellphone, 81% own a smartphone, 75% own a computer, and 21% regularly wear a smartwatch or wearable fitness tracker.^{8–10} A more recent consumer adoption report with a sample of representative US adults found that ownership of wearables increased from 33% in 2019 to 43% in 2020, a change likely influenced by the COVID-19

pandemic.¹¹ These widespread technologies may be leveraged to improve CVD self-management and risk reduction.¹² However, there is rising concern about a digital divide in technology access by demographic, socioeconomic, and cognitive characteristics.^{13–16}

Recent studies have reported that people of underrepresented racial and ethnic groups and people with lower socioeconomic status (SES) experience lower access to technology.^{14,15} On the other hand, although older age and cognitive impairment have been considered possible barriers to mHealth access, some studies found a potential willingness to use mHealth among older populations, as well as an uptick in the use of mHealth among people with cognitive impairment.^{16–18} People of underrepresented racial and ethnic groups, people with lower SES, and older adults are also at higher risk for CVD.^{19–21} Because increased access to health information technology could help improve quality of care, it has been speculated that mHealth could be applied to decrease racial and ethnic, socioeconomic, and age-based disparities in CVD risk.¹² However, most previous studies on mHealth access and uptake consisted of a majority of White participants or adults aged <65 years.^{6,22–29} Those studies that focused on either older adults or people of underrepresented racial and ethnic groups were limited by small sample sizes.³⁰ Further investigation of potential inequities in mHealth access across various boundaries, with a focus on populations carrying a higher burden of CVD risk, is needed.

To address this gap in understanding the role of mHealth among older age adults at risk for CVD, we analyzed the mHealth access of participants from follow-up survey data administered in the MESA (Multi-Ethnic Study of Atherosclerosis). We aimed to evaluate the digital divide along demographic, socioeconomic, and cognitive boundaries for the mHealth access measures of internet access, computing device ownership, and fitness tracker ownership. We hypothesized that each of the individual risk factors, including increased age, being a member of an underrepresented racial and ethnic group, lower SES, and having a lower Cognitive Abilities Screening Instrument (CASI) score, would be associated with not having internet access, owning a computing device, and owning a fitness tracker.

METHODS

Study Design and Participants

The MESA is a community-based, prospective, observational cohort study among adults aged 45 to 84 years and free of known CVD at baseline in 2000 to 2002.³¹ The initial baseline cohort was recruited from 6 US communities (Baltimore City and Baltimore County, MD; Chicago, IL; Forsyth County, NC; Los

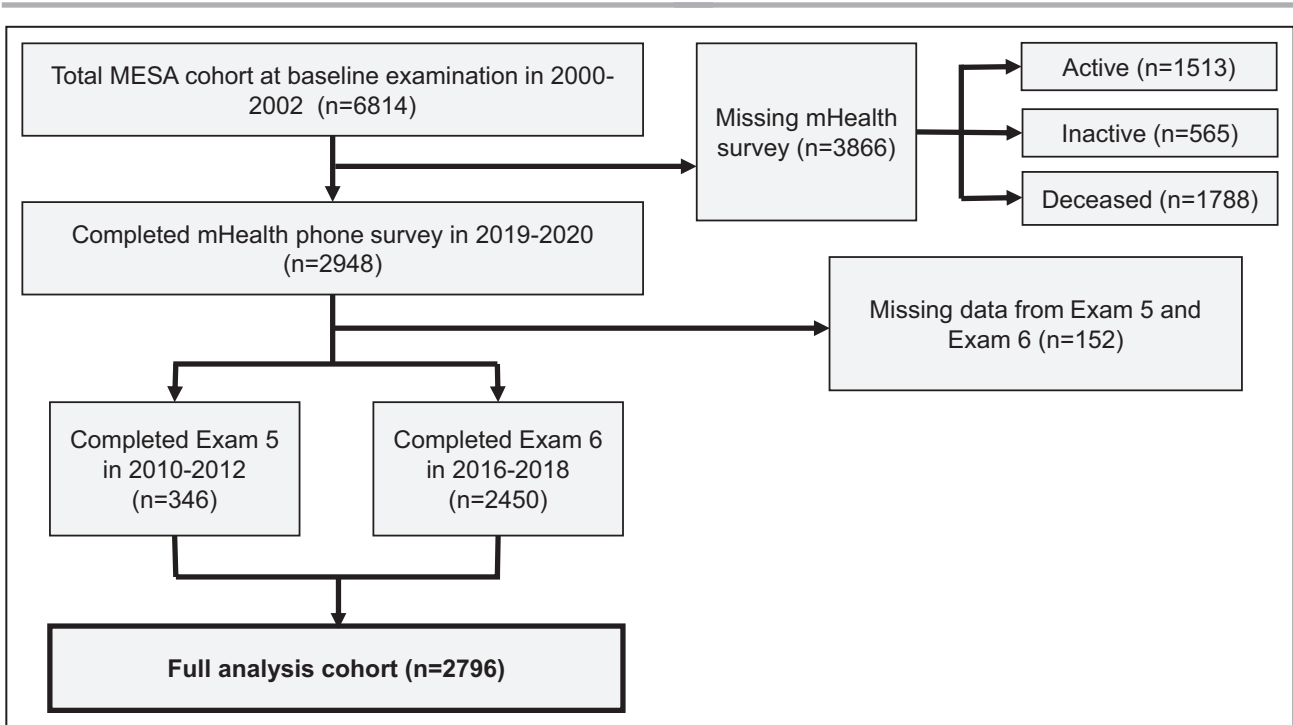


Figure 1. Flow diagram to select eligible cohort for analysis. MESA indicates Multi-Ethnic Study of Atherosclerosis; and mHealth, mobile health.

Angeles County, CA; Northern Manhattan and the Bronx, NY; and St. Paul, MN). Institutional review board approval was obtained at all MESA sites, and participants provided informed written consent. MESA data are available through the National Heart, Lung, and Blood Institute’s Biologic Specimen and Data Repository. Of 6814 participants who underwent a baseline examination, 2948 completed an mHealth phone survey in 2019 to 2020. Of the participants who did not complete the mHealth survey, 1513 were active MESA participants, 565 were inactive, meaning they were lost to follow-up, and 1788 were deceased. From this subset, participants (n=152) who did not participate in either the fifth (2010–2012) or sixth examination (2016–2018) to provide any information on family income were excluded, leaving 2796 participants, aged

62 to 102 years at the time of the mHealth phone survey, in the final sample for analysis (Figure 1, Figure 2).

mHealth Access Measures

mHealth access status was assessed from responses to each of 3 survey questions during telephone follow-up surveys in 2019 to 2020. Participants were asked (1) Do you have access to the internet? (2) Do you have a computing device such as a smartphone, laptop, desktop, tablet, iPad, Kindle Fire, or similar device? (3) Do you have a fitness tracker such as a Fitbit, Apple Watch, or similar device? To mitigate language barriers, in-person and telephone questionnaires were administered in the participant’s preferred language (English, Spanish, Mandarin, or Cantonese).

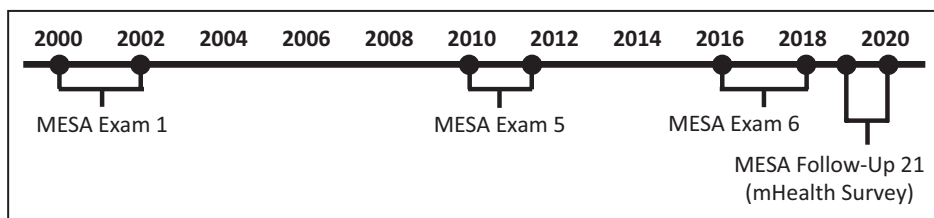


Figure 2. Timeline of all examinations and assessments. The MESA (Multi-Ethnic Study of Atherosclerosis) Examination 1 was the baseline examination for all participants, and Examinations 5 and 6 were 2 follow-up examinations. All 3 examinations were administered in person at a MESA site, as was the Cognitive Abilities Screening Instrument assessment. MESA Follow-Up 21, which included the mobile health (mHealth) survey, was administered by telephone.

Demographic, Socioeconomic, and Cognitive Assessment

Participant age was taken to be the age at the telephone follow-up survey in 2019 to 2020. Information on sex, race and ethnicity, and highest level of education were obtained by a self-administered questionnaire at the baseline exam. Total gross annual family income was collected in 2 waves of exams, the first in 2010 to 2012 and the second in 2016 to 2018. The most recent self-reported response was used for each participant; data from 2010 to 2012 were used for 346 participants, and data from 2016 to 2018 were used for the remaining 2450 participants. The 15 family income categories used in data collection were consolidated into 2 categories for our analysis. Lower income was considered <\$50,000 annually and higher income ≥\$50,000 annually. The 9 levels of education categories used in data collection were consolidated into 4 categories: less than high school, high school graduate, which included obtaining a General Educational Development certificate, some college, which included obtaining a technical school certificate or associate's degree, and bachelor's degree or higher. The 7 health insurance status categories used in data collection were consolidated into 2 categories for our analysis: health maintenance organization (HMO)/private and other health insurance status, which included being uninsured. Tables S1 and S2 provide the exact groupings of data collection categories into data analysis categories.

The CASI was completed first in 2010 to 2012 and again in 2016 to 2018. The most recent score was used for all participants. It consists of 30 questions used to compute a total score ranging from 0 to 100, with a higher score indicating a greater level of global cognitive function.³² Participants could elect to complete the assessment in English, Spanish, or Chinese. The total CASI score for a participant was only included in the analysis if the tester deemed the screening valid and if the number of missing CASI components was ≤3. A score could be marked invalid because of poor hearing, poor eyesight, impaired motor control, a language barrier, impaired alertness and attentiveness, significant physical or mental discomfort, or other reasons at the tester's discretion. Of the 2796 participants in our final sample, 2652 completed the CASI and had valid scores either in 2010 to 2012 (n=1271) or in 2016 to 2018 (n=1381).

Statistical Analysis

When comparing the demographic, socioeconomic, and cognitive characteristics of participants by the 3 mHealth access variables, the differences in the distribution of categorical and continuous variables were assessed by Pearson χ^2 tests and Welch 2-sample *t* tests, respectively. A multivariable logistic regression

model estimated odds ratio (OR) and 95% CI for each outcome given individual exposure variable, while adjusting for all other exposure variables and for one covariate, general health status. Exposure variables included age, sex, race and ethnicity, family income, education level, health insurance status, and CASI score, and outcome variables included internet access, computing device ownership, and fitness tracker ownership. Two-sided *P* values <0.05 were considered statistically significant. Multicollinearity of the logistic regression models and multiplicative interactions between each exposure variable and all other exposure variables were also assessed. Testing for multicollinearity revealed no significant collinearity in any logistic regression model, with variance inflation factors all below 1.5. All analyses were performed using R version 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria).

RESULTS

The Table lists the characteristics of the 2796 participants. Mean (SD) age was 76.6 (8.6) years, 54.8% were women, 25.0% were Black, 20.8% were Hispanic, and 14.2% were Chinese. Family income was <\$50,000 for 52.3% and ≥\$50,000 for 47.7%; the highest level of education was below a bachelor's degree for 58.6% and completing a bachelor's degree or higher for 41.4%; 53.0% (n=1298) had HMO or private health insurance. The median (interquartile range) CASI score was 90.5 (85.0–95.0) out of 100. General health status was reported by 46.4% of participants as excellent or very good, by 36.5% as good, and by 17.1% as fair or poor. Internet access was reported by 62.8% of participants, 65.4% reported owning a computing device, and 8.9% reported owning a fitness tracker. The sample of all participants excluded from the analysis was older (mean (SD) age 82.6 (10.5) years), had a lower percentage of women (51.5%), White (37.4%) and Chinese (10.1%) participants, a higher percentage of Black (29.7%) and Hispanic (22.8%) participants, an overall lower level of education, and a similar level of general health status.

The Table also lists mHealth measures stratified by demographic, SES, and CASI score categories. For all mHealth access measures, in general, participants with access were more likely to be younger, White, have a higher family income, higher education level, higher CASI score, have HMO/private health insurance, and self-reported general health status as very good or excellent. Participants who did not have internet access or own a computing device were more often women, but those who did not own a fitness tracker were more often men. Relative to White participants, Chinese participants were more likely to report not having internet access or own a fitness tracker, but did own a computing device.

Table. Demographic, Socioeconomic, and Cognitive Characteristics by Mobile Health Outcome

	All, N=2796, 100.0%*	No internet access, n=1040, 37.2%	Internet access, n=1756, 62.8%	P value	No computing device, n=968, 34.6%	Computing device,† n=1828, 65.4%	P value	No fitness tracker, n=2548, 91.1%	Fitness tracker,‡ n=248, 8.9%	P value
Age, y										
Mean [SD]	76.6 [8.6]	81.0 [8.5]	74.0 [7.6]	<0.001	81.2 [8.5]	74.2 [7.7]	<0.001	77.1 [8.7]	72.1 [6.7]	<0.001
Sex										
Women	1532 (54.8)	637 (61.3)	895 (51.0)	<0.001	601 (62.1)	931 (50.9)	<0.001	1390 (54.6)	142 (57.3)	0.45
Men	1264 (45.2)	403 (38.8)	861 (49.0)		367 (38.0)	897 (49.1)		1158 (45.4)	106 (42.7)	
Race and ethnicity										
White	1119 (40.0)	268 (25.8)	851 (48.5)	<0.001	281 (29.0)	838 (45.8)	<0.001	979 (38.4)	140 (56.5)	<0.001
Black	698 (25.0)	286 (27.5)	412 (23.5)		274 (28.3)	424 (23.2)		636 (25.0)	62 (25.0)	
Hispanic	581 (20.8)	305 (29.3)	276 (15.7)		293 (30.3)	288 (15.8)		553 (21.7)	28 (11.3)	
Chinese	398 (14.2)	181 (17.4)	217 (12.4)		120 (12.4)	278 (15.2)		380 (14.9)	18 (7.3)	
Family income										
≥\$50000 (reference)	1272 (47.7)	242 (23.0)	1030 (58.8)	<0.001	233 (23.8)	1039 (55.2)	<0.001	1099 (42.7)	173 (66.5)	<0.001
<\$50000	1396 (52.3)	727 (70.0)	669 (38.2)		662 (66.6)	734 (38.8)		1328 (50.3)	68 (25.5)	
Education										
Bachelor's degree and higher	1156 (41.4)	239 (23.1)	917 (52.3)	<0.001	234 (23.3)	922 (50.5)	<0.001	1016 (40.0)	140 (56.5)	<0.001
Some college	809 (29.0)	265 (25.6)	544 (31.0)		249 (25.9)	560 (30.7)		731 (28.8)	78 (31.5)	
High school graduate	471 (16.9)	267 (25.8)	204 (11.6)		243 (25.2)	228 (12.5)		448 (17.6)	23 (9.3)	
Less than high school	353 (12.7)	265 (25.6)	88 (5.0)		237 (24.6)	116 (6.4)		346 (13.6)	7 (2.8)	
Health insurance										
Other	1150 (47.0)	514 (50.0)	636 (39.9)	<0.001	437 (45.4)	713 (43.0)	<0.001	1059 (47.7)	91 (39.6)	0.02
HMO/private	1298 (53.0)	342 (33.0)	956 (60.0)		352 (36.6)	946 (57.0)		1159 (52.3)	139 (60.4)	
CASI score										
Mean [SD]	88.9 [8.0]	84.9 [9.0]	91.2 [6.3]	<0.001	84.9 [9.2]	91.0 [6.4]	<0.001	88.5 [8.1]	92.7 [5.2]	<0.001
General health										
Excellent, very good	1137 (46.4)	268 (31.3)	869 (54.6)	<0.001	256 (32.4)	881 (53.1)	<0.001	983 (44.3)	154 (67.9)	<0.001
Good	893 (36.5)	353 (41.2)	540 (33.9)		332 (42.0)	561 (33.8)		831 (37.4)	62 (27.0)	
Fair, poor	419 (17.1)	236 (27.5)	183 (11.5)		202 (25.6)	217 (13.1)		405 (18.3)	14 (0.6)	

CASI indicates Cognitive Abilities Screening Instrument; and HMO, health maintenance organization.

*All table entries contain column percentages, except the header row contains row percentages. Categorical variables are presented as number (percentage) and continuous variables, age and Cognitive Abilities Screening Instrument (CASI) score, are presented as mean [SD].

†Computing device includes smartphone, laptop, desktop, and tablet.

‡Fitness tracker includes Fitbit, Apple Watch, and similar devices.

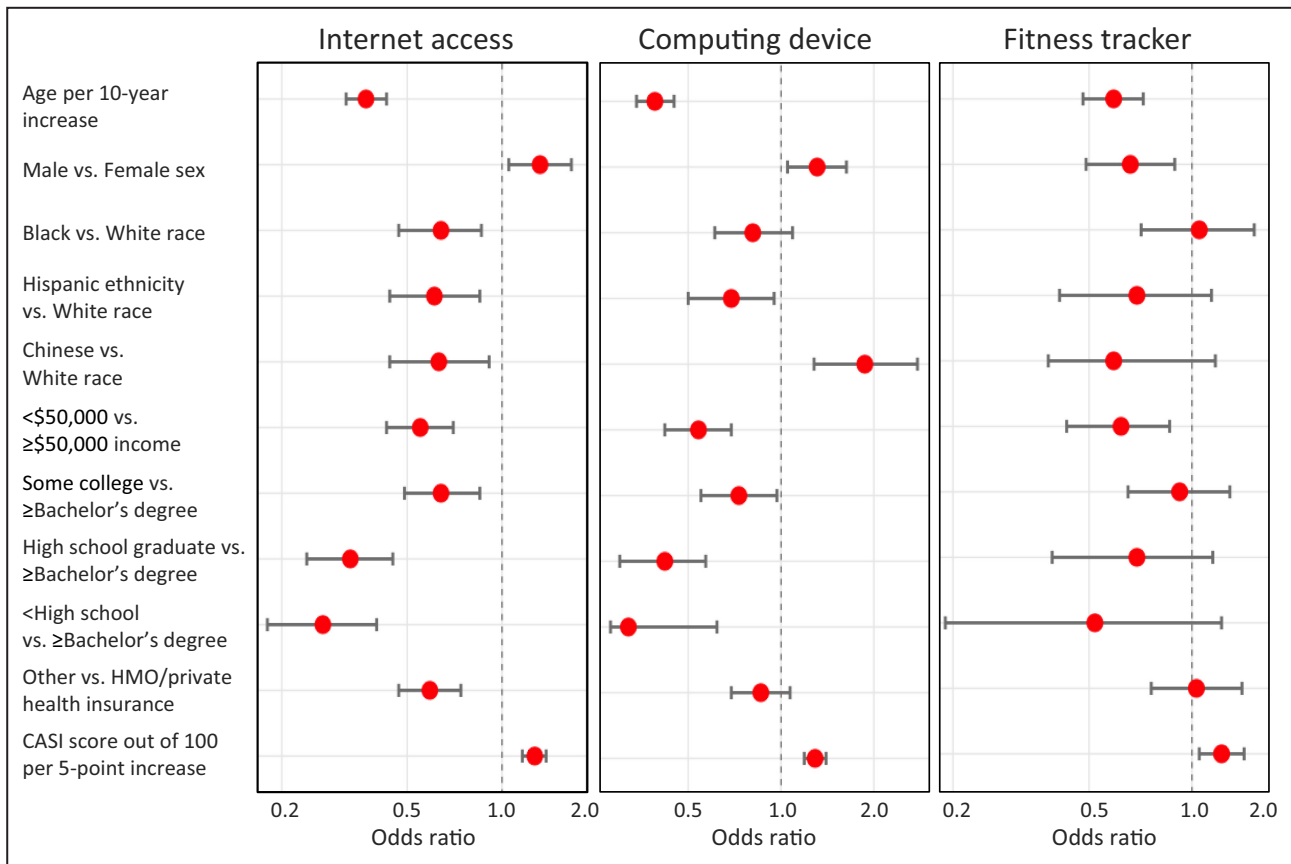


Figure 3. Multivariable logistic regression model for association between mobile health outcomes and demographic, socioeconomic, and cognitive characteristics.

The model was adjusted for all exposure variables including age, sex, race and ethnicity, family income, education level, health insurance status, and Cognitive Abilities Screening Instrument (CASI) score, and a confounding variable, general health status. Computing device includes smartphone, laptop, desktop, and tablet. Fitness tracker includes Fitbit, Apple Watch, and similar devices. Odds ratios with 95% CIs are shown on a logarithmic scale. HMO indicates health maintenance organization.

Figure 3 displays the results of multivariable logistic regression modeling for each of the 3 mHealth access variables. Associations with demographic, socioeconomic, and cognitive characteristics were generally similar across all 3 outcomes, except with sex and Chinese ethnicity, which had inconsistent patterns. Older age per 10 years was associated with lower odds of internet access (OR, 0.37 [95% CI, 0.32–0.43]), computing device ownership (OR, 0.39 [95% CI, 0.34–0.45]), and fitness tracker ownership (OR, 0.59 [95% CI, 0.48–0.72]). Similar results were seen with lower income (<\$50 000 versus ≥\$50 000) for internet access (OR, 0.55 [95% CI, 0.43–0.70]), for computing device ownership (OR, 0.54 [95% CI, 0.42–0.69]), and for fitness tracker ownership (OR, 0.62 [95% CI, 0.43–0.86]). Higher CASI score per 5 points were associated with higher odds of internet access (OR, 1.27 [95% CI, 1.16–1.38]), computing device ownership (OR, 1.29 [95% CI, 1.19–1.40]), and fitness tracker ownership (OR, 1.22 [95% CI, 1.05–1.42]).

The point estimates and patterns were similar, but confidence intervals were generally wider for most predictors of fitness track ownership compared with

internet access and computing device ownership. When compared with White participants, Hispanic participants had lower odds of internet access (OR, 0.61 [95% CI, 0.44–0.85]) and computing device ownership (OR, 0.69 [95% CI, 0.50–0.95]), but not fitness tracker ownership. Similarly, education less than a bachelor's degree was associated with lower odds of internet access (ORs, 0.27–0.64) and computing device ownership (ORs, 0.32–0.73), but there was no association with fitness tracker ownership. Additionally, for internet access only, lower odds were seen for Black participants when compared with White participants (OR, 0.64 [95% CI, 0.47–0.86]) and other health insurance ownership when compared with HMO/private health insurance ownership (OR, 0.59 [95% CI, 0.47–0.74]).

We did not find a consistent trend across all 3 mHealth measures for Chinese participants (versus White participants) or men (versus women). Although there were lower odds of internet access (OR, 0.63 [95% CI, 0.44–0.91]) for Chinese participants, there were higher odds of computing device ownership (OR, 1.87 [95% CI, 1.28–2.77]). Men had higher odds

of internet access (OR, 1.32 [95% CI, 1.05–1.66]) and computing device ownership (OR, 1.31 [95% CI, 1.05–1.63]), but lower odds of fitness tracker ownership (OR, 0.70 [95% CI, 0.49–0.89]). Numerical results for the multivariable logistic regression models are presented in Table S2. No statistically significant interactions were found between any 2 exposure variables.

DISCUSSION

In this study of mHealth access in a large multiethnic cohort of community-dwelling US adults free of known CVD in 2000 to 2002, older age, within this cohort of older adults, and lower SES were associated with lower access to mHealth, whereas a higher level of global cognitive function was associated with greater access to mHealth. However, there were indications of a large penetration of technology within the population of older adults who did not grow up with internet or computing device access. Among participants aged 85 years or older, 33.3% had internet access and 36.8% owned a computing device. Among participants aged 75 to 84 years, 58.9% had internet access and 61.0% owned a computing device. With some exceptions, there were lower odds of mHealth access among self-reported Black, Hispanic, or Chinese individuals (relative to White). Relative to women, men had higher odds of internet access and computing device ownership, but lower odds of owning a fitness tracker.

We saw similar trends in associations of internet and computing device access with previous studies for age, Hispanic or Latino ethnicity, and some SES classifications.^{23,27,28,30} However, the first 3 of these studies analyzed younger populations, with the first 2 having mean participant ages of 44 and 57 years, respectively, and the third having >80% of participants aged <65 years. The fourth study analyzed an older population but did not account for race and ethnicity or any socioeconomic characteristics beyond education level. Our findings expand on previous knowledge of mHealth disparities by examining associations with these and additional characteristics within a large, multiethnic cohort of older adults. The prevalence of mHealth access within this cohort was lower compared with the general US population,^{9–12} but was similar to that of a representative sample of US adults aged 65 years or older. For example, within the general US population, 64% of adults aged 65 years or older had home broadband, and 61% owned a smartphone; 17% of adults aged 50 years or older owned a fitness tracker.^{8–10}

Divide in Fitness Tracker Ownership

There have been emerging applications for fitness trackers in the prevention of CVD and its risk factors,

but the prevalence of fitness tracker ownership was particularly low among the MESA cohort compared with other mHealth measures. Physical inactivity is an important modifiable risk factor for CVD, and wearable fitness trackers can provide motivation, tracking, and accountability for increased regular physical activity.³³ Although many currently available fitness trackers are targeted at a younger population, and older adults experience lower rates of fitness tracker ownership, recent studies composed of participants aged 60 years or older indicate that older adults are increasingly receptive to and gain health benefits from using a fitness tracker.^{34,35} Per the September 2019 guidance document on low-risk devices, the US Food and Drug Administration will not evaluate general wellness devices, including common fitness trackers such as the Fitbit and Apple Watch.³⁶ This is a reason for these devices being infrequently included in health care service and costs generally not covered by insurance companies. However, pilot programs suggest that not only patients, but also insurance companies, can benefit from integration of wearable fitness trackers into insurance plans.³⁷

Here, we saw that several demographic, socioeconomic, and cognitive characteristics were associated with fitness tracker ownership, indicating the presence of a digital divide for this mHealth technology. Specifically, there were lower odds of fitness tracker ownership for individuals who were older, male, Chinese, and of lower income groups, and higher odds of fitness tracker ownership for individuals with higher CASI score. The associations with age and male sex are in line with the findings in a previous study of Canadian adults with mean (SD) age 53.9 (16.7) years and free of CVD.³⁸ Men were less likely to own a fitness tracker but more likely to have internet access or a computing device. One possible explanation for this discordance could be that women were more interested and reported more active in seeking of health-related information.³⁹ However, these results may be false positives given that many statistical tests were performed, so additional analysis within different cohorts is needed. As fitness trackers become increasingly prevalent, hospitals, health systems, employers, and insurance companies should start addressing disparities in access to help close these gaps rather than exacerbate them.

Racial and Ethnic Disparities

In this analysis, we found racial and ethnic disparities in mHealth access measures despite the multivariable logistic regression model adjusting for SES in the form of annual income, education level, and health insurance status. Compared with White participants, Hispanic participants were less likely to have internet

access or own a computing device, Black participants were less likely to have internet access, and Chinese participants were less likely to have internet access or own a fitness tracker, although they were more likely to own a computing device. People of underrepresented racial and ethnic groups were less likely to have mHealth access even after adjusting for socioeconomic differences; one possible explanation comes from the marginalization-related diminished returns framework. Marginalization-related diminished returns refer to decreased health- or resource-related benefits of increased SES conferred to people of underrepresented racial and ethnic groups relative to White people. Diminished gains can be a result of a variety of social and structural factors, including but not limited to institutional and interpersonal racism, discrimination, segregation, and racial and ethnic differences in generational wealth.⁴⁰ Individuals who identify as people of underrepresented racial and ethnic groups may also experience higher stress as a result of efforts to increase their SES, which can contribute to diminished returns.⁴⁰ These factors may make it more difficult for people of underrepresented racial and ethnic groups to access or take advantage of resources that come with increased SES.⁴¹ However, because of a lack of data, current or previous occupations were not included in the regression model as SES indicators. Further investigation into racial and ethnic disparities in mHealth access despite adjustment for SES is needed to determine the cause of these disparities.

Health Insurance Disparities

In addition to mHealth devices being costly for individuals in lower income brackets, health insurance status may present another barrier to mHealth access. Health insurance companies such as UnitedHealthcare, Aetna, Qantas Assure, John Hancock, and Oscar Health have launched programs incorporating fitness tracking into their policies, but these programs are generally not targeted at Medicare, Medicaid, and lower-income patients.⁴² We found that even after adjustment for other SES metrics of education level and annual income, internet access varied by health insurance status. Participants paying for health care with Medicare, Medicaid, military/Veterans Affairs insurance, an insurance not listed, or without health insurance were less likely to have internet access than participants with HMO or private insurance. This result highlights the necessity for mHealth interventions established through all insurance companies, but especially through Medicare, Medicaid, or Veterans Affairs, to consider that payees may not have access to the internet and provide alternative options accordingly. The US Department of Veterans Affairs currently offers a Digital Divide Consult program that assists patients in accessing the internet

and a video-capable device.⁴³ The expansion of this program and creation of similar programs may be effective ways to bridge health insurance-related mHealth disparities. The emerging field of mHealth relies heavily on smartphone health applications and wearable health trackers that may require use of the internet to share data with a clinician.⁴² For patients without internet access to receive the same benefits of mHealth, they would have to be provided an alternative way to send data to clinicians. Possible options may be to direct patients to existing low-cost broadband programs^{44,45} or provide loaner smart devices with prepaid data plans.⁴⁶

Cognitive Ability Disparities

Lower level of global cognitive function has been presented as a key barrier for individuals, particularly those within older populations, to use mHealth devices.⁴⁷ Because participants with higher cognitive function scores had increased levels of internet access, computing device ownership, and fitness tracker ownership, independent of older age and all other demographic and socioeconomic characteristics, targeted solutions are needed to increase mHealth access among individuals with lower cognitive function scores. In recent years, there has been an increasing number of mHealth technologies available to people with cognitive decline and their caretakers; access to the internet, computing devices, and fitness trackers should be considered when developing or implementing these mHealth interventions.⁴⁸ One option is to direct individuals with lower cognitive function or vision impairment to devices designed specifically for older adults.⁴⁹

Strengths and Limitations

This study is one of the first to evaluate the prevalence of mHealth access in a large cohort of older adults who self-identified as one of 4 racial and ethnic groups. The MESA includes detailed assessments of potential predictors as well as confounders of potential associations. It is notable that this study focused on older adults and people of underrepresented racial and ethnic groups, populations that are at greater risk for CVD^{19–21}; in particular, participants had a mean age of >75 years. Analyzing a large, multiethnic cohort of older adults provided insight into the potential for mHealth to aid in CVD prevention, as well as highlighting the need to consider demographic, socioeconomic, and cognitive characteristics when implementing mHealth interventions. The in-person and telephone questionnaires were administered in the participant's preferred language to avoid erroneous data caused by a language barrier.

As a cross-sectional analysis, the study was limited in being unable to provide causal inferences; only prevalence, not incidence, of mHealth access was investigated. Additionally, some annual family income data

were retrieved from the first wave of exams in 2010 to 2012, whereas the remainder of the data were collected in 2016 to 2018. Similarly, because CASI was administered as part of ancillary studies, just under half of CASI scores were obtained in 2010 to 2012, whereas the remainder were collected in 2016 to 2018. It is possible some participants experienced a change in annual income or level of cognitive function within this range of 4 to 8 years. When restricting analysis to participants who had CASI scores in 2016 to 2018 only, the results were qualitatively the same. The study was susceptible to selection bias, because only about 40% of participants from the baseline exam participated in the follow-up phone call on mHealth and were included in the final analysis. In particular, it was susceptible to survival bias, because 1788 of the 3866 participants were excluded because they were deceased and did not complete the mHealth phone survey. Additionally, compared with the full sample of participants excluded from the analysis, the group of participants included were younger, more likely to be women, White, and Chinese participants, and had an overall higher level of education. Because the sample included was younger than the excluded group, this analysis may have overestimated the percentage of mHealth access, and findings of demographic, socioeconomic, and cognitive associations may have been affected. The mHealth survey was administered over the phone, so it is possible that a lower percentage of nonresponders owned a computing device, a category that includes smartphones, compared with those who participated in the survey. The data may also have been skewed by self-reporting bias, because all demographic and socioeconomic characteristics, as well as the three mHealth access measures, were determined using in-person and phone questionnaires. Mental health status including depression may also influence the accessibility of mHealth. However, lacking depression measures chronologically close to the mHealth survey prevented us from assessing the impact on association estimates. Because our study did not directly analyze the impact of mHealth on clinical outcomes, and we make the assumption that mHealth could have a positive impact on cardiovascular health based on existing literature, we cannot rule out potential negative effects such as sedentary behavior or anxiety. In particular, it is possible that spending more time accessing the internet or using computing devices could lead to less time spent being physically active.

Future research should aim to further elucidate the digital divide by considering specific types of computing devices (eg, smartphone, laptop, desktop, tablet) and fitness trackers (eg, smartwatches, wearable activity trackers) owned. Studies including additional survey questions may also distinguish between mHealth access and uptake, which includes frequency and quality of use. Because the prevalence of technology

use in the United States is continually increasing, but older adults generally have lower rates of use, further insight may be gained from longitudinal studies that evaluate mHealth uptake over time.

Important demographic, socioeconomic, and cognitive characteristics were associated with internet access, computing device ownership, and fitness tracker ownership, indicating the presence of a digital divide. In general, populations with higher prevalence of CVD risk factors also had lower access to mHealth technology. Understanding the digital divide is essential to guide future policies and programs to address it, and to reach their full potential in CVD care, mHealth interventions should consider individual barriers to access.

ARTICLE INFORMATION

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Affiliations

Krieger School of Arts and Sciences, Johns Hopkins University, Baltimore, MD (R.J.S.P.); Division of Cardiology, Department of Medicine, Ciccarone Center for the Prevention of Cardiovascular Disease, Johns Hopkins University School of Medicine, Baltimore, MD (J.D., F.A.M., M.J.B., W.S.P., S.S.M.); David Geffen School of Medicine at UCLA, Los Angeles, CA (R.S.); and Department of Medicine, Larner College of Medicine at the University of Vermont, Burlington, VT (T.B.P.).

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Disclosures

Under a license agreement between Corrie Health (a mobile health technology company) and the Johns Hopkins University, the University owns equity in Corrie Health and the University, and Dr Marvel and Dr Martin are entitled to royalty distributions related to the technology. Additionally, Drs Marvel and Martin are founders of and hold equity in Corrie Health. This arrangement has been reviewed and approved by Johns Hopkins University in accordance with its conflict of interest policies. Outside of this work, Dr Martin also reports consulting fees for serving as a scientific advisor to Amgen, AstraZeneca, Dalcor, Esperion, iHealth, Kaneka, Novartis, Novo Nordisk, Sanofi, and 89bio, and research support from Amgen, Apple, and Google. The remaining authors have no disclosures to report.

Supplemental Material

Tables S1–S2

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SUPPLEMENTAL MATERIAL

Table S1. Categorization of Family Income, Education Level, and Health Insurance For Analysis.

Data collection categories	Data analysis categories
Family income	
Less than \$5,000	
\$5,000-\$7,999	
\$8,000-\$11,999	
\$12,000-\$15,999	
\$16,000-\$19,999	
\$20,000-\$24,999	Less than \$50,000
\$25,000-\$29,999	
\$30,000-\$34,999	
\$35,000-\$39,999	
\$40,000-\$49,999	
\$50,000-\$74,999	
\$75,000-\$99,999	
\$100,000-\$124,999	Greater than or equal to \$50,000
\$125,000-\$149,999	
Greater than or equal to \$150,000	
Education	
No schooling	
Grades 1-8	Less than high school
Grades 9-11	

<p>Completed high school/General Educational Development (GED)</p> <p>Some college but no degree</p> <p>Technical school certificate</p> <p>Associate degree</p> <p>Bachelor's degree</p> <p>Graduate or professional degree</p>	<p>High school graduate</p> <p>Some college</p> <p>Bachelor's degree or more</p>
Health insurance	
<p>Health Maintenance Organization (HMO)</p> <p>Private insurance</p> <p>Medicare</p> <p>Medicaid</p> <p>Military/Veterans Affairs (VA)</p> <p>None</p> <p>Other</p>	<p>HMO/private</p> <p>Other</p>

Table S2. Multivariable Logistic Regression Model for Association Between mHealth Outcomes and Demographic, Socioeconomic, and Cognitive Characteristics.

	Adjusted* internet access OR (95% CI)	P Value	Adjusted* computing device [†] OR (95% CI)	P Value	Adjusted* fitness tracker [‡] OR (95% CI)	P Value
Age						
Age per 10 year increase	0.37 (0.32-0.43)	<0.001	0.39 (0.34-0.45)	<0.001	0.59 (0.48-0.72)	<0.001
Sex						
Female (reference)	1.0		1.0		1.0	
Male	1.32 (1.05-1.66)	0.02	1.31 (1.05-1.63)	0.02	0.70 (0.49-0.89)	0.007
Race and ethnicity						
White (reference)	1.0		1.0		1.0	
Black	0.64 (0.47-0.86)	0.003	0.81 (0.61-1.09)	0.2	1.05 (0.71-1.52)	0.8
Hispanic	0.61 (0.44-0.85)	0.004	0.69 (0.50-0.95)	0.02	0.69 (0.41-1.14)	0.2
Chinese	0.63 (0.44-0.91)	0.01	1.87 (1.28-2.77)	0.001	0.59 (0.38-1.17)	0.2
Family income						
≥\$50,000 (reference)	1.0		1.0		1.0	
<\$50,000	0.55 (0.43-0.70)	<0.001	0.54 (0.42-0.69)	<0.001	0.62 (0.43-0.86)	0.006
Education						
Bachelor's degree or more (reference)	1.0		1.0		1.0	

Some college	0.64 (0.49-0.85)	0.002	0.73 (0.55-0.97)	0.03	0.92 (0.65-1.29)	0.6
High school graduate	0.33 (0.24-0.45)	<0.001	0.42 (0.30-0.57)	<0.001	0.69 (0.39-1.15)	0.2
Less than high school	0.27 (0.18-0.40)	<0.001	0.32 (0.28-0.62)	<0.001	0.52 (0.19-1.22)	0.2
Health insurance						
HMO/private (reference)	1.0		1.0		1.0	
Other	0.59 (0.47-0.74)	<0.001	0.86 (0.69-1.07)	0.1	1.03 (0.76-1.40)	0.8
Cognitive ability						
CASI score per 5 point increase	1.27 (1.16-1.38)	<0.001	1.29 (1.19-1.40)	<0.001	1.22 (1.05-1.42)	0.01

**The model was adjusted for all demographic, socioeconomic, and cognitive characteristics, as well as a confounding variable, general health status. HMO stands for Health Maintenance Organization. CASI stands for Cognitive Abilities Screening Instrument.*

†Computing device includes smartphone, laptop, desktop, and tablet.

‡Fitness tracker includes Fitbit, Apple Watch, and similar devices.